Essays in Labor Economics

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vorgelegt von
Cosima Obst, M.Sc.
geboren am 11.05.1991 in Köln
wohnhaft in Berlin

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Dissertation

Cosima Obst

Erstgutachter: Prof. Dr. Marco Caliendo

Zweitgutachterin: Prof. Dr. Lisa Bruttel

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Potsdam, May 2022 Cosima Obst

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Chapter 1

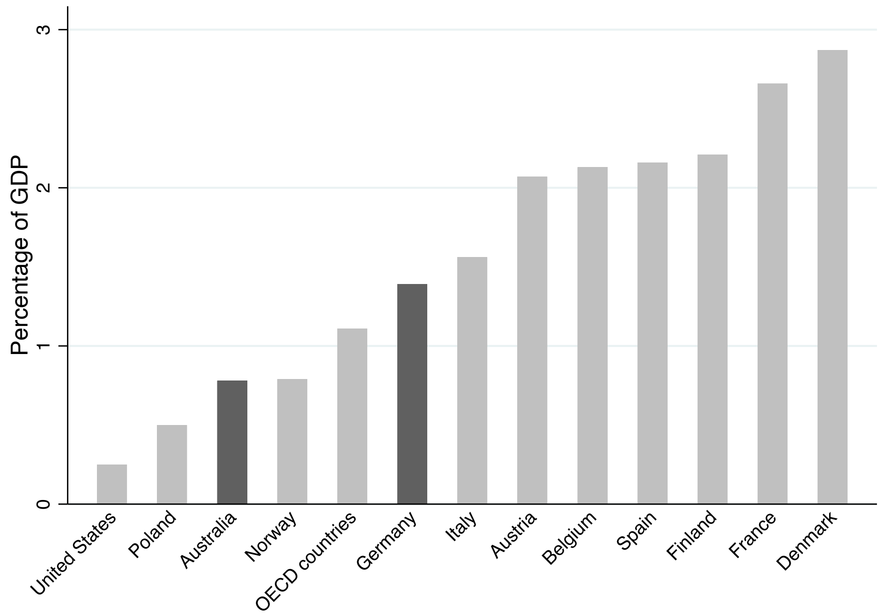
Introduction

1.1 Motivation

Labor Market Policies (LMP) have gained popularity in many countries as they lend themselves to targeted interventions in many areas of the labor market and the integration therein (Auer and Leschke, 2005; Crépon and Van Den Berg, 2016). Many policies, such as employment incentives and public job creations, focus on the re-integration of the unemployed (Brown and Koettl, 2015). However, various LMPs are targeted at maintaining and enhancing the employability of the working population. For instance, parental leave and child care opportunities aim at encouraging the compatibility of families and careers (Olivetti and Petrongolo, 2017), minimum wages are implemented in many countries to prevent the poverty of low-income workers (International Labour Office, 2020), and short-time work regulations attempt to shield workers from widespread shocks (Boeri and Bruecker, 2011). All three examples are targeted at supporting or protecting the working population. Other policies are targeted at certain groups, such as start-up subsidies for unemployed (Caliendo, 2016; Caliendo and Künn, 2011), and supported employment for individuals with reduced capacities to work (Morgan McInnes *et al.*, 2010). Finally, the literature distinguishes between active and passive LPM (Auer and Leschke, 2005), where conditions are tied to the schemes (e.g. spending regulations) in the former and no conditions are imposed in the latter type (e.g. minimum wage for the entire working population).

Due to the diversity and flexibility, LMP depict an attractive manipulation of the labor market. Figure 1.1 demonstrates the share of gross domestic product (GDP) allocated to LMP expenditures across various countries in the year 2018.[1] On average, OECD countries are seen to invest roughly 1.1% of their national GDP into LMPs. Both Germany and Australia – which receive much attention in this dissertation – display similar levels of expenditure with 1.4% and 0.8% of their respective national GDP. However, across different countries there are sizeable differences: The USA invest the least with 0.25%, where Denmark takes the lead with almost 2.9%.

Figure 1.1: Total Expenditure on Labor Market Programmes
Percentage of GDP in 2018



Source: OECD (2022), "Labour market programmes: expenditure and participants", last accessed on 21 March 2022.
Notes: The figure shows the total expenditure for active and passive labor market programmes in percent of the GDP for selected OECD countries in 2018. The year 2018 was chosen as this is the last year which did not include any programs in response to the Covid-19 pandemic.

The high levels of expenditures lend weight to the international repute of LMPs, but also calls for a profitable cost-benefit analysis of implemented LMPs. For this, two points are pivotal. First, before implementing a policy, it is vital to have a good understanding of the status quo: Which disadvantageous situation arises in the labor market and, importantly,

[1] 2018 is the last year which did not include programmes in response to the Covid-19 pandemic. Information provided for the year 2019 includes expenditures from early 2020, see OECD (2022).

which mechanisms evoke this issue? Comprehension of the underlying relationships gives way to provide well informed policy recommendations and, thus, implement suitable LMPs. Second, once LMPs are implemented, a thorough evaluation of their effectiveness is required: it is central to examine whether the implemented LMP is successful in achieving its original objectives. Additionally, potential unintended side effects (e.g. spillover-effects) ought to be assessed as well. The importance of the evaluation of LMPs has also been recognized in politics. For instance in Germany, the evaluation of LMPs has found root in the law which states that the effects of such policies are to be examined regularly and in a timely manner.[2] The feedback from regular monitoring is invaluable and can be utilized to determine the continuation of the programs (Auer and Leschke, 2005). Taking such evaluation results into account, some policies are adjusted to improve the results (e.g. the minimum wage in Germany, Mindestlohnkommission, 2016, 2018), while others are abolished (e.g. job creation schemes in Germany, Hujer *et al.*, 2004; Caliendo *et al.*, 2008).

This thesis contributes to the literature on both aspects discussed above: First, I analyze potential mechanisms behind investments in work-related training. Understanding such mechanisms can provide insights on how to increase the take-up rate of training courses, potentially with LMPs. Specifically, I aim at shedding light on how the personality and attitudes of workers might contribute to under-investments in work-related training. Second, I take a close look at the introduction of the minimum wage in Germany in 2015 and evaluate which effects this policy had on different aspects of the labor market. In sections 1.2 and 1.3, I motivate the importance of training investments and of the minimum wage introduction, respectively. Afterwards in section 1.4, I provide an overview of the main thesis chapters.

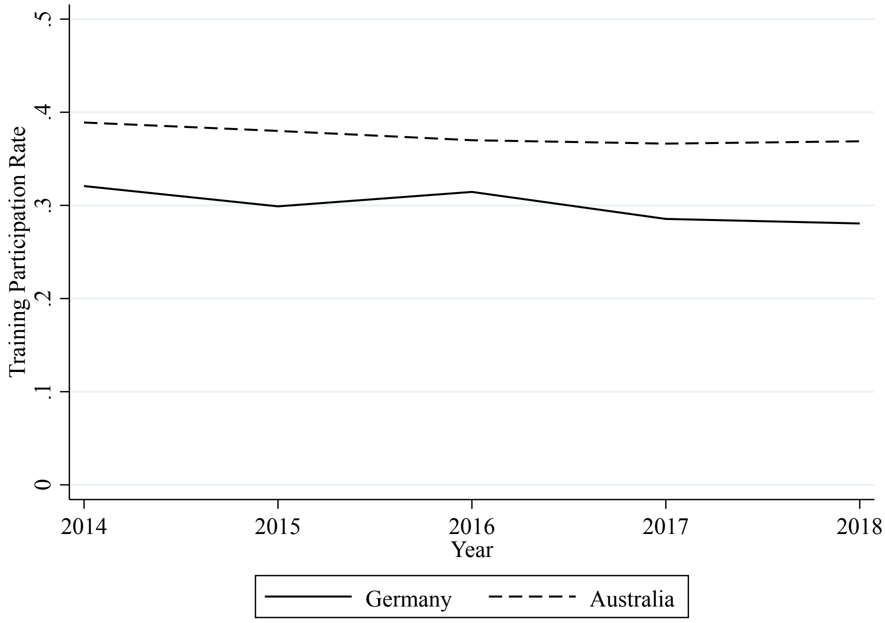
1.2 Work-Related Training

The labor market experiences everlasting changes. For instance, firm's production processes are regularly adapted due to technological advancements and globalization. Changes in such processes, e.g. through the introduction of new soft- or hardware, inevitably demand for new skills of the workers and renders others obsolete. In the wake of changes in the skill demand, workers are required to regularly update their skill set in order to stay relevant

[2] SGB II, §55, `https://www.gesetze-im-internet.de/sgb_2/__55.html`, last accessed on 14 March 2022.

in the labor market, effectively calling for lifelong learning for the employed population. This notion puts the spotlight on the usefulness of work-related training. A large body of literature focuses on the returns to training and draws an overall consistent picture of training being effective: Participation in work-related training has been associated with higher worker performances (Bartel, 1995), wages (Frazis and Loewenstein, 2005; Haelermans and Borghans, 2012), promotion chances (Pergamit and Veum, 1999; Melero, 2010), job security (Büchel and Pannenberg, 2004), and increased firm productivity (Konings and Vanormelingen, 2015; Dearden *et al.*, 2006). Consequently, governments and organizations recognize the importance of lifelong learning and aim at encouraging participation in education and training (International Labour Organization, 2008; European Commission, 2010).

Figure 1.2: Training Participation Rates by Year for Germany and Australia



Source: Socio-Economic Panel (SOEP), data for years 2014-2018, version 35, SOEP, 2019, doi:10.5684/soep.v35. The Household, Income and Labour Dynamics in Australia (HILDA), data for years 2014-2018, general release 19, HILDA, 2020, doi:10.26193/3QRFMZ. Own calculations.
Notes: The figure shows the training participation rates for Germany (solid line) and Australia (dashed line) in the timeframe 2014-2018. The population of interest is the employed population aged 25-60.

However, training participation rates have been observed to be rather low. Exemplary, Figure 1.2 depicts the participation rates for Germany and Australia over the years 2014-

2018. From the working population aged 25-60, the share remains consistently beneath 40% for both countries. This in turn implies that in each year over half of the working population does not engage in training and are at risk of being left behind. As a result, it is of interest to consider the implementation of LMPs which could potentially increase the take-up rate of work-related training.

To identify effective policy recommendations it is pivotal to identify the workers who choose not to invest into training and shed light on the underlying mechanisms and reasons behind their lack of participation. Only then is it possible to address the cause of under-investments and successfully motivate the workers to invest into lifelong learning. In this sense, multiple studies analyze the determinants of training participation taking into account the characteristics of the worker as well as of the firm and job. For instance, younger and educated workers are observed to receive more training (Weaver and Habibov, 2017; Bassanini *et al.*, 2007), and workers with temporary contracts and in smaller firms are associated with less training (Maximiano, 2012; Oosterbeek, 1996). Importantly, workers who do not invest (e.g. the less educated) would receive comparably high returns (Blundell *et al.*, 1999; Bassanini *et al.*, 2007), which potentially compounds the existing skill differentials.

The previous literature has left the role of non-cognitive skills, preferences, and attitudes in the training context widely undiscussed. However, it is conceivable that such traits influence the expectations regarding the training investments and their returns, and, thus, play an important role in the training investment decision. Consequently, the first part of this dissertation focuses on three non-cognitive traits of the worker, namely the personality trait locus of control, risk preferences, and the satisfaction with the job. I aim at understanding whether these traits have an influence on the investment decision and which potential mechanisms drive these relationships, in order to derive first policy recommendations. In chapter 1.4, I provide motivations for the relevance of these traits in the context of training investments.

1.3 The Minimum Wage in Germany

A minimum wage is an LMP that is utilized in many countries with the primary goals of protecting workers from poverty and potentially reducing inequality among the work force

(International Labour Office, 2020). In January 2015, Germany introduced their statutory national minimum wage. The minimum wage stipulates that workers earn at least €8.50 per hour.[3] Specifically, this minimum wage applies to actual working hours which includes overtime. Importantly, the minimum wage was introduced nationally, resulting in almost all German workers being eligible. Exemptions apply to minors, trainees, interns, volunteers, and long-term unemployed (compare MiLoG §22). Additionally, the sector-specific minimum wages that had been in place prior held precedence: A transition period was granted for those sectors with a minimum wage below the national €8.50 until 2017 (see MiLoG §23). Nevertheless, the minimum wage affected the vast majority of the population. Additionally, the level was set quite high: based on various data sources and definitions of the population of interest, the share of eligible employees who did not receive the minimum wage prior to its introduction is estimated to be up to 16% and varies significantly by subgroups, such as by region, gender, and employment status (Falck *et al.*, 2013; Kalina and Weinkopf, 2014; Lesch *et al.*, 2014; Amlinger *et al.*, 2016).

Prior to the introduction, a debate on the effectiveness of the minimum wage ensued. Advocates saw the opportunity to protect workers from poverty with this lower bound in hourly wages, to stabilize the social security system, reduce inequality, and even strengthen social cohesion (Bosch, 2007; Kalina and Weinkopf, 2014; BMAS, 2014). International experiences are seen as guidance to successful minimum wages: In the UK, little to no effects were found on employment which can potentially be explained by productivity increases of the low-income workers (e.g. through training) in anticipation of the minimum wage (Metcalf, 2008). However, comparing Germany to other countries might prove difficult because the comparably high level and the eligibility of almost the entire population sets Germany in a unique situation (Caliendo *et al.*, 2019b). Importantly, multiple opponents warned about the risk of substantial negative employment effects (Knabe *et al.*, 2014; Müller and Steiner, 2010, 2011), but also about decreases in social welfare (Bachmann *et al.*, 2014), and increases in black labor (SVR, 2013).

In the wake of this ex-ante discussion, the evaluation of the minimum wage introduction is key. Valuably, the Minimum Wage Commission was formed, which holds the obligation to analyze the effects of the minimum wage on the labor market and to re-evaluate the level

[3] MiLoG, `https://www.gesetze-im-internet.de/milog/`, last accessed on 17 March 2022.

of the floor regularly (MiLoG §9). In this light, the second part of this dissertation assesses the effects of the minimum wage introduction on (i) the hourly wages and monthly earnings and (ii) the working hours of the low-income workers. I aim at identifying positive as well as negative effects of this severe intervention in the labor market. These analyses belong to the first to provide causal evidence based on post-reform data.

As a final note, since the introduction, the minimum wage has been increased incrementally (to €8.84 in 2017, €9.19 in 2019, €9.35 in 2020 Mindestlohnkommission, 2016, 2018) in reaction to a series of evaluations of the Minimum Wage Commission. These increases are not the focus of this dissertation.[4]

1.4 Outline and Contribution

The main part of this dissertation consists of five empirical analyses, which can be divided into two parts. Chapters 2 to 4 aim at understanding the mechanisms of how personality traits and attitudes of the worker contribute to under-investments into training. Chapters 2 and 3 are based on papers that are published or currently under review and were written in co-authorship with Marco Caliendo, Deborah Cobb-Clark, Helke Seitz, and Arne Uhlendorff, while the fourth chapter is single-authored. Afterwards, chapters 5 and 6 aim at evaluating the minimum wage introduction in Germany in 2015 and its effects on the labor market. These two chapters are based on joint work with Patrick Burauel, Marco Caliendo, Markus Grabka, Malte Preuss, Carsten Schröder, and Cortnie Shupe, and are published in the *Journal of Economics and Statistics*. Table 1.1 provides an overview of the main chapters of this dissertation, their underlying papers, co-authors, and publication states.

[4] At the time of writing the chapters 5 and 6, data from the years 2017 onwards were not yet available. More recent studies also take the minimum wage increases into account (see e.g. Bachmann *et al.*, 2020; Koch *et al.*, 2020; Lubczyk *et al.*, 2020; Pestel *et al.*, 2020).

Table 1.1: Overview of Chapters

Chapter	Title	Co-Authors	Published Version
2	Locus of Control and Investment in Training	Marco Caliendo, Deborah A. Cobb-Clark, Helke Seitz, Arne Uhlendorff	Forthcoming in *The Journal of Human Resources* and IZA Discussion Paper No. 10406 Institut zur Zukunft der Arbeit, Bonn.
3	Risk Preferences and Training Investments	Marco Caliendo, Deborah A. Cobb-Clark, Arne Uhlendorff	Revise and Resubmit in *Journal of Economic Behavior* *& Organization* and IZA Discussion Paper No. 13828 *Institut zur Zukunft der Arbeit, Bonn.*
4	Job Satisfaction and Training Investments	-	Submitted at *Education Economics* and CEPA Discussion Paper No. 47 *University of Potsdam*
5	The Impact of the German Minimum Wage on Individual Wages and Monthly Earnings	Patrick Burauel, Marco Caliendo, Markus M. Grabka, Malte Preuss, Carsten Schröder, Cortnie Shupe	*Journal of Economics and Statistics* 240.2-3 (2020): 201-231.
6	The Impact of the German Minimum Wage on Working Hours	Patrick Burauel, Marco Caliendo, Markus M. Grabka, Malte Preuss, Carsten Schröder	*Journal of Economics and Statistics* 240.2-3 (2020): 233–267.

In the following, the motivations, research questions, contributions, and findings of each chapter are summarized.

Chapter 2: Locus of Control and Investment in Training

Behavioral choices depend on the perception of the causal link between one's own behavior and its consequences. This perception is measured by the personality trait locus of control (Rotter, 1966), which ranges from highly internal to highly external individuals. Individuals with an internal locus of control believe that control over their life lies internally with themselves: their life's outcomes depend on their own actions. In contrast, external individuals are convinced that life's outcomes depend on external factors such as luck, fate, and other people. The literature finds a strong link between an internal locus of control and labor market success, as it is central to investment decisions such as health (Cobb-Clark *et al.*, 2014), educational attainment (Coleman and Deleire, 2003), and job search (Caliendo *et al.*, 2015). Importantly, the literature links locus of control to their belief's about the returns to their investment, i.e. the return to the effort they exert. With higher expected returns, internal individuals are expected to have higher investment probabilities, e.g. into education (for an overview see Cobb-Clark, 2015). Consequently, this chapter analyses the role of locus of control in the work-related training investment decision and makes three main contributions.

The first contribution is our economic model of work-related training decisions which incorporates the worker's locus of control. We argue that locus of control enters the decision process via the expected returns of training; higher levels of an internal locus of control is associated with increased return expectations. Importantly, we expect the effect of locus of control to vary between training that is viewed as rather general in contrast to specific. Following Becker (1962), we link the transferability of skills with the distribution of net training returns, where the returns for the worker are higher when training is relatively transferable (general) than when it is not (specific). Consequently, we expect a positive link between locus of control and the expected returns as well as the probability of participating in general training, while there is no such link regarding specific training.

Our second contribution is the empirical testing of the hypotheses derived from our theoretical model. Using representative data from the Socio-Economic Panel (SOEP) in Germany, we check the relationship between locus of control and the probability of participating in training. Vitally, we consider the likelihood of participating in any type of training, more general, and more specific training. We find a strong positive relationship that is driven by general training, while no relationship is evident for specific training. We further show that our results are very robust, e.g. to changes of the definition of general and specific training. We conclude that the distinction between general and specific training is fundamental to understand the incentives of participating in training.

Finally, we provide further empirical evidence regarding the channel of locus of control by analysing the workers' expectations about the probability that they will receive a pay raise. While this is only an indirect measure of expected returns to training, we find for those who participated in general training that the probability of expecting a pay raise increases with internal locus of control. However, locus of control does not affect the expected pay raise for individuals who participated in specific training. In contrast, we do not find a dependency between locus of control and actual post-training wages. Overall, these findings imply that locus of control influences the expected returns to (general) training, while the actual returns are independent of locus of control.

Our results suggests that an external locus of control can contribute to an under-investment into work-related training. As locus of control links subjective beliefs about training returns to the training decision, informing external workers about the returns to training might be useful in increasing the motivation of external workers to participate.

Chapter 3: Risk Preferences and Training Investments

When considering investments into training, there are two types of risk that can impact the investment decision. First, the acquisition of human capital is risky due to the uncertainty about the returns (e.g. Williams, 1979; Levhari and Weiss, 1974). Second, updating skills can be seen as an insurance investment to reduce the risk of labor market shocks. In both cases, an individual is likely to take their risk preference into account. Individual attitudes towards risk have been recognized as important for the acquisition of human capital in the context of schooling and education (for an overview see Heckman and Montalto, 2018). Importantly, multiple studies find a negative association between risk aversion and schooling investments (Brown *et al.*, 2006) pointing towards schooling being viewed as a risky investment. Conversely, some studies find a positive relationship (Harrison *et al.*, 2007) which points towards the insurance motivation. Consequently, the question arises whether workers take their risk attitude into account in the context of training investments as well.

In this chapter, we contribute to the literature by proposing a theoretical model which incorporates the risk attitude of the worker in the training investment decision. We model the riskiness of the return to training via a probability with which the wage increases after participation while the costs of training are fixed. Additionally, the insurance mechanism is modelled by decreasing the likelihood of a job (and hence wage) loss after participating in training. If the investment risk of training dominates, our model predicts risk-averse workers to invest less. In turn, the pick-up rate is expected to be higher for risk-averse workers whenever the predominate role of training is the insurance against labor market shocks. Importantly, we follow Becker (1962) and argue that workers do not receive monetary returns to training if the new skills are not transferable to other firms. In this case, the zero-return to training relinquishes the risk associated with training. Consequently, we argue that the relationship between risk attitudes and training investment is driven by general rather than specific training.

As our second contribution, we turn to the data to check which of the two channels is dominant. Again, we use the SOEP in Germany and find evidence for a positive relationship between risk affinity and the likelihood of participating in training. This finding suggests that for the working population the riskiness of the training return is prevalent over the insurance benefits of training. Importantly, this result holds for (rather) general training, while we find no relationship between risk attitudes and the likelihood of investing into specific training. We strengthen our findings by demonstrating the robustness of our results regarding our modelling choices, e.g. with respect to the timing of our measures and the autonomy of the training decision.

Lastly, our third contribution relates to the underpinning mechanisms. We turn to subgroups of the labor force for which arguably one mechanism is likely to dominate the other. For instance, individuals with a temporary contract are more likely to place a larger value on the insurance mechanism. In contrast, individuals who are employed in sectors with highly variable wages likely face a higher investment risk for training. Indeed, we find that the strength of the relationship between risk attitudes and training investments depends on the context, as the riskiness of training is ubiquitous, while the insurance benefit is likely concentrated among certain subgroups, e.g. the recently unemployed.

These findings provide an understanding of how risk attitudes can influence the training participation decision. Subgroups that largely benefit from the insurance mechanism could be enlightened of such benefits to training. In contrast, risk averse individuals who prefer to not take on the risks of training could be encouraged to participate by informing them on the actual riskiness of training (if possible) or by covering (parts) of the costs (either by the firm or in the context of an LMP).

Chapter 4: Job Satisfaction and Training Investments

Previous literature finds that job satisfaction influences behavioral choices in the workplace which can impact the organizational functioning of firms (Verhofstadt *et al.*, 2003). Importantly, satisfied workers have been found to exhibit higher levels of organizational commitment and efforts to maintain their position, e.g. by working harder and shirking less

(Boles *et al.*, 2007; Clark *et al.*, 1998). However, it is not possible to ensure that a worker continuously experiences high levels of job satisfaction (Rusbult *et al.*, 1988). Consequently, it is of great importance to understand the consequences of job dissatisfaction. Psychologists categorize the behavioral reaction of workers to job dissatisfaction into (i) leaving the job (exit), (ii) improving the dissatisfactory situation (voice), (iii) remaining loyal to the firm and bearing the dissatisfaction (loyalty), and (iv) behaving disregardful and neglectful towards duties (neglect) (Farrell, 1983; Jodlbauer *et al.*, 2012). In this vein, a series of studies find a negative relationship between job satisfaction and labor turnover (see e.g. Clark *et al.*, 1998; Boswell *et al.*, 2005; Chen *et al.*, 2011), absenteeism (Hammer *et al.*, 1981), and error rates (Petty and Bruning, 1980). Consequently, this chapter analyses whether dissatisfied workers are willing to invest into job-related training.

The first contribution of this chapter is the theoretical model which incorporates job satisfaction into the training decision. Importantly, I argue that job satisfaction influences the potential non-monetary returns and costs of training. The non-monetary returns either arise from a point of satisfaction (e.g. the wish to take on new responsibilities) or from a state of dissatisfaction (e.g. the wish to be able to perform a certain task). The former is increasing in job satisfaction, the latter decreasing. Consequently, there is a U-shaped relationship between job satisfaction and the sum of non-monetary returns. Additionally, the non-monetary costs of training are negatively related to job satisfaction. This results in two potential scenarios: First, individuals react with the exit channel (intention to leave the job) or with the voice channel (intention to improve the situation). Here, the benefits outweigh the costs for rather dissatisfied workers, which results in an overall U-shaped relationship between job satisfaction and training investments. Second, individuals react with the neglect channel (disregard duties) as the costs outweigh the benefits. Here, an overall positive relationship between job satisfaction and training investments emerges.

It is an empirical question, which of the two scenarios is dominant. Hence, I turn to the Household, Income and Labour Dynamics in Australia Survey (HILDA) which provides rich information regarding both the training investments and job satisfaction across many years. As the second contribution, I take a close look at the functional form of the relationship between job satisfaction and training investments. The results point tentatively towards an overall positive relationship. This implies that on average the unsatisfied workers react with neglect and are less willing to invest into training. These findings remain stable across various robustness checks.

The third contribution focuses on the three different channels. Specifically, I aim at isolating the exit from the voice channel. This enables a simple comparison of the neglect channel with the exit and with the voice channel, respectively. I consider the aim of training which can give insight into the motivation and, thus, the channel behind the investment decision. Additionally, I check heterogeneities across quit intentions. Both analyses indicate that the exit channel is *less* dominated by the neglect reaction than the voice channel is.

Finally, I check whether there are heterogenous effects across different facets of job satisfaction (e.g. the satisfaction with pay). Indeed, here I find evidence that the voice channel gains importance in some domains. This emphasizes the complexity of the job satisfaction construct and the importance of taking the source of dissatisfaction into consideration as not all problems can be solved with training.

These findings suggest that on average dissatisfied workers are less willing to invest into training. It might be of benefit for firms to encourage their workers to voice their dissatisfaction in order to identify suitable steps to improve the situation, for example with training. However, due to the complexity of job satisfaction more research is required to give adequate policy recommendations.

Chapter 5: The Impact of the German Minimum Wage on Individual Wages and Monthly Earnings

The minimum wage introduction in Germany in 2015 poses a substantial intervention into the labor market. The goal was to increase the gross hourly wages of the low-wage workers. However, the high level of the minimum wage and the eligibility of almost the entire working population raised concerns about negative side effects such as job losses and a reduction in social welfare (Bachmann *et al.*, 2014; Knabe *et al.*, 2014). Consequently, a thorough evaluation of the effects of this minimum wage on various aspects of the labor market is appropriate. Hence, in this chapter, we analyze whether the main goal of the minimum wage was accomplished by identifying the impact of the introduction on the hourly wages and monthly earnings.

Our analysis belongs to the first evaluations which utilize post reform data as we exploit information on working hours and earnings in the SOEP to calculate hourly wages between 1998 and 2016. Our first contribution to the literature is an extensive descriptive analysis of changes in the wages. We present various approaches, such as graphical depictions of relative changes by wage decile and transition matrices between wage segments. Overall, we find a consistent picture of increased wage growths in the periods post minimum wage introduction. Importantly, we see a decrease in the share of individuals who earned less than €8.50 from 12% to 7% between 2014 and 2016. As the share was not reduced to 0%, we therefore present evidence of non-compliance with the minimum wage in the first 2 years after its introduction.

As a second contribution, we present causal evidence of the minimum wage on the hourly wage growth. Using differential trend adjusted difference-in-differences, we find a causal increase in the wage growth for individuals who earned less than €8.50 prior to the introduction both in 2015 and 2016, but not enough to ensure wages above the floor, again pointing towards non-compliance. We further check whether the overall economic situation of low-income workers could be improved by analyzing the monthly earnings. In 2015, no impact can be identified, raising the question whether the increased hourly wages were met with lower working hours. Nevertheless, an increase in monthly earnings are observed in 2016.

Our third contribution is constituted by additional analyses by employment type (due to varying incentives) and with respect to potential spillover effects. Indeed, we find strong heterogenous effects for marginally employed and between full- and part-time workers. Further, we find no evidence that individuals who earned slightly above €8.50 were directly impacted by the minimum wage pointing to no negative nor positive spillover effects.

In sum, our results provide evidence that the minimum wage was successful in increasing the growth of the hourly wages while the effect on monthly earnings was delayed. Further, the evidence suggests that the enforcement was lacking, as a large share of workers still received less than the wage floor in 2016.

Chapter 6: The Impact of the German Minimum Wage on Working Hours

Building on the previous chapter, we now turn to the effect of the minimum wage introduction in the hours worked. One of the main concerns about the minimum wage introduction, was the expected negative effect on employment (Knabe *et al.*, 2014; SVR, 2013). Consequently, the developments of employment in response to the introduction has received much attention in the literature showing either no (Ahlfeldt *et al.*, 2018) or negative effects (Caliendo *et al.*, 2018; Schmitz, 2017) on overall employment, i.e. on the "extensive margin". However, another potential side effect on employment is the "intensive margin" where the working hours of the employed may react to the minimum wage introduction. Therefore, we analyze the effect of the minimum wage on the working hours.

The main contribution of this chapter is the causal analysis of the working hours. We utilize the SOEP data for 2012 to 2016 and employ a simple difference-in-differences approach. Importantly, we first only consider workers subject to social security contributions. For those who received less than €8.50 prior to the introduction, we find a significant reduction in working hours in 2015. Importantly, this reduction is less sharp when considering actual rather than contractual working hours, suggesting that overtime has not changed due to the minimum wage introduction. Further, we find no reduction in the working hours over a two year period up to 2016. These findings are in line with those from chapter 5 as an increase in hourly wages with a simultaneous decrease in working hours resulted in constant monthly earnings in 2015. However, as the working hours did not continue to decrease in 2016, we see a slight increase in monthly earnings here.

As a second contribution, we take a closer look at marginally employed workers. Due to the exemption of social security contribution for jobs with an income up to €450 per month, marginally employed workers have a direct incentive to limit their monthly earnings to €450. Consequently, they are expected to reduce their working hours in reaction to the minimum wage introduction. Indeed, we find a stronger negative effect for this group, however, these results are statistically weak, most likely due to the limited number of observations.

Finally, we address two critical points of our analysis. For one, we provide evidence that our results are robust with respect to potential measurement errors. For another, we find no spillover effects on the working hours of those workers who earned slightly more than €8.50 prior to the introduction. Thus, we are reinforced that our results are causally interpretable.

Chapter 2

Locus of Control and Investment in Training*

Abstract

We extend standard models of work-related training by explicitly incorporating workers' locus of control into the investment decision through the returns they expect. Our model predicts that higher internal control results in increased take-up of general, but not specific, training. This prediction is empirically validated using data from the German Socio-Economic Panel (SOEP). We provide empirical evidence that locus of control influences participation in training through its effect on workers' expectations about future wage increases rather than actual wage increases. Our results provide an important explanation for underinvestment in training and suggest that those with an external sense of control may require additional training support.

2.1 Introduction

Globalization and technological change are rapidly transforming the workplace, generating demand for new skills while rendering other skills obsolete. Equipping workers with the ability to thrive in this changing environment has become a strategic imperative. National governments are working hard to facilitate continuous, lifelong investment in worker training in order to ensure that workers' skills remain up-to-date, firms continue to be com-

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petitive, and living standards are maintained. Training systems are also being touted as mechanisms for achieving social goals including reduced inequality, active citizenship, and social cohesion. The International Labour Organisation, for example, has an explicit goal of promoting social inclusion through expanded access to education and training for those who are disadvantaged (International Labour Organization, 2008, p. vi).

Work-related training, however, often compounds, rather than mitigates, existing skill differentials – potentially increasing social and economic inequality. In particular, workers with higher ability (as measured by aptitude scores), more formal education, and higher occupational status receive more work-related training than do their less-skilled coworkers.[1] This disparity is puzzling since less educated workers, in fact, receive relatively high returns from training (see Blundell *et al.*, 1999; Bassanini *et al.*, 2007) and firms appear to be equally willing to train them (Leuven and Oosterbeek, 1999; Maximiano, 2012). Underinvestment in training may arise for many reasons. There is extensive evidence, for example, that individuals often underestimate the returns to formal education and that the provision of information about those returns can result in increased investment (e.g. Nguyen, 2008; Jensen, 2010, 2012). Information gaps may be particularly severe in the training market because, although the return to education has been studied extensively, we know very little about the return to employment-related training (Haelermans and Borghans, 2012). Present-biased preferences can also lead individuals to invest less in training than if their preferences were time-consistent. Finally, individuals' soft skills (e.g. self-confidence, willingness to compete, intrinsic motivation, etc.) also influence the human capital investments that they make (Koch *et al.*, 2015). Developing a deeper understanding of what leads some workers to underinvest in training is fundamental to ensuring that work-related training systems have the potential to deliver social as well as economic benefits.

The aim of this paper is to advance the literature by adopting a behavioral perspective on the training investment decision. Specifically, we draw inspiration from Becker (1962) in developing a stylized model of the decision by firms and workers to invest in work-related education and training. Firms are assumed to have perfect information about the

[1] For reviews of the work-related education and training literature see Asplund (2005); Bishop (1996); Blundell *et al.* (1999); Bassanini *et al.* (2007); Leuven (2005); Wolter and Ryan (2011); Haelermans and Borghans (2012); Frazis and Loewenstein (2007). In particular, there is evidence that general education and employer training are often complements; more skilled workers participate in more training (e.g. Asplund, 2005; Bassanini *et al.*, 2007; Booth, 1991).

productivity of training and its degree of generality, while workers are instead assumed to have subjective beliefs about the returns to training. These beliefs depend on their locus of control. We then use this simplified two-period model to derive testable predictions about the influence that the degree of training generality has on the role of locus of control in training decisions.

Locus of control is a psychological concept that is best described as a "generalized attitude, belief or expectancy regarding the nature of the causal relationship between one's own behavior and its consequences" (Rotter, 1966). As people differ in the reinforcement that they have received in the past, Rotter argues that they will also differ in the degree to which they generally attribute reinforcement to their own actions and that these beliefs regarding the internal versus external nature of reinforcement constituted a personality trait.[2] Those with internal locus of control tend to believe that much of what happens in life is influenced by their own behavior, whereas those with external locus of control are more likely to believe that life's outcomes are driven by external forces, e.g. luck, chance, fate or others.[3] Given these psychological underpinnings, it is quite natural to link locus of control to human capital investments through the returns that individuals expect. Consequently, we allow locus of control to affect training participation through the influence it has on workers' subjective expectations about the relationship between training and future wage growth. Our specific interest in locus of control is motivated by the growing literature demonstrating its importance in many other human capital investment decisions including health (Cobb-Clark *et al.*, 2014), educational attainment (Coleman and Deleire, 2003; Jaik and Wolter, 2016), job search (Caliendo *et al.*, 2015; McGee, 2015), internal migration (Caliendo *et al.*, 2019a) and self-employment (Hansemark, 2003; Caliendo *et al.*, 2016). We are aware of two studies which link locus of control to job training. Fourage *et al.* (2013) find that Dutch workers with an internal locus of control have a higher self-reported willingness to train, while Offerhaus (2013) demonstrates that internal-locus-of-control German workers

[2]See also Ng *et al.* (2006) who note that "some people have a dispositional tendency to believe they have more control over the external environment than others" (p.1058).

[3]Over the years, psychologists have developed numerous typologies for characterizing people's personalities. One of the most frequently studied is the Big Five (Five Factor) model of personality traits – i.e., extraversion, agreeableness, conscientiousness, neuroticism (the opposite of emotional stability) and openness to experience – which is meant to represent personality at the broadest level of abstraction (see John and Srivastava, 2001). Locus of control is a separate personality construct. It is most closely related to the Big Five trait of neuroticism (Bono and Judge, 2003). Meta-analysis demonstrates that locus of control is comparable to the Big Five in predicting work outcomes (Ng *et al.*, 2006).

are more likely to participate in work-related, professionally organized training courses. Our research extends these previous studies by providing a theoretical foundation for – and empirical evidence of – the differential effect of locus of control on general versus specific training.

Specifically, our model predicts that internal-locus-of-control (hereafter "internal") workers will engage in more general training than their "external" coworkers because their subjective investment returns are higher. We expect little relationship between specific training and locus of control, however, because the returns to specific training largely accrue to firms rather than workers. We empirically test these predictions using data from the German Socio-Economic Panel (SOEP). Consistent with our model, we find that locus of control is related to participation in general but not specific training. Moreover, we find evidence that locus of control influences participation in general training through its effect on workers' expectations about future wage growth. Specifically, general training is associated with an increase in the expected likelihood of receiving a future pay raise that is much larger for those with an internal rather than external locus of control. However, we find no evidence that the wage returns to general training actually depend on locus of control when we analyze realized post-training wages. This suggests that workers are forming different subjective expectations – which depend on their locus of control – about the same underlying post-general-training wage distribution. Interestingly, locus of control is unrelated to realized wages and expectations about future wage increases in the case of specific training.

We make a substantial advance on the literature by formally incorporating locus of control into an economic model of work-related education and training, carefully accounting for the nature of training itself as well as for the role of firms and workers in the training decision. This allows us to analyze the channel through which locus of control operates and generate empirical predictions that can then be tested. We take a broad perspective on work-related education and training, considering both training that is offered by employers during work hours (i.e. on-the-job) and education taking place in external institutions outside work hours (off-the-job). This broad-brush approach demands that we consider the perspectives of both firms and workers in the training decision which adds complexity to our theoretical framework. At the same time, it also adds richness to the empirical analysis allowing us to assess the robustness of our results to alternative notions of general versus specific training.

Our research identifies a fundamental distinction – as yet unrecognized in the literature – in the role of locus of control in general versus specific training. Becker (1962) was the first to highlight the role of skill transferability in the allocation of training costs, arguing that, in competitive markets, firms are unwilling to pay for training that is completely transferable ("perfectly general"), while workers are unwilling to pay for training that is completely nontransferable ("perfectly specific"). Subsequent research demonstrates that this sharp bifurcation is blurred in the face of labor market rigidities, non-competitive market structures, and training that is both general and specific (see Acemoglu and Pischke, 1999a; Asplund, 2005; Frazis and Loewenstein, 2007, for reviews). Nonetheless, the conceptual link between skill transferability and the distribution of net training returns across workers and firms remains fundamental to understanding the incentives for training to occur. It is this conceptual link that is also at the heart of our finding that workers' perceptions of control will have a more profound effect on training investments if training is relatively transferable (general) than if it is not (specific). In short, workers' differential responsiveness to investment returns matters more if they can capture those returns than if they cannot. Crucially, this result does not depend on our simplifying assumption that markets are perfectly competitive. Instead, it is easily generalized to a variety of non-competitive environments in which greater skill transferability increases workers' ability to benefit from the training they receive (see Section 2.2.3).

The remainder of the paper is structured as follows. Our model of training is developed in Section 2.2, while the data are described in Section 2.3. In Section 2.4, we provide empirical evidence for the testable implications of our theoretical model. Our conclusions and suggestions for future research can be found in Section 2.5.

2.2 Theoretical Framework

2.2.1 Modeling the Training Investment Decision

We begin with a conceptual framework in which both workers and firms participate in the decision to invest in work-related training. Workers have an incentive to participate in training if that investment yields positive future returns. Although the returns to training can be conceptualized as positive effects on labor market outcomes in general, e.g. wages, performance, promotions, occupational status, etc., we focus specifically on wage returns in our model. Firms' decisions to invest in worker training rest on whether or not the investment results in increased productivity, measured in value added per worker.

We make a number of simplifying assumptions. Firms and workers are assumed to be risk-neutral, to face no liquidity constraints, and to maximize expected discounted profit and income streams, respectively. Both the labor market and product market are perfectly competitive and output prices are normalized to 1. In the first period ($t = 0$), the wage of worker i, w_{i0}, corresponds to his or her marginal revenue product (mP_L) which is the same in all firms. Training investments are joint decisions of worker i and firm f; they take place if the net present value of the training is non-negative for both the worker and the firm and if it is positive for at least one of them.

Let K capture the increase in productivity associated with training. The degree of generality of the training is given by γ which takes a value between 0 and 1. When $\gamma = 0$, training increases the productivity of worker i only at the current firm f. Following Becker (1962) we will refer to this as "perfectly specific" training. If training is "perfectly general", $\gamma = 1$ and the human capital embodied in the training is fully transferable to other firms, that is, the productivity of trained workers increases by K in all firms. We account for firms' asymmetric information with respect to production process and industry conditions, by assuming that the firm has perfect information about the training's productivity returns (K) and degree of generality (γ). In contrast, workers form expectations about their own returns to training which is given by the product of these two parameters (see Section 2.2.2).

The cost of training C is constant across workers.[4] Training costs are known to both workers and firms in period $t = 0$. The worker and the firm share training costs C in proportion to α which is exogenously given. In particular, the firm offers to pay $(1 - \alpha)C$ while the worker is left to pay αC.

In period $t = 0$, the worker and the firm decide whether or not to invest in training which has a given degree of generality γ. Let T_i take the value 1 if training occurs and 0

[4]We consider the scenario in which training costs include a stochastic component that is related to workers' characteristics, in particular their locus of control, in Section 2.2.3.

otherwise. Worker productivity in period $t = 1$ is given by $mP_L + KT_i$ in firm f and by $mP_L + K\gamma T_i$ in every other firm. Worker i stays at the current firm f in period $t = 1$ if his or her wage is equal to or greater than the potential wage offer at outside firms. Because the labor market is assumed to be perfectly competitive, there are no labor market frictions (e.g imperfect information, job changing costs, etc.) and workers can change employers without cost. In period $t = 1$, the worker will receive a wage offer of $mP_L + K\gamma T_i$ which corresponds to his or her marginal revenue product at outside firms. The current firm f will pay this competitive market wage. This implies that the returns to the training investment are $K\gamma T_i$ for the worker and $K(1 - \gamma)T_i$ for the firm.

Thus, as in Becker (1962), the worker is the residual claimant – and bears the full cost of training ($\alpha = 1$) – when training is perfectly general. If training is perfectly specific, on the other hand, the firm receives all returns from training and pays all training costs ($\alpha = 0$). In reality, however, training is unlikely to be either perfectly-specific or perfectly-general. Work-related training typically includes some components which may be specific to the current employer as well as other components which increase productivity both inside and outside the current firm.[5] In what follows, we incorporate locus of control into the training investment decision, allowing the degree of training generality to vary.

2.2.2 The Role of Locus of Control in the Investment Decision

We have assumed that the firm knows both the relationship between the investment in training and the resulting increase in productivity, K, as well as the degree to which the training can be utilized by outside firms, γ. These seem to us to be reasonable assumptions given that firms are in a position to know much more than workers about both their own production technology and the aggregate economic conditions in the wider industry. Together, these assumptions imply that the firm has perfect information about the worker's productivity in period $t = 1$, $K\gamma T_i$, if he or she undertakes training in period $t = 0$.

In contrast, workers do not have perfect information about the relationship between training investments and subsequent wage increases. We adopt a behavioral perspective on expectation formation by allowing workers' subjective beliefs about the return to training,

[5] Lazear (2009) in fact argues that firm-specific training does not exist. Instead, he views all skills as general implying that it is only the skill mix and the weights attached to particular skills that are specific to each employer.

$(K\gamma)^*$, to depend on their locus of control.[6] The concept of locus of control emerged out of social learning theory more than 50 years ago. In his seminal work, Rotter (1954) proposed a theory of learning in which reinforcing (i.e. rewarding or punishing) a behavior leads expectations of future reinforcement to be stronger when individuals believe reinforcement is causally related to their own behavior than when they do not. Because the history of reinforcement varies, Rotter argued that individuals will differ in the extent to which they generally attribute what happens to them to their own actions (Rotter, 1954). Individuals with an external locus of control do not perceive a strong link between their own behavior and future outcomes. Consequently, we argue that they are unlikely to believe that any training investments undertaken today will affect their productivity – and hence wages – tomorrow. Those with an internal locus of control, in contrast, see a direct causal link between their own choices (e.g. investment in training) and future outcomes (wages). Thus, although the true impact of training on future productivity and wages is assumed to be constant, more internal workers expect a higher wage return to their training investments.

We capture this dichotomy in our model by adopting the following multiplicative specification for the relationship between locus of control and subjective beliefs about investment returns:

$$(K\gamma)^* = K\gamma * f(loc) \tag{2.1}$$

where loc denotes locus of control; $f(loc)$ is both positive and increasing in internal locus of control; $\frac{\partial (K\gamma)^*}{\partial loc} > 0$.

Firms and workers have an incentive to undertake training whenever that training is expected to yield benefits that exceed the costs. Thus, a training investment occurs if the expected net present value of training is positive for either the firm and/or the worker and is non-negative for both. The value function of the firm depends on the true increase in firm-specific productivity, while the value function of the worker depends on his or her subjective beliefs about the returns to the training. We can write the expected net present

[6] Due to the multiplicative form of the returns to training, the predictions of our theoretical model are the same if we instead allow only K or only γ to depend on locus of control. With the data at hand, we cannot separately identify workers' expectations regarding K and γ making these models empirically equivalent.

values of the training for the worker $V_i(T)$ and the firm $V_f(T)$ as follows:

$$V_i(T) = \gamma f(loc)K - (1+\rho)\alpha C \tag{2.2}$$

$$V_f(T) = (1-\gamma)K - (1+\rho)(1-\alpha)C \tag{2.3}$$

where ρ is the discount rate.

Our model predicts that when training is at least partially transferable to outside firms, workers with an internal locus of control have a higher expected net present value from training and, consequently, are more likely to participate in training.

$$\frac{\partial V_i(T)}{\partial loc} = \gamma f'(loc)K > 0 \tag{2.4}$$

$$\frac{\partial V_f(T)}{\partial loc} = 0 \tag{2.5}$$

In contrast, firms' incentives to invest in training are unrelated to workers' locus of control.

Moreover, the effect of workers' locus of control on their incentives to invest in training depends on the degree of training generality. Specifically, an increase in the extent to which workers' have an internal locus of control results in a larger increase in their willingness to invest in training if that training is highly transferable (mainly general) than when it is not (mainly specific).

$$\frac{\partial^2 V_i(T)}{\partial loc \partial \gamma} = f'(loc)K > 0 \tag{2.6}$$

The intuition is straightforward. The more general the training, the larger the share of the training benefits that workers will be able to capture in the form of future wage increases. Thus, the more important are their expectations about those future benefits in driving their behavior. When training is largely firm-specific, workers will capture a much smaller share of the rents generated by training and their expectations regarding the benefits of training are less important.

In the limit, when training is perfectly specific ($\gamma = 0$), it is not transferable to outside firms and only the current firm benefits from the future increase in worker productivity. Therefore, as in Becker (1962), the firm will pay the full cost C of training the worker. The firm invests in training if the expected net present value of training to the firm is positive, i.e. if the discounted productivity gain in period $t = 1$ exceeds the training costs incurred in the first period $t = 0$. Given this, our model results in the prediction that investments in perfectly specific training will be independent of workers' locus of control. The decision to invest in perfectly specific training is driven solely by firms that have perfect information about the costs and benefits of worker training. On the other hand, when training is perfectly general ($\gamma = 1$), workers receive the full value of the productivity increase associated with training in the form of higher wages. Therefore, firms will be unwilling to share the costs of general training and workers will have to pay all training costs C. In this case, the investment decision effectively lies in the hands of workers. Specifically, participation in training will depend on whether workers expect their post-training productivity (and hence wage) to increase in present value by more than the cost of training. This, in turn, depends on workers' locus of control.

Empirical Predictions Baseline Model: Taken together, our model results in several empirical predictions. First, unless training is perfectly-specific and cannot be transferred at all to outside firms, workers with an internal locus of control will be more likely to participate in training. This differential in the training propensities of internal versus external workers increases with the degree of training generality. Moreover, we have assumed that locus of control influences worker expectations about the returns to training. We therefore expect a positive relationship between workers' internal locus of control and their expectations about future post-training wage increases. This relationship is predicted to be stronger for more general as opposed to more specific training (see equation 2.6). At the same time, because we have assumed that locus of control is unrelated to productivity, workers' actual post-training wages are predicted to be independent of their locus of control.

2.2.3 Model Extensions

In what follows, we consider whether our empirical predictions continue to hold if the key assumptions of our baseline model are relaxed.

Risk Aversion, and Biased Beliefs: It is important to note that our predictions do not depend on workers being risk neutral. Risk aversion would result in workers choosing not to invest in some training – despite it delivering positive expected benefits. This underinvestment in risky training is expected to be more extensive the more general training is, because workers' exposure to the costs and benefits of training increase the greater the degree of training generality. Expected wage gains are discounted because expected utility is lower as a result of the uncertainty (Stevens, 1999). Nonetheless, we still expect internal workers to be more likely to invest in general training than their external coworkers because they are more responsive to the potential benefits of training when they exist.

It is also interesting to consider the implications of our model for training investments when the true productivity payoff to training differs from workers' subjective beliefs about those payoffs. Specifically, workers may believe the returns to training are below the true returns (i.e. that $(K\gamma)^* < K\gamma$). In this case, our model implies that there will be under-investment in training. Moreover, the degree of underinvestment is more severe the more general is the training because workers' beliefs weigh more heavily in the investment decision. Workers' beliefs thus constitute a form of asymmetric information which can result in less investment than is optimal. Chang and Wang (1996) reach similar conclusions when modeling the asymmetry in information between the current and outside employers regarding the productivity of training.[7] At the same time, workers may instead be overly optimistic regarding the value of training leading to an over-investment in training. As before, our model predicts that the degree of inefficiency will be greater the more transferable is the training.

We know very little about whether people's cognitive biases are related to their locus of control. Those with an internal locus of control may, in fact, suffer from an "illusion of control" which psychologists define as an unjustified belief in the ability to control events that cannot be influenced in reality (see Langer, 1975). Consistent with this, Pinger *et al.* (2018) find that internally controlled people are more likely to search for patterns in random data and make inefficient investment choices by acting when doing nothing is the better option. An illusion of control could result in people being overly optimistic about the transferability of training, for example. Similarly, internal households invest in more risky assets in part because they perceive the risks of doing so to be lower (Salamanca *et al.*, 2020). Whether locus of control is also related to the miscalibration of investment returns through either overconfidence (underestimation of the variance) or optimism (overestimation of the mean)

[7] See Bassanini and Ok (2005) who review a number of training and capital market imperfections and co-ordination failures that also may give rise to under investment in training.

remains an open question which would benefit from future research.

Cost Sharing Rules, Labor Market Frictions and Market Structure: Becker's key insight regarding the role of skill transferability in driving the allocation of training benefits fundamentally relies on markets being perfectly competitive (Becker, 1962). Imperfect competition breaks the strict correspondence between wages and productivity; allowing firms to earn rents by paying wages that are lower than worker productivity. If the productivity-wage gap increases with the level of skills, a situation which Acemoglu and Pischke (1999a,b) refer to as a compressed wage structure, firms may find it profitable to pay for training even if it is general. Thus, in theory, a firm may pay for general training in a wide range of circumstances including if: i) it has monopsony or monopoly power (e.g. Stevens, 1994b; Acemoglu and Pischke, 1999a); ii) matching and search frictions exist (e.g. Acemoglu, 1997; Acemoglu and Pischke, 1999b; Stevens, 1994a); iii) information is asymmetric (e.g. Katz and Ziderman, 1990; Acemoglu and Pischke, 1998); iv) general and specific training are complementary (e.g. Stevens, 1994b; Franz and Soskice, 1995; Acemoglu and Pischke, 1999a,b; Kessler and Lülfesmann, 2006); or v) worker productivity depends on coworker skill levels (Booth and Zoega, 2000).[8] In line with these model extensions, there exist a number of empirical studies providing evidence that employers pay at least partly for general training (Leuven and Oosterbeek, 1999; Booth and Bryan, 2007, see for example). At the same time, Hashimoto (1981) develops a model in which firms and workers share the costs and benefits of specific training as a form of long-term commitment device to prevent costly job separations.

In our model, this implies that the proportion of training costs paid by workers (α) will depend – among other things – on the degree of skill transferability (γ). It is important to note, however, that although we assume α to be exogenous, the predictions from our baseline model are not dependent on a specific sharing rule for the costs. Irrespective of the cost sharing rule, we expect there to be a positive relationship between internal locus of control and participating in training, because the expected returns from training increase the more internal workers are, making it more likely that the benefits of training outweigh the costs (see equation 2.4).

Labor market frictions and market imperfections drive a wedge between worker pro-

[8]See Gersbach and Schmutzler (2012) for references on information asymmetries and complementarities.

ductivity and wages, implying that wages will be less than marginal revenue product. The key insights of our theoretical model remain unchanged in the face of noncompetitive markets, however, so long as wages continue to depend positively on worker productivity. In this case, human capital investments that raise productivity will also result in higher wages – although potentially to a lesser degree than when markets are perfectly competitive. Workers with a more internal locus of control will continue to have higher expected returns to their training investments than will their co-workers who are more external, leading them to be more willing to participate in training. Similarly, we expect the differential between internal and external workers to be apparent when we consider future wage expectations (consistent with our key model assumption), but not when we examine realized wage outcomes.

Training Costs, Productivity, and Locus of Control: Our model assumes that training costs (C) are constant. In reality, however, there are many reasons to believe that training costs might differ across workers in ways that may be related to their locus of control. Suppose training costs are given by the following: $C_i = c + \epsilon_i$ where ϵ_i captures some element of the training cost that is relevant only to workers' training decisions. Well-known barriers to financing human capital investments, for example, may lead some workers to be credit constrained, resulting in suboptimal levels of training (Acemoglu and Pischke, 1999a). Credit constraints are likely to be less binding, and hence the cost of financing training lower, for those with an internal locus of control because these individuals tend to have higher earnings (e.g. Anger and Heineck, 2010; Semykina and Linz, 2007; Groves, 2005) as well as more savings and greater wealth (Cobb-Clark *et al.*, 2016). If training costs are negatively related to locus of control, then it remains the case that we would expect workers with an internal locus of control to be more likely to invest in general training, but no more likely than their external co-workers to invest in specific training. Conditional on investing in training, expected and realized wage gains will be unrelated to locus of control because the increase in worker productivity is unrelated to locus of control.

We have also assumed that workers' locus of control affects their expectations about the returns to training rather than the returns themselves. However, there is evidence that internal workers have higher job turnover (Ahn, 2015). This shortens the period over which firms are able to re-coop their training costs and reduces the discounted present value of training investments for internal workers. While employers may not directly observe workers' locus of control, there is empirical evidence that they do form expectations about workers' chances of remaining in the job when making training decisions (see Royalty, 1996). Similarly, workers' beliefs about their future job separations will influence their expected returns to training. Those with an internal locus of control may be more likely to separate as a result of increased job search and higher migration propensities raising the value of general relative to specific training (Caliendo *et al.*, 2015, 2019a). Those with an internal locus of control are also more assertive during negotiations (Volkema and Fleck, 2012), implying that internal workers may be able to raise their own returns to training by negotiating lower training costs or higher post-training wages. Similar, there is ample evidence that internal workers enjoy more labor market success (see Cobb-Clark, 2015; Heywood *et al.*, 2017). This raises the possibility that locus of control is a form of "ability" which results in the productivity gains being larger for internal workers undertaking training. Taken together, these mechanisms imply that the relationship between training productivity and locus of control is theoretically ambiguous.

Nonetheless, we can investigate the plausibility of these alternative explanations by considering the way that training participation, expectations about future wage increases, and realized wages depend on locus of control. Specifically, if the firm's returns to training are lower when training internal workers, perhaps because of increased job turnover, then we would expect those workers with an internal locus of control to be less likely to engage in training. On the other hand, if having an internal locus of control conveys a productivity advantage to workers, we would expect a positive relationship between the incidence of training and internal locus of control. Higher subjective returns and higher actual returns are observationally equivalent with respect to training rates. However, we expect to see a link between locus of control and subjective returns reflected in expectations regarding future wage increases, while a link between locus of control and actual returns would be reflected in realized wage outcomes conditional on training.

Summary: The predictions of our baseline model continue to hold in the face of a range of model extensions. In effect, the link between skill transferability and the distribution of net training returns produces a positive interaction between workers' degree of internal control and the extent to which training is transferable. Internal workers will be more likely than their external co-workers to invest in training when it is transferable to other firms; internal and external workers will make similar training investments when it is not. We will now test these predictions against our data.

2.3 Data

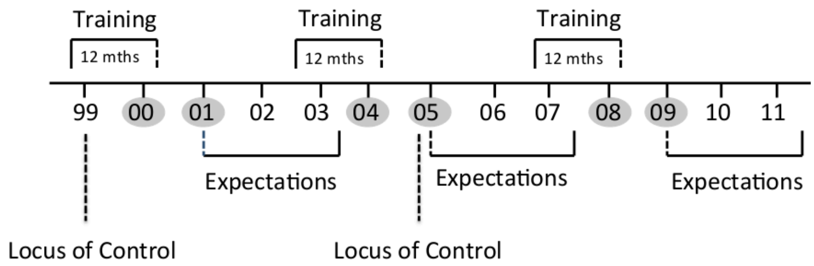
2.3.1 Estimation Sample

The data come from the German Socio-Economic Panel (SOEP), which is an annual representative household panel survey. The SOEP collects household- and individual-level information on topics such as demographic events, education, labor market behavior, earnings and economic preferences (e.g. risk, time, and social preferences). The first wave of the survey took place in 1984 with a sample size of approximately 6,000 households and 12,000 individuals. Over the subsequent 30 years, the SOEP sampling frame has been extended to the former German Democratic Republic and top-up samples of high-income and guest-worker households. The SOEP sample in 2013 comprised approximately 12,000 households and 22,000 individuals.

The SOEP data are perfectly suited for our purposes because in 2000, 2004 and 2008 detailed questions about training activities were included in the survey and locus of control was measured in 1999 and 2005. Moreover, in each subsequent year (2001, 2005 and 2009), the data contain information about individuals' subjective expectations regarding the likelihood of a future wage increase. Information about expected future wage increase conditional on training participation is helpful in assessing whether the link between locus of control and training participation operates through expected returns or productivity differentials. Figure 2.1 provides an overview of the data structure.

We restrict our sample to the working-aged population between the ages of 25 and 60. As we are interested in work-related training and not in training during phases of unemployment, we restrict our analysis to individuals who were employed at the time of training. We also exclude individuals who were self-employed at the time of interview. Finally, the sample is reduced by item non-response in the locus of control and other explanatory variables, resulting in a sample of 12,203 (7,411) person-year (unique individual) observations.

Figure 2.1: Description of the Data Structure



Source: Own illustration.
Notes: The figure gives an overview of the variables used from which data waves in the present analysis. We use the data waves from the years 2000, 2004 and 2008 in our analysis, as they contain information about the characteristics of training participated in. The variable measuring the participation in *training* refers to the three years prior to the interview date. However, we defined individuals as training participants if they report participation in training within the 12 months prior to the date of interview. Information about locus of control and wage expectations were not observed in our three data waves and therefore had to be imputed from other years. Information about *locus of control* are available in the years 1999 and 2005. Locus of control observed in the year 1999 was imputed in the data waves of the years 2000 and 2004, and we use the locus of control measured in 2005 in our last data wave. Wage *expectations* referring to the next following years are observed one year after each data wave and had to be backward imputed.

Of these, 4,120 individuals are observed once, while 1,790 and 1,501 individuals are observed two and three times respectively.

2.3.2 Training Measures

In 2000, 2004 and 2008, respondents under the age of 65 were asked about their engagement in further education over the three-year period prior to the interview. In particular, self-reports about the number of professionally-oriented courses undertaken along with detailed information (e.g. course duration, starting date, costs, etc.) about the three most recent courses are available. We define individuals to be training participants if they undertook at least one course within the 12 months prior to the respective SOEP interview.

Our theoretical framework highlights the importance of distinguishing between general training that is transferrable to other firms and training that is firm-specific. We do this using responses to the following question: *"To what extent could you use the newly acquired* *skills if you got a new job in a different company?"*. This allows us to construct a measure of general versus specific training that parallels the notion of skill transferability inherent in Becker (1962). Specifically, we categorize response categories *"For the most part"* and *"Completely"* as general training and response categories *"Not at all"* and *"Only to a limited extent"* as specific training. In 2004 and 2008, we have this information for up to three different courses, while in 2000 the skill-transferability question did not target a specific course. Consequently, we assume that in 2000 responses to this question pertain to the most recent training course undertaken. Using this definition, we identify 1,925 general-only training events, 1,081 specific-only training events and 159 events in which both types of training occurred within the preceding 12 months. Each of these training events corresponds to a person-year observation in our data. For the remaining 9,038 person-year observations, neither general nor specific training is reported.[9]

Information about the nature of general versus specific training is reported in Table2.1. The results in Panel A highlight the high degree of skill transferability embedded in the training that workers are undertaking. Fully, 42 percent of general training courses were rated by respondents as being completely transferable to jobs in different companies, while 58 percent were seen as being mostly transferable. In 73 percent of cases, respondents undertaking specific training believe that this training would have at least some limited transferability beyond their current employer. Only 27 percent view their newly-acquired skills as applicable only to their current firm and not at all useful in other companies.[10] At the same time, specific training is more likely to be convened by the employer, to be shorter, and to take place during work hours (see Panel B). Consistent with the previous literature (e.g. Booth and Bryan, 2007), we also find that the vast majority of employers do provide financial support for general training. At the same time, workers undertaking general training are significantly less likely to receive any financial assistance and pay significantly more for their training than do their coworkers undertaking specific training.

[9]Descriptive statistics for our dependent and independent variables are reported by training status in Appendix Table 2.8.

[10]We consider the robustness of our results to alternative definitions of general training as well as to the exclusion of the year 2000 in Section 2.4.4.

Table 2.1: Descriptives Course Characteristics

	(1) General Training	(2) Specific Training
Observations[a]	1,925	1,081
A. Transferability of Skills		
To what extend could you use the newly acquired skills if you got a new job in a different company?		
Not At All	0.00	0.27
Limited	0.00	0.73
To A Large Extent	0.58	0.00
Completely	0.42	0.00
B. Further Course Characteristics		
Total course duration (weeks)[b]	4.21	1.70***
Hours of Instruction every week	16.42	16.11
Correspondence course	0.04	0.04
What was the purpose of this instruction?		
Retraining for a different profession or job	0.01	0.00
Introduction to a new job	0.05	0.04
Qualification for professional advancement	0.25	0.14***
Adjustment to new demands in current job	0.76	0.79**
Other	0.10	0.13***
Did the course take place during working hours		
During Working Time	0.66	0.76***
Some Of Both	0.12	0.11
Outside Working Time	0.21	0.13***
Did you receive a participation certificate?	0.80	0.64***
Who held the course:		
Employer	0.43	0.61***
Private Institute	0.20	0.10***
Did you receive financial support from your employer?		
Yes, From The Employer	0.73	0.77*
Yes, From another Source	0.07	0.06
Dummy for no own Costs	0.84	0.89***
Own Costs	577.95	220.56***
Looking back, was this further education worth it for you professionally?		
Very Much	0.44	0.19***
A Little	0.38	0.55***
Not At All	0.07	0.16***
Do Not Know Yet	0.10	0.10

Source: Socio-Economic Panel (SOEP), data for years 1999 - 2008, version 33, SOEP, 2017, doi:10.5684/soep.v33, own calculations.
Notes: * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$.
[a] The number of observation of the presented survey question vary slightly due to item non-response. The 159 individuals who participated in both general and specific training within one cross-section have been excluded from the descriptives. In case individuals participated in more than one course (of the same type) within one cross-section, we took the information available of the most recent course.
[b] Own calculation, based on information of the length (days, weeks, months) of each course.

2.3.3 Locus of Control

Locus of control is measured in 1999 and 2005 using a series of self-reported items from the Rotter (1966) scale. Item responses in 1999 are reported on a four-point Likert scale ranging from *Totally agree* (1) to *Totally disagree* (4), while in 2005 a seven-point Likert scale ranging from *Totally disagree* (1) to *Totally agree* (7) is used. We begin by harmonizing our 1999 and 2005 locus of control measures by both recoding and stretching the 1999 response scale so that the response scales correspond in both years.[11] A description of each item and its corresponding mean can be found in Table 2.2 for both 1999 and 2005.

Table 2.2: Locus of Control Items 1999 and 2005

Variable	Wave 1999[a]	2005[b]
Observations	7,047	5,156
Components of locus of control (Mean, 1999 Scale: 1-4, 2005 Scale: 1-7)		
I1: How my life goes depends on me (I)	3.30	5.54
I2: Compared to other people, I have not achieved what I deserve (E)	2.08	3.12
I3: What a person achieves in life is above all a question of fate or luck (E)	2.19	3.39
I5: I frequently have the experience that other people have a controlling influence over my life (E)	1.99	3.04
I6: One has to work hard in order to succeed (I)	3.46	6.02
I7: If I run up against difficulties in life, I often doubt my abilities (E)	2.02	3.29
I8: The opportunities that I have in life are determined by the social conditions (E)	2.68	4.47
I10: I have little control over the things that happen in my life (E)	1.77	2.51

Source: Socio-Economic Panel (SOEP), data for years 1999 - 2008, version 33, SOEP, 2017, doi:10.5684/soep.v33, own calculations.
Notes: In both years, item 4 "If a person is socially or politically active, he/she can have an effect on social conditions" and 9 "Inborn abilities are more important than any efforts one can make" are not included in the prediction of the latent factor.
Items marked with (I)/(E) refer to internal/external items. External items are reversed prior to factor analysis in order to indicate an internal locus of control for high values.
[a] In 1999 the LoC was surveyed on a 4-point likert scale from 1 for "Totally Disagree" to 4 for "Totally Agree". The scale was reversed in the data preparation in order to indicate agreement for high values as it is also the case in the other wave of 2005. For later harmonization, the scale was stretched to the length of a 7-point likert scale.
[b] In 2005 the LoC was surveyed on a 7-point likert scale from 1 for "Disagree Completely" to 7 for "Agree Completely"

Following the literature (Piatek and Pinger, 2016; Cobb-Clark *et al.*, 2014), our measure of locus of control is constructed using a two-step process. First, factor analysis is used to identify two underlying latent variables (factors) interpretable as internal and external locus of control, respectively. This process isolates six items that load onto external locus of control and two items that load onto internal locus of control (see Figure 2.4(A) and 2.4(B)). Second, we reverse the coding of the response scale for the six external items so that higher values denote higher levels of disagreement. We then use all eight items to conduct a factor analysis, separately by year, in which a single latent factor is extracted. This process allows us to identify separate loadings (weights) for each item which are then applied in constructing a continuous index that is increasing in internal locus of control. To facilitate the interpretation of our results, we use a standardized index (mean = 0; standard deviation = 1) in our estimation models. The distribution of our continuous, standardized locus of control measure is shown in Figure 2.4(C) for the year 1999 and in Figure 2.4(D)

[11]Specifically, the original 1999 response scale is recoded as follows: 1 to 7; 2 to 5; 3 to 3; and 4 to 1.

for the year 2005.

We minimize concerns about reverse causality by relying on a pre-determined measure of locus of control in all of our analyses. When multiple measures are available, we choose the most recent since it provides the most accurate information on individuals' locus of control at the time training decisions are made. That is, 1999 measures of locus of control are used when analyzing the training outcomes reported in 2000 and 2004, while the 2005 locus of control measure is utilized in analyzing 2008 training outcomes.[12]

2.3.4 Expected Wage Increases, Realized Wages and Control Variables

In the survey waves immediately following the training module, i.e. in 2001, 2005, and 2009, the SOEP collected data on respondents' expectations regarding their future wage increases. Specifically, respondents were asked: *"How likely is it that you personally receive a pay raise above the rate negotiated by the union or staff in general in the next two years?"*. Responses are recorded in deciles, i.e. $0, 10, 20, ..., 100\%$. Those individuals who participated in general training in the previous wave have on average a higher expected probability of wage growth (22.4 percent) compared to their coworkers engaged in specific training (15.4 percent) or not participating in training at all (14.7 percent, see Table2.8). Moreover, those undertaking general training are more likely to expect at least some wage growth in the future. In Section 2.4.3, we analyze the relationship between training and subjective expectations about the likelihood of future wage increases for those respondents with an internal versus external locus of control in order to assess the potential for locus of control to influence training decisions through expectations about the returns to training. We also analyze the way that locus of control and training participation are related to realized gross wages in $t + 1$ in Section 2.4.3. General training participants (18.7€) earn on average more per hour than participants in specific training (17.7€) and non-participants (14.9€) (see Table 2.8).

Our analysis also includes an extensive set of controls for: i) socio-economic characteristics (age, gender, marital status, number of children, disability, educational attainment, household income and both employment and unemployment experience); ii) personality traits (i.e. the Big Five); iii) regional conditions (regional indicators, local unemployment rates, regional GDP, etc.); iv) job-specific characteristics (e.g. occupation, tenure, con-

[12] We consider the sensitivity of our results to alternative measures of locus of control in Section 2.4.4.

tract type, trade union/association membership, etc.); and v) firm-specific characteristics (firm size and industry). Most of our control variables are measured at the same time as training participation (2000, 2004, 2008). However, data on trade union/association membership and Big Five personality information is not collected in these years, requiring it to be imputed. Specifically, Big Five personality traits are imputed from 2005, while trade union/association membership data is imputed from 2001, 2003, and 2007.[13]

Many of these controls have been previously identified in the literature as important correlates of the decision to engage in training. The probability of receiving training increases with workers' educational level (Leuven and Oosterbeek, 1999; Oosterbeek, 1996, 1998; Bassanini *et al.*, 2007; Lynch, 1992; Lynch and Black, 1998; Arulampalam and Booth, 1997), for example, while older workers are less likely to participate in training compared to their younger coworkers (Maximiano, 2012; Oosterbeek, 1996, 1998). The evidence for a gender differential in the uptake of training is more mixed. Lynch (1992) finds that women are less likely to participate in training, while Maximiano (2012) and Oosterbeek (1996) find no gender difference and Lynch and Black (1998) find that women are more likely to participate in training. Unsurprisingly, training is also related to both job and firm characteristics. Maximiano (2012) and Oosterbeek (1996) find that workers with a permanent contract are more likely to receive training. Leuven and Oosterbeek (1999) instead find no significant differences of the type of working contract on training incidence, though contract type is associated with training intensity. Finally, workers in smaller companies have a lower probability of receiving training (see Maximiano, 2012; Lynch and Black, 1998; Oosterbeek, 1996).

Appendix Table 2.8 presents descriptive statistics – by training status – for all of the conditioning variables in our empirical analysis. Standard t-tests indicate that individuals engaging in either specific or general training are significantly different in many respects relative to their co-workers who do not participate in either form of training. In particular, training recipients are on average more educated, are less likely to be a blue collar worker, and have fewer years of unemployment experience.

[13]Details about the construction of these variables are available from the authors upon request.

2.4 Results

2.4.1 Estimation Strategy

Our objective is to estimate the relationship between workers' locus of control and their participation in general or specific training. Our theoretical model predicts that workers with an internal locus of control will engage in general training more frequently than their external co-workers because their expected subjective investment returns are higher. In contrast, we expect little relationship between specific training and locus of control because training returns largely accrue to firms rather than workers.

In what follows, we conduct three separate empirical analyses. We first estimate the relationship between training participation and locus of control (see Section 2.4.2). We then examine whether the evidence indicates that locus of control affects the training decision by influencing workers' expectations about future wage increases. Finally, we assess whether realized wages after training differ with respect to the locus of control (see Section 2.4.3). In Section 2.4.4, we report the results of a number of robustness tests.

We specify the probability of participating in training (T^j_{it}) as a logit model:

$$P(T^j)_{it} \quad = \quad \frac{\exp(\alpha_0 + \alpha_1 LoC_{i0} + \mathbf{X'_{it}}\boldsymbol{\alpha_2})}{1 + \exp(\alpha_0 + \alpha_1 LoC_{i0} + \mathbf{X'_{it}}\boldsymbol{\alpha_2})} \tag{2.7}$$

where i indexes individuals, t indexes time, and $j = (A, G, S)$ indexes training type (i.e. any, general, and specific training respectively). Each model pools observations from the waves 2000, 2004, and 2008 and controls for internal locus of control (LoC) as well as a vector ($\mathbf{X_{it}}$) of detailed measures of i) socio-economic characteristics; ii) personality traits; iii) regional conditions; iv) job-specific characteristics; and v) firm-specific characteristics (firm size and industry) (see Section 2.3.4). Recall that our measure of locus of control is predetermined at the time training occurs, minimizing concerns about reverse causality, while we account for a detailed set of controls in order to reduce the potential for unobserved heterogeneity to confound our estimates. The parameter of interest is α_1 which captures the impact of locus of control on the probability of participating in different types of training.

In addition, we model expectations regarding future wage increases (EWI_{it+1}) and observed hourly wages (W_{it+1}) in $t + 1$ as functions of training status, i.e. general training

($T^G{}_{it}$) or specific training ($T^S{}_{it}$) versus the base case of no training, and the interaction of training status with locus of control. Our estimating equations are given by the following linear regressions:

$$\begin{aligned} EWI_{it+1} &= \beta_0 + \beta_1 LoC_{i0} + \beta_2 T^G_{it} + \beta_3 T^S_{it} \\ &+\beta_4 LoC_{i0} \cdot T^G_{it} + \beta_5 LoC_{i0} \cdot T^S_{it} + \mathbf{X'_{it}} \boldsymbol{\beta_6} + \epsilon_{it} \quad (2.8) \\ \ln W_{it+1} &= \gamma_0 + \gamma_1 LoC_{i0} + \gamma_2 T^G_{it} + \gamma_3 T^S_{it} \\ &+\gamma_4 LoC_{i0} \cdot T^G_{it} + \gamma_5 LoC_{i0} \cdot T^S_{it} + \mathbf{X'_{it}} \boldsymbol{\gamma_6} + e_{it} \quad (2.9) \end{aligned}$$

We control for the same set of observed characteristics $\mathbf{X_{it}}$ as in equation (2.7). Here β_4 and β_5 reflect the relationship between the locus of control and expected returns to different types of training, while γ_4 and γ_5 capture potential differences in hourly wages depending on the locus of control after general and specific training; ϵ_{it} and e_{it} are the i.i.d error terms.

2.4.2 Participation in Training

We begin by using a binomial logit model to estimate the relationship between internal locus of control and participation in training. The results, i.e. marginal effects and standard errors, are reported in Table 2.3 for three alternative training outcomes: i) any training irrespective of type (Panel A); ii) general training (Panel B); and iii) specific training (Panel C). Individuals who participate in both types of training in the same year are included as participants in all three estimations.[14] In each case, we estimate a series of models increasing in controls. Column (1) reports the unconditional effect of locus of control on training participation while column (5) reports the effect of locus of control on training conditioning on our full set of controls (see Section 2.4.1).[15] Given the construction of our locus of control measure, the results can be interpreted as the percentage point (pp) change in training incidence associated with a one standard deviation change in internal locus of control.

[14] We test the robustness of our results to the exclusion of individuals who participate in both types of training in the same year in Section 2.4.4.

[15] Full estimation results are available in Appendix Table 2.9.

Table 2.3: Logit Estimation Results: Participation in Training on LoC (std.) (Marginal Effects)

	(1)	(2)	(3)	(4)	(5)
A. Training (Mean = 0.26)					
Locus of Control (std.)	0.044***	0.043***	0.024***	0.015***	0.014***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
B. General Training (Mean = 0.17)					
Locus of Control (std.)	0.041***	0.040***	0.028***	0.020***	0.017***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
C. Specific Training (Mean = 0.10)					
Locus of Control (std.)	0.008***	0.007***	0.000	-0.002	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Control Variables					
Locus of Control	✓	✓	✓	✓	✓
year, regional		✓	✓	✓	✓
socio-demographics			✓	✓	✓
job, firm				✓	✓
Big Five					✓
Observations	12,203	12,203	12,203	12,203	12,203

Source: Socio-Economic Panel (SOEP), data for years 1999 - 2008, version 33, SOEP, 2017, doi:10.5684/soep.v33, own calculations.
Notes: Full estimation results (including all control variables) are available in Table 2.9 in the Appendix. Standard errors are in parentheses and clustered on person-level. * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$.

Workers with an internal locus of control are more likely to engage in work-related education and training. Our unconditional estimate implies that each standard deviation increase in internal locus of control is associated with a 4.4 pp increase in the chances that a worker undertakes some form of training. Although the estimated marginal effect of locus of control on the incidence of training falls as we increasingly control for detailed individual-, regional-, job-, and firm-level characteristics, it remains statistically significant and economically meaningful. Specifically, in our full specification, we find that a one standard deviation increase in locus of control increases the probability of training taking place by 1.4 pp, which corresponds to an effect of almost 5.4 percent. This is consistent with previous evidence that having an internal locus of control is associated with both an increased willingness to engage in training (Fourage *et al.*, 2013) and higher rates of training (Offerhaus, 2013).

As expected, there is a particularly strong relationship between locus of control and the incidence of general training. Unconditionally, workers are estimated to be 4.1 pp more likely to engage in general training with each standard deviation increase in their internal locus of control. This effect is reduced by half to 2.0 pp once we control for year and regional fixed effects, socio-demographic characteristics and detailed job and firm characteristics (column

4). Controlling for individuals' Big Five personality traits results in a further reduction in effect size of approximately 15 percent (column 5). The resulting estimated effect (1.7 pp) corresponds to an effect size of roughly 10 percent; nearly double that associated with training overall. In contrast, the relationship between locus of control and specific training is both economically unimportant and statistically insignificant once socio-demographic characteristics are controlled. Failing to distinguish between alternative types of training masks this crucial distinction in the role of locus of control.

While we observe a substantial decrease in the estimated effect on participation in general training from column (1) to column (5), it is important to note that our data contain a very rich set of control variables, including detailed information about job and firm characteristics, as well as individual characteristics that are often not observed, like the Big Five personality traits. The evolution of the estimated effect from column (3) to column (5) can be interpreted as evidence that the relationship between locus of control and participation in general training is likely not driven by unobserved firm and individual characteristics. However, we will analyse the sensitivity of our results with respect to omitted variables following Oster (2019) in Section 2.4.4.

Taken together, these findings are consistent with the predictions of our theoretical model. A greater degree of internal control results in individuals being more likely to invest in training when it is transferable to other firms and having similar levels of investment when it is not.

2.4.3 Expected Wage Increases and Realized Wages

We turn now to investigating whether there is evidence that locus of control affects training decisions by influencing workers' subjective beliefs about training returns. Unfortunately, we do not have direct information about the a priori wage returns that workers would expect in the event they were and were not to undertake training. Instead we have data on workers' expectations about the probability that they will receive a pay raise above the rate negotiated by the union or staff in general. We argue that these expectations regarding future wage increases post-training are an indirect measure of the returns that workers expect from training. Consequently, we estimate a series of models of the likelihood that individuals expect future wage increases conditional on locus of control, participation in general or specific training and other control variables. The results are summarized in Table 2.4, while complete results are presented in Appendix Table 2.10.

Table 2.4: OLS Estimation Results: Pay Raise Expectations on LoC (std.)

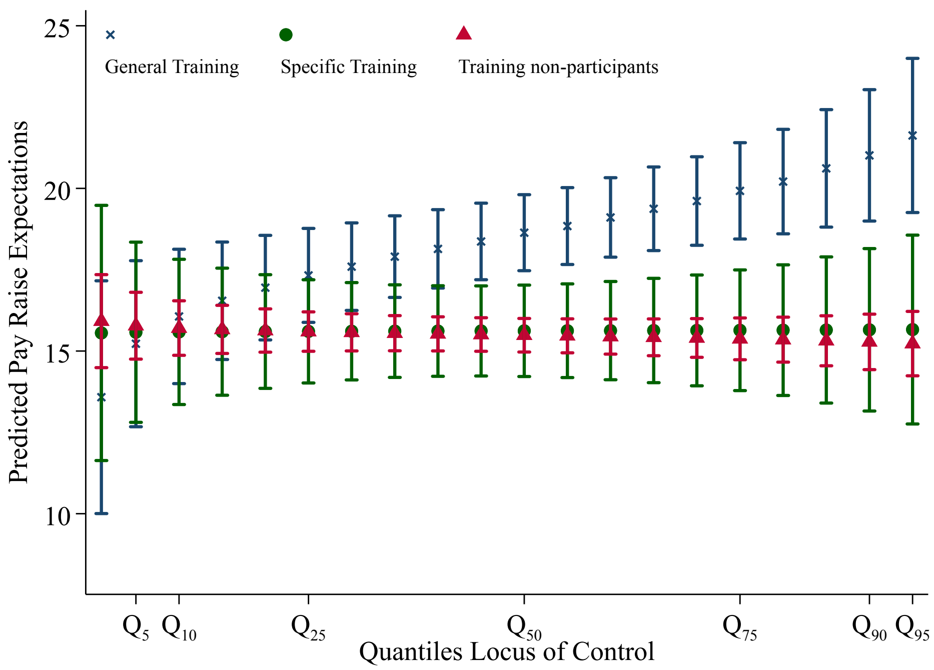
	(1)	(2)	(3)	(4)	(5)
Locus of Control (std.)	1.094***	1.112***	0.227	0.011	-0.183
	(0.273)	(0.274)	(0.263)	(0.258)	(0.268)
General Training	6.787***	6.812***	4.166***	3.299***	3.158***
	(0.703)	(0.700)	(0.677)	(0.660)	(0.658)
Specific Training	0.425	0.922	-0.500	0.247	0.163
	(0.803)	(0.794)	(0.776)	(0.760)	(0.757)
General Training * Locus of Control (std.)	2.456***	2.166***	2.344***	2.196***	2.154***
	(0.786)	(0.775)	(0.726)	(0.696)	(0.694)
Specific Training * Locus of Control (std.)	0.213	0.074	0.192	0.327	0.252
	(0.850)	(0.839)	(0.808)	(0.797)	(0.795)
Control Variables					
Locus of Control	✓	✓	✓	✓	✓
year, regional		✓	✓	✓	✓
socio-demographics			✓	✓	✓
job, firm				✓	✓
Big Five					✓
Observations	12,203	12,203	12,203	12,203	12,203
$\overline{R}^2$	0.017	0.036	0.124	0.169	0.173

Source: Socio-Economic Panel (SOEP), data for years 1999 - 2008, version 33 , SOEP, 2017, doi:10.5684/soep.v33, own calculations.
Notes: The dependent variable is the expectation about the probability that workers will receive a pay raise above the rate negotiated by the union or staff in general. Full estimation results (including all control variables) are available in Table 2.10 in the Appendix. Standard errors are in parentheses and clustered on person-level.
* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$.

Workers who participated in general training in the previous wave are significantly more likely to expect a pay raise above the negotiated rate, whereas there is no relationship between specific training and expected pay raises. These findings are not particularly surprising in light of Becker's (1962) argument that trainees largely capture the returns to general training, while the returns to specific training are captured predominately by firms. Expectations regarding future pay raises are also related to the extent to which workers believe that what happens in life is under their control. The estimated effect of locus of control varies widely with model specification, however. In our preferred (full) specification, an internal locus of control is associated with a small and insignificant decrease in the chances of expecting a future pay raise everything else equal.

We are particularly interested in the relationship between locus of control and expectations about future wage increases conditional on workers' previous training decisions. This effect is captured in the estimated interaction between locus of control and both general and specific training. Specifically, we find that there is a significant positive interaction between an internal locus of control and general training. That is, amongst those receiving general training, the probability of expecting a pay raise increases significantly with internal locus of control. In contrast, the subjective pay raise expectations of workers receiving specific training are independent of their locus of control. These results continue to hold in models with detailed controls for year and regional controls (column 2), socio-demographic characteristics (column 3), job and firm-characteristics (column 4) and Big Five Personality (column 5).

Figure 2.2: Predicted Pay Raise Expectations by Locus of Control



Source: Socio-Economic Panel (SOEP), data for years 1999 - 2008, version 33, SOEP, 2017, doi: 10.5684/soep.v33, own illustration.
Notes: The figure shows different locus of control quantiles plotted against the predicted expectations about the probability that workers will receive a pay raise above the rate negotiated by the union or staff in general (based on the estimation in column (5) of Table 2.4). We show these expectations for non-training participants (red, triangle), only general training participants (blue, cross), and only specific training participants (green, circle). The triangles / crosses / circles in the middle of the vertical bars show the predicted mean expectations for the respective training outcome. The horizontal ending points of the vertical bars denote the lower and upper end of the 95% confidence interval.

The relationship between locus of control, training participation, and expected pay raises is shown graphically in Figure 2.2 (based on the full specification in column 5). Specifically, we plot predicted expectations regarding future pay raises (y-axis) at different quantiles of the locus of control distribution (x-axis), for general (blue, cross), specific (green, circle) and non-training participants (red, triangle). The crosses, circles and triangles in the middle of the vertical bars indicate the predicted means, while the horizontal lines indicate 95 percent confidence intervals. The more internal general training participants are, the higher is the likelihood that they expect a future pay raise, ranging from a probability of about 13.6 percent on average in the lowest quintile to more than 21.6 percent in the highest quintile. In contrast, those undertaking specific training have constant expectations regarding future pay raises throughout the locus of control distribution, while the expected likelihood of receiving a future pay raise falls slightly as training non-participants become more internal.

These results strongly suggest that locus of control is linked to training decisions through workers' expectations regarding the likely returns. In particular, there is a strong positive relationship between locus of control and expected future pay raises for those workers who are most likely to capture the returns from training (i.e. those participating in general training) and either no or a negative relationship for those who are not (i.e. those participating in specific training or no training respectively).

Finally, we analyze the association of locus of control and training participation with realized wages in $t+1$. Estimation results are summarized in Table 2.5; complete results are available in Table 2.11. We assume that the decision to participate in training takes place in period t (which can be either in 2000, 2004 or 2008) and we estimate the relationship between training status in t and wages realized in period $t+1$. We lose approximately 848 employed individuals from our sample due to missing wage or working hours information in $t+1$. Column (1), Table 2.5 shows the unconditional effect of locus of control and training participation on hourly gross wage in $t+1$.

Table 2.5: OLS Estimation Results: Gross Log Hourly Wage $(t+1)$

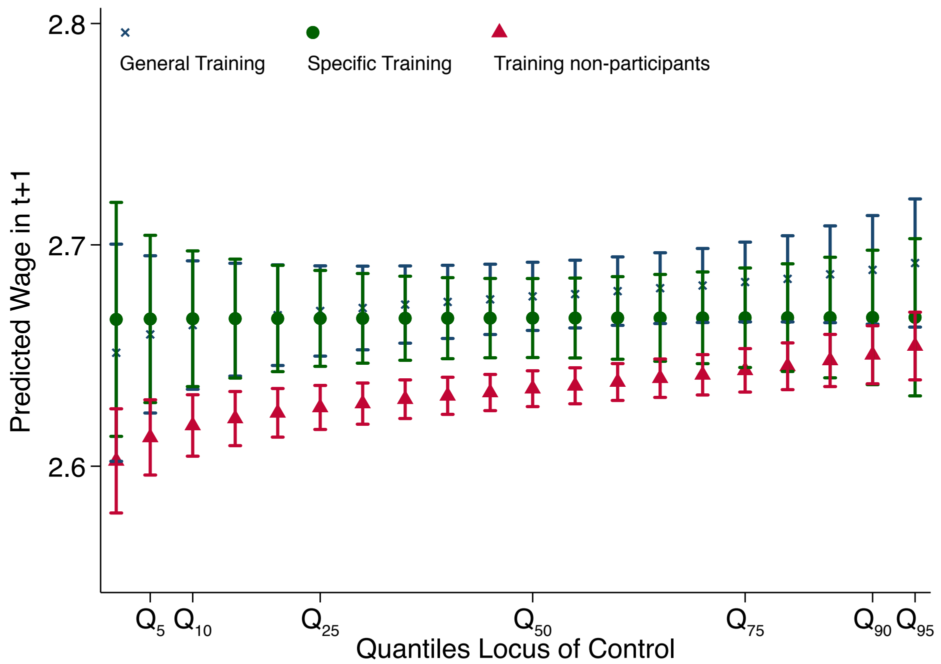
	(1)	(2)	(3)	(4)	(5)
Locus of Control (std.)	0.061***	0.062***	0.024***	0.013***	0.013***
	(0.006)	(0.006)	(0.005)	(0.004)	(0.004)
General Training	0.207***	0.205***	0.117***	0.045***	0.045***
	(0.012)	(0.012)	(0.010)	(0.009)	(0.009)
Specific Training	0.186***	0.200***	0.104***	0.036***	0.036***
	(0.013)	(0.013)	(0.011)	(0.010)	(0.010)
General Training * Locus of Control (std.)	0.014	0.002	-0.004	-0.003	-0.003
	(0.013)	(0.013)	(0.011)	(0.009)	(0.009)
Specific Training * Locus of Control (std.)	-0.015	-0.022	-0.007	-0.012	-0.013
	(0.015)	(0.014)	(0.012)	(0.010)	(0.010)
Control Variables					
Locus of Control	✓	✓	✓	✓	✓
year, regional		✓	✓	✓	✓
socio-demographics			✓	✓	✓
job, firm				✓	✓
Big Five					✓
Observations	11,355	11,355	11,355	11,355	11,355
$\overline{R}^2$	0.060	0.134	0.409	0.539	0.540

Source: Socio-Economic Panel (SOEP), data for years 1999 - 2008, version 33, SOEP, 2017, doi:10.5684/soep.v33, own calculations.
Notes: Full estimation results (including all control variables) are available in Table 2.11 in the Appendix. Standard errors are in parentheses and clustered on person-level. * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$.

We find that being internal is significantly positively related to wages. Moreover, participation in either general or specific training is associated with significantly higher wages. Consistent with our model, the wage return to general participation is larger than the wage return to specific training, though empirically the differences are small and insignificant. This suggests that, in practice, work-related training may involve the development of both specific and general skills (see Lazear, 2009). There is an insignificant interaction between training (general or specific) and locus of control in determining realized wages which is robust as we increasingly add controls. In short, the post-training wages of training participants do not depend on their locus of control, suggesting that the return to training participation is independent of locus of control (see also Figure 2.3 that graphically depicts the relationship between locus of control, training participation and realized wages in $t+1$). This is inconsistent with the idea that workers with an internal locus of control engage in more training because they are more productive in training, i.e. because they receive larger productivity gains as a result.[16]

[16]If training has only a long-run, but no short-run impact on productivity – which workers correctly anticipate – it is possible that the observed effect of locus of control on training propensities stems from disparities in actual training returns, rather than subjective beliefs about training returns. In this special case, our analysis would not completely rule out the possibility that having an internal locus of control conveys a productivity advantage in the longer run.

Figure 2.3: Predicted Gross Log Hourly Wage ($t + 1$) by Locus of Control



Source: Socio-Economic Panel (SOEP), data for years 1999 - 2008, version 33, SOEP, 2017, doi: 10.5684/soep.v33, own illustration.
Notes: The figure shows different locus of control quantiles plotted against the predicted wage in $t + 1$ (based on the estimation in column (5) of Table 2.5) for non-training participants (red, triangle), only general training participants (blue, cross), and only specific training participants (green, circle). The triangles / crosses / circles in the middle of the vertical bars show the predicted mean expectations for the respective training outcome. The horizontal ending points of the vertical bars denote the lower and upper end of the 95% confidence interval.

2.4.4 Robustness Analysis

We conduct a number of robustness checks in order to assess the sensitivity of our conclusions to sample choice, model specification, the parameterization of our key variables of interest, and potential omitted variable bias (see Tables 2.6 and 2.7). Results for our model of training participation are reported in Panel (A), while results for our models of expected wage increases and realized wages in $t + 1$ are reported in Panels (B) and (C) respectively. To facilitate comparisons, Column (1) reproduces the training results (logit marginal effects), expected pay raise results (OLS coefficients) and realized wage results (OLS coefficients) from our preferred specifications (column 5) in Tables 2.3, 2.4 and 2.5 respectively.

Table 2.6: Robustness Analysis for Training Participation, Pay Raise Expectations and Gross Log Hourly Wage (t+1) – Part 1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Logit Estimation Results: Participation in Training (Marginal Effects)								
General and Specific Training								
Locus of Control (LoC) (std.)	0.014***	0.015***	0.014***	0.014***	0.015***	0.014***	0.013***	0.013***
	(0.004)	(0.005)	(0.005)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)
Observations	12,203	8,633	12,044	12,203	10,081	11,875	12,203	12,203
General Training								
Locus of Control (LoC) (std.)	0.017***	0.018***	0.017***	0.013***	0.015***	0.017***	0.017***	0.016***
	(0.004)	(0.005)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Observations	12,203	8,633	12,044	12,203	10,081	11,875	12,203	12,203
Specific Training								
Locus of Control (LoC) (std.)	-0.001	-0.000	-0.002	0.002	0.001	-0.001	-0.002	-0.001
	(0.003)	(0.004)	(0.003)	(0.004)	(0.002)	(0.003)	(0.003)	(0.003)
Observations	12,203	8,633	12,044	12,203	10,081	11,875	12,203	12,203
B. OLS Estimation Results: Pay Raise Expectations								
Locus of Control (LoC) (std.)	-0.183	-0.391	-0.131	-0.181	-0.165	-0.172	-0.166	-0.090
	(0.268)	(0.307)	(0.286)	(0.269)	(0.271)	(0.269)	(0.267)	(0.281)
General Training	3.158***	1.695**	3.025***	3.112***	2.975***	3.352***	3.195***	3.155***
	(0.658)	(0.728)	(0.698)	(1.008)	(1.053)	(0.683)	(0.659)	(0.659)
Specific Training	0.163	0.060	0.285	1.808***	-0.636	0.404	0.166	0.181
	(0.757)	(0.829)	(0.789)	(0.629)	(1.410)	(0.836)	(0.759)	(0.760)
General Training * Locus of Control (std.)	2.154***	2.026***	2.045***	3.295***	3.076***	2.140***	2.036***	2.255***
	(0.694)	(0.734)	(0.768)	(1.110)	(1.144)	(0.723)	(0.683)	(0.710)
Specific Training * Locus of Control (std.)	0.252	-0.299	0.098	0.900	2.312*	0.124	0.319	0.301
	(0.795)	(0.845)	(0.887)	(0.618)	(1.322)	(0.880)	(0.802)	(0.818)
Observations	12,203	8,633	12,044	12,203	10,081	11,875	12,203	12,203
C. OLS Estimation Results: Gross Log Hourly Wage (t+1)								
Locus of Control (LoC) (std.)	0.013***	0.013***	0.014***	0.013***	0.011**	0.013***	0.012***	0.013***
	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
General Training	0.045***	0.042***	0.050***	0.044***	0.041***	0.046***	0.045***	0.045***
	(0.009)	(0.010)	(0.009)	(0.013)	(0.014)	(0.009)	(0.009)	(0.009)
Specific Training	0.036***	0.030***	0.045***	0.048***	0.038**	0.042***	0.036***	0.036***
	(0.010)	(0.011)	(0.010)	(0.008)	(0.017)	(0.011)	(0.010)	(0.010)
General Training * Locus of Control (std.)	-0.003	-0.005	-0.003	0.000	-0.003	-0.002	-0.003	-0.001
	(0.009)	(0.010)	(0.011)	(0.015)	(0.016)	(0.010)	(0.009)	(0.010)
Specific Training * Locus of Control (std.)	-0.013	-0.008	-0.011	-0.008	-0.004	-0.016	-0.012	-0.015
	(0.010)	(0.012)	(0.012)	(0.008)	(0.018)	(0.011)	(0.010)	(0.011)
Observations	11,355	8,008	11,202	11,355	9,331	11,037	11,355	11,355
Control Variables								
Locus of Control, Training	✓	✓	✓	✓	✓	✓	✓	✓
year, regional	✓	✓	✓	✓	✓	✓	✓	✓
socio-demographics	✓	✓	✓	✓	✓	✓	✓	✓
job, firm	✓	✓	✓	✓	✓	✓	✓	✓
Big Five Personality	✓	✓	✓	✓	✓	✓	✓	✓

Source: Socio-Economic Panel (SOEP), data for years 1999-2008, version 33, SOEP, 2017, doi:10.5684/soep.v33, own calculations.
Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard Errors are in parentheses and clustered on person-level.
Sensitivity tests are presented in the different columns, we tested the following specifications:
(1): Main results from column (5) in Tables 2.3, 2.4 and 2.5 respectively
(2): Excluding year 2000
(3): Excluding individuals participating in general and specific training within one cross-section
(4): Changing definition of general training (general=completely; specific=for the most part, only to a limited extend, not at all)
(5): Changing definition of general training (general=completely; specific=not at all)
(6): Excluding those who say 'training not worth it'
(7): Locus of Control index is average of items (all items equally weighted)
(8): Locus of Control based on first observation only

Sample Choice: Unlike the case in 2004 and 2008, the SOEP skill-transferability question in 2000 cannot be linked to a specific training course, requiring us to assume that individuals' responses refer to the latest course undertaken (see Section 2.4.2). In column (2) of Table 2.6, we report results from a restricted estimation sample in which we drop the data from year 2000. In addition, a small number of respondents (n = 159) participate in both general and specific training within a 12 month period. Column (3) reports the results we obtain when these individuals are excluded from the sample. In both cases, we find that our results are substantively the same indicating that our conclusions are robust to these two sampling choices.

Definition of General and Specific Training: We also consider the robustness of our results to the distinction we make between general versus specific training. Specifically, we narrow the definition of general training to include only training in which skills are *"Completely"* transferable to another company. All other categories of training are considered to be specific training. We find a somewhat weaker, though still statistically significant, relationship between locus of control and general training, while there continues to be no significant relationship between locus of control and specific training (see column (4) of Table 2.6). Thus, the conclusion that locus of control is related to general, but not specific, training continues to hold under this alternative definition. Moreover, the association between specific training and future wage expectations becomes larger and statistically significant which is unsurprising given that "specific training" now also encompasses training that is "to a large extent" transferable to other firms. In order to sharpen the distinction between general and specific training, we also considered an alternative definition which captures the extremes of the skill-transferability scale. That is, training is general only when it is "completely" transferable and specific only when it is "not at all transferable". All other training events are dropped from the sample. These results are reported in column (5). All of our results are virtually unchanged with the exception that the positive interaction between locus of control and specific training in influencing future wage expectations becomes much larger, and is now statistically significant at a 10 percent level.

We also consider the possibility that trainees report that the skills they acquired cannot be transferred to another firm because they believe that the training is not useful in general;

not because it is firm-specific. We investigate this by excluding all individuals who report that 'training was not worth it' from the analysis. We find no evidence that our results are being driven by perceptions of the usefulness of training (see column 6). In line with this, we do not observe any evidence that locus of control is correlated with the statement that the "training was not worth it". This holds for general and for specific training (see Table 2.12 in the Appendix).

Finally, our analysis assumes that, for any given training event, the self-reported extent to which the acquired skills could be used in other companies is not correlated with locus of control. If this assumption does not hold, and if workers with an internal locus of control are more likely to report that any given training is general, this would lead to an upward bias in the relationship between the locus of control and participation in general training. Unfortunately, there is no direct way to test this assumption with our data.

To shed light on whether our categorization of training as general or specific is correlated with locus of control, we investigate whether the observed characteristics of the two types of training types are correlated with locus of control. If individuals with an internal locus of control are more likely to believe that training is transferable, we would expect systematic differences in the observed characteristics of general training between individuals with a more internal locus of control and those with a more external locus of control. To test this, we regress each of our observed training characteristics on a dummy which is equal to one for individuals who have a locus of control index above the median and zero otherwise, controlling for a set of observed characteristics. The corresponding results are reported in Table 2.13 in the Appendix. In the vast majority of cases, we do not find significant differences with respect to locus of control. We do observe significant differences for a few characteristics in the case of specific training in column (2), however, none of these differences are statistically significant if we look at general training in column (1).[17] Overall, this makes us confident that our findings are not driven by internal workers simply being more optimistic about the transferability of any given training.

Definition of Locus of Control: Our locus of control index is based on the most

[17] The lack of a correlation between locus of control and specific training also indicates that our results cannot be completely explained by internal workers simply being more optimistic about the transferability of any given training. Were this the case, given the way we have categorized training, we would expect to observe internal workers being more likely to participate in general training and less likely to participate in specific training.

recent pre-determined survey items which are aggregated using weights that result from a factor analysis conducted separately by each year. Our results are unchanged if we instead construct an alternative index in which all locus of control items are weighted equally (see column (7) of Table 2.6) or if we use the earliest possible (instead of the most recent) locus of control items for each individual (see column 8).

Risk Attitudes: In Table 2.7, we also investigate whether our results are stable when controlling for individuals' reported risk attitudes. As briefly discussed in section 2.2.2, risk aversion might lead to an underinvestment in general training. If individual risk aversion is unobserved and correlated with locus of control, this might bias our results. In the SOEP we observe individual risk attitudes in the years 2004 and 2008. Column (2) presents estimation results including only the observations from these years and controlling for risk aversion. Our results are virtually the same as the results in column (2) of Table 2.6, which are based on the same years of observation without controlling for risk attitudes.

Potentially Endogenous Variables: Next, we consider the sensitivity of our results to our choice of model specification. Specifically, column (3) of Table 2.7 presents estimation results from a model which excludes potentially endogenous variables such as education, occupation type (blue, white collar), extent of occupational autonomy, ISCO-occupation and NACE-sector classification. The inclusion of these variables likely moderates the effect of locus of control. As expected, their exclusion strengthens the effect of locus of control on general training and sharpens the distinction between general and specific training in influencing future wage expectations.

Model Choice: To account for the large number of individuals reporting that they have no expectation of receiving a future wage increase, we also estimate a Tobit model of expectations regarding future pay raises and find very similar results (see column (4) of Table 2.7).

Table 2.7: Robustness Analysis for Training Participation, Pay Raise Expectations and Gross Log Hourly Wage (t+1) – Part 2

	(1)	(2)	(3)	(4)	(5)	(6)
A. Logit Estimation Results: Participation in Training (Marginal Effects)						
General and Specific Training						
Locus of Control (LoC) (std.)	0.014***	0.014***	0.027***			
	(0.004)	(0.005)	(0.004)			
Observations	12,203	8,620	12,203			
General Training						
Locus of Control (LoC) (std.)	0.017***	0.018***	0.027***			
	(0.004)	(0.005)	(0.004)			
Observations	12,203	8,620	12,203			
Specific Training						
Locus of Control (LoC) (std.)	-0.001	-0.000	0.003			
	(0.003)	(0.004)	(0.003)			
Observations	12,203	8,620	12,203			
B. OLS Estimation Results: Pay Raise Expectations						
Locus of Control (LoC) (std.)	-0.183	-0.422	0.150	-1.092*	-0.504	-0.640
	(0.268)	(0.307)	(0.273)	(0.591)	(0.543)	(0.610)
General Training	3.158***	1.650**	4.691***	5.188***	3.099***	2.973***
	(0.658)	(0.728)	(0.672)	(1.246)	(0.958)	(1.020)
Specific Training	0.163	0.049	0.248	-0.910	1.611	1.827
	(0.757)	(0.829)	(0.766)	(1.612)	(1.073)	(1.129)
General Training * Locus of Control (std.)	2.154***	1.993***	2.159***	3.732***	1.053	1.917*
	(0.694)	(0.735)	(0.726)	(1.304)	(1.011)	(1.074)
Specific Training * Locus of Control (std.)	0.252	-0.262	0.052	0.966	-0.373	0.511
	(0.795)	(0.846)	(0.815)	(1.787)	(1.114)	(1.173)
Observations	12,203	8,620	12,203	12,203	12,203	4,578
C. OLS Estimation Results: Gross Log Hourly Wage (t+1)						
Locus of Control (LoC) (std.)	0.013***	0.013***	0.032***		-0.003	-0.006
	(0.004)	(0.005)	(0.005)		(0.006)	(0.007)
General Training	0.045***	0.042***	0.139***		0.019*	0.010
	(0.009)	(0.010)	(0.010)		(0.010)	(0.010)
Specific Training	0.036***	0.030***	0.097***		-0.004	-0.002
	(0.010)	(0.011)	(0.011)		(0.012)	(0.012)
General Training * Locus of Control (std.)	-0.003	-0.005	-0.006		-0.014	-0.011
	(0.009)	(0.010)	(0.011)		(0.010)	(0.010)
Specific Training * Locus of Control (std.)	-0.013	-0.008	-0.024**		0.011	0.012
	(0.010)	(0.012)	(0.012)		(0.012)	(0.013)
Observations	11,355	7,999	11,355		11,355	4,177
Control Variables						
Locus of Control, Training	✓	✓	✓	✓	✓	✓
year, regional	✓	✓	✓	✓	✓	✓
socio-demographics	✓	✓	✓*	✓	✓	✓
job, firm	✓	✓	✓*	✓	✓	✓
Big Five	✓	✓	✓	✓	✓	✓

Source: Socio-Economic Panel (SOEP), data for years 1999-2008, version 33, SOEP, 2017, doi:10.5684/soep.v33, own calculations.

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard Errors are in parentheses and clustered on person-level.
Sensitivity tests are presented in the different columns, we tested the following specifications:
(1): Main results from column (5) in Tables 2.3, 2.4 and 2.5 respectively
(2): Including general risk attitudes (only available in 2004 and 2008)
(3): Excluding potentially endogenous variables (education, blue/white collar worker, occupational autonomy, manager, ISCO, NACE)
remaining Job + Firm control variables are: firm size, type of contract, member trade union/ association
(4): Tobit Model
(5): Fixed Effects Estimation
(6): First Difference Estimation

Unobserved Heterogeneity: Finally, we investigate the potential for omitted variables to bias our results. Our data sample pools three cross-sectional waves of SOEP data (2000, 2004, 2008). In principle, we could estimate fixed-effects models to account for any time-invariant unobserved heterogeneity. However, 55.6 percent of the individuals in our sample are observed only once ruling them out for any fixed-effects estimation. There is also very limited within-individual variation over time in locus of control making it difficult to estimate its effect using fixed-effects regression.[18]

We can, however, investigate the within-individual variation in training participation by using a fixed-effects model to estimate the interaction between training participation and locus of control for the sub-sample of respondents with multiple observations. Around one third (31.8 percent) of individuals with multiple observations also report some variation in their training status. Consequently, we have re-estimated our expected pay raise and realized wage models using both fixed-effect and first-difference estimation (see columns (5) and (6) in Table 2.7). We find that the interaction between locus of control and general training is positive – and significant in the first-difference model – while the interaction between locus of control and specific training is small and clearly insignificant. These results are generally consistent with our theoretical prediction that the disparity in expected pay raises for internal versus external workers is larger for general rather than specific training. The results, however, are rather imprecise, given the small sample size and limited identifying variation, implying that they should be interpreted with caution. We do not find any evidence for significant interaction effects between locus of control and participation in training in the case of realized wages. These results confirm our findings based on pooled cross-section estimation. Again, however, they need to be interpreted with caution due to the limited sample size.

We also investigate the potential for omitted variables to bias our results using the bounding analysis suggested by Oster (2019). Despite our extraordinary rich set of controls which include detailed job- and firm-characteristics, socio-demographic characteristics and the Big Five personality traits, we cannot completely rule out the possibility that some unobserved heterogeneity remains. Oster (2019) provides a method of calculating consis-

[18]The average change in our locus of control index across waves for those with multiple locus of control measures is only 0.08 points. Given that our locus of control scale ranges from 1 to 7 and has an average of 5.0, this degree of intra-individual variation is very low.

tent estimates of biased-adjusted treatment effects given assumptions about: i) the relative degree of selection on observed and unobserved variables (δ); and ii) the R-squared from a hypothetical regression of the outcome on the treatment and both observed and unobserved controls (R_{max}). $\delta = 1$ implies that observed and unobserved factors are equally important in explaining the outcome; $\delta > 1$ ($\delta < 1$) implies a larger (smaller) impact of unobserved than observed factors. Given the assumed bounds for δ and R_{max}, researchers can then calculate an identified set for the treatment effect of interest. If this set excludes zero, the results from the controlled regressions can be considered robust to omitted variable bias.

Consequently, we focus on our main result – the estimated effect of locus of control on participation in general training – and we re-estimate the results reported in Table 2.3 using OLS and including an indicator for above-median locus of control. Comparing columns (1) and (5) in Table 2.14 reveals that the estimated effect of locus of control on general training decreases from 0.068 in a model with no controls to 0.023 in our full specification. The identified set of coefficients includes zero only if δ exceeds 0.37.[19] This suggests that the estimated coefficient would be significantly positive as long as the degree of selection on unobservables relative to our detailed observed characteristics does not exceed a value of 0.37. For example, if there are unobserved variables which have similarly explanatory power as our large set of explanatory variables ($\delta = 1$), then our results would become insignificant.

2.5 Conclusions

Nations face enormous challenges in ensuring that the economic prosperity delivered by globalization and rapid technological change is enjoyed by all members of society. The risk is that many disadvantaged, undereducated and less-skilled individuals will struggle to remain competitive and may, as a result, fall even further behind. The European Commission has recently called for the integration of work and education "into a single lifelong learning process, open to innovation and open to all" (European Commission, 2010, p. 5). Whether this successfully allows marginalized groups to remain economically active and engaged

[19]The estimated effect in our full model is $\tilde{\beta} = 0.0226$ and the corresponding $\tilde{R}^2 = 0.0936$. In a model with no controls, we find that $\dot{\beta} = 0.0683$, with $\tilde{R}^2 = 0.0082$. With $\delta = 1$ the identified coefficient set is $[\tilde{\beta}, \beta^{*'}] = [0.0226, -0.0375]$; with $\delta = 0.37$ it is $[\tilde{\beta}, \beta^{*'}] = [0.0226, 0.0004]$. Full estimation results are available on request from the authors.

in meaningful employment depends largely on their willingness to take-up work-related training opportunities.

This paper adopts a behavioral perspective on the tendency for some workers to underinvest in their own training. Specifically, we account for the role of workers and firms in the training decision and allow workers' subjective beliefs about the investment returns to training to be influenced by their sense of control over what happens in life. A greater degree of internal control is predicted to make individuals more likely to invest in training when it is transferable to outside firms, but no more likely to invest in training when it is not. We then provide empirical evidence that, consistent with our theoretical model, having an internal locus of control is associated with higher participation in general but not specific training. Moreover, we argue that our results are consistent with locus of control affecting training investments through its influence on workers' expected investment returns, rather than through training costs or post-training productivity. Specifically, general training is associated with a higher likelihood of expecting a future pay raise for those with an internal rather than external locus of control, even though actual post-general-training wages – and presumably productivity – do not depend on locus of control. There is also no evidence of any link between locus of control and expectations about pay raises or post-training wages in the case of specific training.

Crucially, it is the link between skill transferability and the allocation of training returns across firms and workers which leads workers' perceptions of control to have a more profound effect on their decisions regarding general rather than specific training. We formally demonstrate this using a stylized, two-period investment model with competitive markets and risk-neutral agents. However, this key result is also easily generalized to a variety of non-competitive market structures and to risk-averse workers so long as increased skill transferability ultimately enhances workers' ability to capture the benefits of the training they receive. When this is true, we expect workers with an internal locus of control to respond to these incentives by investing in training. In contrast, those with an external locus of control are expected to be much less responsive to investment returns even when they exist.

These insights about workers' differential responsiveness to general versus specific training also extend beyond their perceptions of control. Many things – for example, cognitive biases, risk-aversion, impatience, etc. – can lead subjective expected investment returns to deviate from objective returns; vary across individuals; and matter for important economic decisions. In these circumstances, we would expect the disparity in workers' responses to objective investment returns to be larger when those returns accrue to them than when they do not.

The relationship between workers' investment decisions and their locus of control suggests that those with a more external sense of control are likely to require more intensive assistance in meeting their training goals. Moreover, as work-related training decisions appear to be linked to beliefs about training returns, there is also the potential for objective information regarding the returns to training to be useful in motivating external workers. Similar information interventions are being explored as a means of increasing disadvantaged students' propensity to attend college (Peter and Zambre, 2016) and influencing students' choice of college major (Wiswall and Zafar, 2015).

Future research will no doubt be useful in extending these results along several dimensions. There is a particular need for research that models the role of cognitive biases, risk and time preferences, and personality traits in work-related training investments. Training decisions are particularly interesting because – unlike other types of human capital decisions – they are not unilateral; training investments result from a joint decision making process between workers and firms. This implies that disparity in workers' and firms' expectations regarding training returns is potentially an important explanation for the apparent underinvestment in training that we observe. Developing models that have more realistic behavioral foundations is likely to have large payoffs in explaining why some individuals underinvest in training. In particular, it would be useful to analyze the joint decision process of workers and firms in more detail to shed light on the investment and bargaining strategy of firms facing workers with diverse subjective expectations about the returns to training.

2.6 Appendix

Table 2.8: Summary Statistics of Explanatory Variables

	(1) No Training	(2) General Training	(3) Specific Training
Observations[a]	9,038	1,925	1,081
Share of estimation sample[a]	0.74	0.16	0.09
Locus of Control[b,c]	4.40	4.59***	4.45**
Locus of Control (std.)[c]	-0.06	0.23***	0.04***
Wage Expectations[c,d]	14.74	22.44***	15.36
Share with Expectation of 0%	0.58	0.48***	0.60
Realized Gross Wage (per hour) in $t+1$ (in €)[c,e]	14.86	18.71***	17.70***
Socio-Economic Variables			
Age[c]	42.57	41.43***	43.02
Female	0.48	0.46*	0.44**
Married	0.71	0.69**	0.72
Number of Children[c]	0.67	0.70	0.61**
Disabled	0.06	0.05**	0.06
German Nationality	0.90	0.97***	0.96***
Owner of House/Dwelling	0.52	0.57***	0.59***
No School Degree	0.02	0.00***	0.00***
Lower/Intermediate School Degree	0.76	0.57***	0.63***
Highschool Degree	0.22	0.43***	0.37***
No Vocational Training	0.27	0.27	0.24**
Apprenticeship	0.47	0.38***	0.38***
Vocational School	0.26	0.34***	0.38***
University Degree	0.19	0.38***	0.37***
Work Experience (FT + PT) (in years)[c]	20.02	18.70***	20.51
Unemployment Experience (in years)[c]	0.63	0.37***	0.33***
Real Net HH income last month of 2 years ago (in 1000 €)[c]	2.98	3.30***	3.26***
Regional Information			
East Germany	0.26	0.28	0.34***
South Germany	0.28	0.25***	0.21***
North Germany	0.11	0.11	0.11
City States	0.05	0.06***	0.06*
Unemployment Rate[c]	9.57	9.59	10.26***
GDP[c]	27.67	28.44***	27.04**
Job-Specific Characteristics			
White-collar Worker	0.53	0.75***	0.66***
Blue-collar Worker	0.41	0.13***	0.16***
Member Tradeunion	0.19	0.21*	0.27***
Member Tradeassiocation	0.06	0.13***	0.10***
High Occupational Autonomy	0.20	0.44***	0.36***
Manager	0.14	0.32***	0.22***
Tenure (in years)[c]	11.22	11.59	14.13***
Contract - Permanent	0.88	0.91***	0.91***
Contract - Temporary	0.06	0.05	0.04**
Contract - Other	0.06	0.04***	0.05**
Managers (ISCO88)	0.04	0.09***	0.05
Professionals (ISCO88)	0.13	0.28***	0.27***
Technicians and associate professionals (ISCO88)	0.21	0.32***	0.32***
Clerical support workers (ISCO88)	0.13	0.09***	0.12
Service and sales workers (ISCO88)	0.11	0.08***	0.08***
Skilled agricultural, forestry and fishery workers (ISCO88)	0.01	0.00	0.01
Craft and related trades workers (ISCO88)	0.17	0.10***	0.09***
Plant and machine operators, and assemblers (ISCO88)	0.11	0.03***	0.04***
Firm-Specific Characteristics			
Small Firmsize	0.57	0.46***	0.37***
Medium Firmsize	0.22	0.24**	0.26***
Large Firmsize	0.21	0.29***	0.37***
NACE - Manufacturing	0.12	0.13	0.10**
NACE - Agriculture	0.01	0.01**	0.02*
NACE - Mining, Quarrying, Energy, Water	0.01	0.02**	0.03***
NACE - Chemicals/Pulp/Paper	0.07	0.04***	0.04***

(Table continues on the next page)

Table 2.8: Summary Statistics of Explanatory Variables (Continued)

	(1)	(2)	(3)
NACE - Construction	0.07	0.04***	0.03***
NACE - Iron/Steel	0.06	0.04***	0.03***
NACE - Textile/Apparel	0.01	0.00***	0.00***
NACE - Wholesale/Retail	0.14	0.07***	0.06***
NACE - Transportation/Communication	0.06	0.04***	0.06
NACE - Public Service	0.26	0.42***	0.45***
NACE - Financials/Private Services	0.12	0.13	0.12
Personality Characterstics			
Big Five Factor Openness[c]	4.42	4.68***	4.56***
Big Five Factor Conscientiousness[c]	6.05	6.04	5.92***
Big Five Factor Extraversion[c]	4.81	4.99***	4.86
Big Five Factor Agreeableness[c]	5.43	5.43	5.30***
Big Five Factor Neuroticism[c]	3.92	3.74***	3.87

Source: Socio-Economic Panel (SOEP), data for years 1999 - 2008, version 33, SOEP, 2017, doi:10.5684/soep.v33, own calculations.

* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

Notes: Table shows mean values of explanatory variables by training status. Result of mean comparison tests are indicated by asterisks. The test compared non-training participants to specific and general training participants. The summary statistics in columns (2) and (3) refer to those people who exclusively participate in general or specific training.

[a] The number of non-training, general and specific training participants does not add up to the estimation sample size as 159 people participate in general and specific training which are excluded from the descriptives. The share of people who participate in both types of training is 0.01

[b] The locus of control index in the descriptives table is the average sum over all internal and reversed external items.

[c] Denotes continuous variable.

[d] Wage expectations refer to the perceived likeliness of receiving a pay raise above the rate negotiated by the union of staff in general in the next two years.

[e] The number of observations for non-training participants are 8,345, for general training 1,827, for specific training 1,030, and for both 153.

Table 2.9: Logit Estimation Results: Participation in Training, General Training, Specific Training

	(1) Training	(2) General Training	(3) Specific Training
Locus of Control (std.)	0.014***	0.017***	-0.001
	(0.004)	(0.004)	(0.003)
Age	-0.004***	-0.004***	-0.000
	(0.001)	(0.001)	(0.001)
Female	-0.022**	-0.008	-0.015**
	(0.010)	(0.009)	(0.007)
Married	0.006	-0.003	0.006
	(0.010)	(0.009)	(0.007)
Number of Children	-0.001	0.003	-0.003
	(0.005)	(0.004)	(0.004)
Disabled	-0.014	-0.008	-0.014
	(0.018)	(0.015)	(0.013)
German Nationality	0.070***	0.065***	0.020
	(0.021)	(0.019)	(0.015)
Owner of House/Dwelling	0.008	0.004	0.001
	(0.009)	(0.008)	(0.006)
School Degree (Ref.: Low/Intermed. School)			
No Degree	-0.089	-0.076	-0.044
	(0.067)	(0.081)	(0.044)
Highschool Degree	0.013	0.016	-0.003
	(0.012)	(0.010)	(0.008)
Vocational Education (Ref.: None)			
Apprenticeship	0.061***	0.036***	0.031***
	(0.012)	(0.011)	(0.009)
Vocational School	0.082***	0.046***	0.039***
	(0.013)	(0.011)	(0.009)
University or College Degree	0.044***	0.016	0.031***
	(0.014)	(0.012)	(0.009)

(Table continues on the next page)

Table 2.9: Logit Estimation Results: Participation in Training, General Training, Specific Training (Continued)

	(1)	(2)	(3)
Work Experience (FT + PT)	0.001	0.001	-0.001
	(0.001)	(0.001)	(0.001)
Unemployment Experience	-0.004	0.000	-0.004
	(0.004)	(0.003)	(0.003)
Real Net HH income last month of 2 years ago (in 1000 €)	-0.007**	-0.003	-0.003
	(0.003)	(0.003)	(0.002)
Region (Ref.: West Germany)			
East Germany	0.029	0.015	0.017
	(0.020)	(0.017)	(0.014)
South Germany	-0.024*	-0.014	-0.013
	(0.013)	(0.011)	(0.009)
North Germany	-0.007	-0.002	-0.001
	(0.015)	(0.013)	(0.010)
City States	0.009	0.014	-0.007
	(0.020)	(0.017)	(0.014)
Unemployment Rate in Region	-0.001	-0.002	0.000
	(0.002)	(0.002)	(0.002)
GDP in 1,000 €in Regions	0.000	0.001	-0.000
	(0.001)	(0.001)	(0.001)
Dummy for year 2000	-0.037***	-0.027***	-0.030***
	(0.010)	(0.009)	(0.008)
Dummy for year 2004	-0.034***	-0.022**	-0.015**
	(0.011)	(0.009)	(0.008)
Occupation Position (Ref.: Civil Servant)			
White-collar Worker	-0.064***	0.004	-0.046***
	(0.022)	(0.018)	(0.014)
Blue-collar Worker	-0.219***	-0.127***	-0.099***
	(0.026)	(0.023)	(0.017)
Member Trade Union	0.035***	0.015	0.016**
	(0.011)	(0.009)	(0.007)
Member Trade Association	0.039***	0.043***	-0.001
	(0.014)	(0.012)	(0.010)
High Occupational Autonomy	0.045**	0.064***	-0.011
	(0.021)	(0.018)	(0.014)
Manager	0.003	-0.010	0.001
	(0.022)	(0.018)	(0.015)
Tenure	0.000	-0.001	0.001**
	(0.001)	(0.001)	(0.000)
Contract Type (Ref.: Temporary)			
Permanent	0.046**	0.031**	0.011
	(0.018)	(0.016)	(0.013)
Other	-0.023	-0.012	-0.011
	(0.026)	(0.023)	(0.018)
ISCO88 (Ref.: Menial Job)			
Managers	0.199***	0.160***	0.078***
	(0.031)	(0.030)	(0.023)
Professionals	0.199***	0.148***	0.097***
	(0.029)	(0.029)	(0.021)
Technicians and associate professionals	0.202***	0.153***	0.089***
	(0.027)	(0.027)	(0.020)
Clerical support workers	0.140***	0.092***	0.084***
	(0.028)	(0.028)	(0.021)
Service and sales workers	0.156***	0.117***	0.072***
	(0.028)	(0.029)	(0.021)
Skilled agricultural, forestry and fishery workers	0.186***	0.180***	0.046
	(0.071)	(0.067)	(0.051)
Craft and related trades workers	0.204***	0.170***	0.080***
	(0.028)	(0.028)	(0.021)
Plant and machine operators, and assemblers	0.102***	0.079**	0.039
	(0.033)	(0.032)	(0.024)
Firm Size (Ref.: Large)			
Small	-0.070***	-0.023***	-0.057***
	(0.010)	(0.009)	(0.007)
Medium	-0.024**	-0.006	-0.022***

(Table continues on the next page)

Table 2.9: Logit Estimation Results: Participation in Training, General Training, Specific Training (Continued)

	(1)	(2)	(3)
	(0.011)	(0.010)	(0.007)
NACE Industry (Ref.: Other)			
Manufacturing	0.043**	0.044***	-0.001
	(0.019)	(0.017)	(0.014)
Agriculture	0.088*	-0.026	0.090**
	(0.052)	(0.046)	(0.036)
Mining, Quarring, Energy, Water	0.096***	0.050	0.047**
	(0.034)	(0.030)	(0.022)
Chemicals/Pulp/Paper	-0.001	-0.002	-0.007
	(0.025)	(0.022)	(0.018)
Construction	-0.017	-0.001	-0.033
	(0.025)	(0.022)	(0.020)
Iron/Steel	-0.007	0.004	-0.014
	(0.025)	(0.022)	(0.019)
Textile/Apparel	-0.179**	-0.101	-0.153*
	(0.075)	(0.063)	(0.088)
Wholesale/Retail	-0.060***	-0.041**	-0.036**
	(0.021)	(0.019)	(0.016)
Transportation/Communication	0.017	0.014	-0.001
	(0.024)	(0.022)	(0.017)
Public Service	0.055***	0.040***	0.017
	(0.017)	(0.015)	(0.013)
Financials/Private Services	0.039**	0.027	0.004
	(0.019)	(0.017)	(0.014)
Big Five Factor Openness	0.011***	0.009***	0.001
	(0.004)	(0.004)	(0.003)
Big Five Factor Conscientiousness	-0.004	0.003	-0.008**
	(0.005)	(0.005)	(0.004)
Big Five Factor Extraversion	0.009**	0.009**	0.001
	(0.004)	(0.004)	(0.003)
Big Five Factor Agreeableness	-0.006	0.001	-0.007**
	(0.005)	(0.004)	(0.003)
Big Five Factor Neuroticism	-0.001	-0.002	0.000
	(0.004)	(0.003)	(0.003)
Observations	12,203	12,203	12,203
$\overline{R^2}$	0.136	0.116	0.095

Source: Socio-Economic Panel (SOEP), data for years 1999 - 2008, version 33, SOEP, 2017, doi:10.5684/soep.v33, own calculations.
Notes: * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$. Standard errors are in parentheses and clustered on person-level.

Table 2.10: OLS Estimation Results: Pay Raise Expectations, controlling for General and Specific Training

	(1)	(2)	(3)	(4)	(5)
Locus of Control (std.)	1.094***	1.112***	0.227	0.011	-0.183
	(0.273)	(0.274)	(0.263)	(0.258)	(0.268)
General Training	6.787***	6.812***	4.166***	3.299***	3.158***
	(0.703)	(0.700)	(0.677)	(0.660)	(0.658)
Specific Training	0.425	0.922	-0.500	0.247	0.163
	(0.803)	(0.794)	(0.776)	(0.760)	(0.757)
General Training * Locus of Control (std.)	2.456***	2.166***	2.344***	2.196***	2.154***
	(0.786)	(0.775)	(0.726)	(0.696)	(0.694)
Specific Training * Locus of Control (std.)	0.213	0.074	0.192	0.327	0.252
	(0.850)	(0.839)	(0.808)	(0.797)	(0.795)
Region (Ref.: West Germany)					
East Germany		0.873	1.165	-0.032	0.205
		(1.151)	(1.106)	(1.081)	(1.082)
South Germany		-1.550*	-1.810**	-2.102***	-2.201***
		(0.821)	(0.766)	(0.730)	(0.729)
North Germany		-2.267**	-2.984***	-3.258***	-3.221***
		(0.931)	(0.893)	(0.844)	(0.840)
City States		1.756	1.231	1.602	1.610

(Table continues on the next page)

Table 2.10: OLS Estimation Results: Pay Raise Expectations, controlling for General and Specific Training (Continued)

	(1)	(2)	(3)	(4)	(5)
		(1.346)	(1.259)	(1.218)	(1.210)
Unemployment Rate in Region		-0.641***	-0.678***	-0.649***	-0.682***
		(0.130)	(0.124)	(0.121)	(0.121)
GDP in 1,000 €in Regions		0.168***	0.128***	0.035	0.037
		(0.046)	(0.043)	(0.042)	(0.042)
Dummy for year 2000		4.894***	3.728***	3.122***	3.318***
		(0.630)	(0.614)	(0.608)	(0.608)
Dummy for year 2004		1.572**	0.872	0.203	0.375
		(0.632)	(0.613)	(0.598)	(0.598)
Age			-0.593***	-0.587***	-0.566***
			(0.059)	(0.058)	(0.057)
Female			-6.076***	-6.007***	-5.845***
			(0.506)	(0.582)	(0.596)
Married			-1.752***	-1.554***	-1.421**
			(0.603)	(0.583)	(0.583)
Number of Children			-0.227	-0.387	-0.347
			(0.305)	(0.294)	(0.292)
Disabled			-2.180**	-1.592*	-1.397
			(0.895)	(0.861)	(0.859)
German Nationality			2.517***	1.480*	1.645*
			(0.913)	(0.879)	(0.878)
Owner of House/Dwelling			0.165	0.272	0.326
			(0.511)	(0.498)	(0.495)
School Degree (Ref.: Low/Intermed. School)					
No Degree			-2.451	-1.659	-1.401
			(1.495)	(1.550)	(1.560)
Highschool Degree			5.631***	3.151***	3.133***
			(0.814)	(0.815)	(0.813)
Vocational Education (Ref.: None)					
Apprenticeship			1.717**	0.626	0.477
			(0.693)	(0.685)	(0.681)
Vocational School			-0.333	-0.118	-0.305
			(0.713)	(0.719)	(0.716)
University or College Degree			2.170***	-0.218	-0.234
			(0.827)	(0.858)	(0.854)
Work Experience (FT + PT)			-0.036	0.063	0.054
			(0.053)	(0.054)	(0.054)
Unemployment Experience			0.067	-0.074	-0.057
			(0.150)	(0.155)	(0.155)
Real Net HH income last month of 2 years ago (in 1000 €)			0.865***	0.625***	0.573***
			(0.196)	(0.192)	(0.191)
Occupation Position (Ref.: Civil Servant)					
White-collar Worker				7.212***	7.373***
				(1.348)	(1.341)
Blue-collar Worker				5.608***	5.943***
				(1.507)	(1.497)
Member Trade Union				-0.979*	-1.124*
				(0.588)	(0.586)
Member Trade Association				-0.327	-0.459
				(0.999)	(0.994)
High Occupational Autonomy				3.651***	3.530**
				(1.401)	(1.393)
Manager				3.945***	3.869***
				(1.506)	(1.499)
Tenure				-0.212***	-0.207***
				(0.030)	(0.029)
Contract Type (Ref.: Temporary)					
Permanent				2.805***	2.805***
				(0.998)	(0.996)
Other				1.997	1.957
				(1.281)	(1.276)
ISCO88 (Ref.: Menial Job)					
Managers				5.747***	5.392***
				(1.550)	(1.544)

(Table continues on the next page)

Table 2.10: OLS Estimation Results: Pay Raise Expectations, controlling for General and Specific Training (Continued)

	(1)	(2)	(3)	(4)	(5)
Professionals				2.932**	2.860**
				(1.268)	(1.264)
Technicians and associate professionals				3.189***	3.125***
				(0.993)	(0.991)
Clerical support workers				2.684**	2.613**
				(1.084)	(1.080)
Service and sales workers				1.154	1.071
				(0.990)	(0.987)
Skilled agricultural, forestry and fishery workers				-0.559	-0.535
				(2.460)	(2.407)
Craft and related trades workers				-1.157	-1.223
				(0.962)	(0.961)
Plant and machine operators, and assemblers				-2.433**	-2.454**
				(1.027)	(1.024)
Firm Size (Ref.: Large)					
Small				-0.767	-0.675
				(0.635)	(0.633)
Medium				-0.746	-0.700
				(0.686)	(0.684)
NACE Industry (Ref.: Other)					
Manufacturing				3.579***	3.599***
				(1.064)	(1.061)
Agriculture				-0.978	-0.753
				(2.008)	(1.969)
Mining, Quarring, Energy, Water				2.741	2.649
				(2.015)	(2.034)
Chemicals/Pulp/Paper				3.781***	3.768***
				(1.211)	(1.210)
Construction				3.001**	2.774**
				(1.265)	(1.265)
Iron/Steel				1.693	1.697
				(1.276)	(1.275)
Textile/Apparel				3.771*	3.852*
				(2.105)	(2.096)
Wholesale/Retail				1.383	1.452
				(1.032)	(1.027)
Transportation/Communication				0.993	0.937
				(1.347)	(1.349)
Public Service				-2.158**	-2.101**
				(0.916)	(0.912)
Financials/Private Services				4.575***	4.525***
				(1.097)	(1.093)
Big Five Factor Openness					0.556**
					(0.218)
Big Five Factor Conscientiousness					-0.063
					(0.314)
Big Five Factor Extraversion					0.792***
					(0.236)
Big Five Factor Agreeableness					-0.960***
					(0.271)
Big Five Factor Neuroticism					-0.615***
					(0.218)
Const.	14.813***	14.738***	39.871***	34.290***	35.082***
	(0.279)	(1.922)	(2.651)	(3.260)	(4.004)
Observations	12,203	12,203	12,203	12,203	12,203
$\overline{R}^2$	0.017	0.036	0.124	0.169	0.173

Source: Socio-Economic Panel (SOEP), data for years 1999 - 2008, version 33, SOEP, 2017, doi:10.5684/soep.v33, own calculations.
Notes: * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$. Standard errors are in parentheses and clustered on person-level.

Table 2.11: OLS Estimation Results: Gross Log Hourly Wage ($t+1$), controlling for General and Specific Training

	(1)	(2)	(3)	(4)	(5)
Locus of Control (std.)	0.061***	0.062***	0.024***	0.013***	0.013***
	(0.006)	(0.006)	(0.005)	(0.004)	(0.004)
General Training	0.207***	0.205***	0.117***	0.045***	0.045***
	(0.012)	(0.012)	(0.010)	(0.009)	(0.009)
Specific Training	0.186***	0.200***	0.104***	0.036***	0.036***
	(0.013)	(0.013)	(0.011)	(0.010)	(0.010)
General Training * Locus of Control (std.)	0.014	0.002	-0.004	-0.003	-0.003
	(0.013)	(0.013)	(0.011)	(0.009)	(0.009)
Specific Training * Locus of Control (std.)	-0.015	-0.022	-0.007	-0.012	-0.013
	(0.015)	(0.014)	(0.012)	(0.010)	(0.010)
Region (Ref.: West Germany)					
East Germany		-0.181***	-0.199***	-0.170***	-0.171***
		(0.026)	(0.021)	(0.018)	(0.018)
South Germany		0.001	-0.007	-0.000	-0.002
		(0.016)	(0.013)	(0.011)	(0.011)
North Germany		0.020	0.009	0.007	0.006
		(0.019)	(0.015)	(0.013)	(0.013)
City States		0.058**	0.101***	0.080***	0.081***
		(0.026)	(0.022)	(0.018)	(0.018)
Unemployment Rate in Region		-0.001	-0.004*	-0.004*	-0.004*
		(0.003)	(0.002)	(0.002)	(0.002)
GDP in 1,000 €in Regions		0.008***	0.004***	0.003***	0.003***
		(0.001)	(0.001)	(0.001)	(0.001)
Dummy for year 2000		0.045***	0.078***	0.072***	0.071***
		(0.011)	(0.010)	(0.009)	(0.009)
Dummy for year 2004		0.070***	0.087***	0.078***	0.078***
		(0.012)	(0.010)	(0.009)	(0.009)
Age			-0.007***	-0.004***	-0.004***
			(0.001)	(0.001)	(0.001)
Female			-0.202***	-0.157***	-0.153***
			(0.009)	(0.009)	(0.010)
Married			-0.039***	-0.011	-0.010
			(0.011)	(0.009)	(0.009)
Number of Children			0.031***	0.026***	0.026***
			(0.005)	(0.004)	(0.004)
Disabled			-0.017	-0.038*	-0.037*
			(0.022)	(0.020)	(0.019)
German Nationality			0.006	-0.005	-0.005
			(0.016)	(0.014)	(0.014)
Owner of House/Dwelling			0.015*	0.003	0.002
			(0.009)	(0.008)	(0.008)
School Degree (Ref.: Low/Intermed. School)					
No Degree			-0.167***	-0.114**	-0.115**
			(0.057)	(0.050)	(0.050)
Highschool Degree			0.179***	0.076***	0.075***
			(0.014)	(0.012)	(0.012)
Vocational Education (Ref.: None)					
Apprenticeship			0.030**	0.025**	0.025**
			(0.013)	(0.011)	(0.011)
Vocational School			0.055***	0.017	0.017
			(0.014)	(0.012)	(0.012)
University or College Degree			0.227***	0.089***	0.090***
			(0.015)	(0.013)	(0.013)
Work Experience (FT + PT)			0.014***	0.007***	0.007***
			(0.001)	(0.001)	(0.001)
Unemployment Experience			-0.042***	-0.018***	-0.018***
			(0.004)	(0.004)	(0.004)
Real Net HH income last month of 2 years ago (in 1000 €)			0.072***	0.049***	0.048***
			(0.005)	(0.004)	(0.004)
Occupation Position (Ref.: Civil Servant)					
White-collar Worker				0.031	0.032
				(0.021)	(0.021)
Blue-collar Worker				-0.043*	-0.043*
				(0.022)	(0.022)

(Table continues on the next page)

Table 2.11: OLS Estimation Results: Gross Log Hourly Wage ($t+1$), controlling for General and Specific Training (Continued)

	(1)	(2)	(3)	(4)	(5)
Member Trade Union				0.039***	0.039***
				(0.008)	(0.008)
Member Trade Association				0.027**	0.027**
				(0.013)	(0.013)
High Occupational Autonomy				0.080***	0.081***
				(0.020)	(0.020)
Manager				0.099***	0.097***
				(0.021)	(0.021)
Tenure				0.005***	0.005***
				(0.000)	(0.000)
Contract Type (Ref.: Temporary)					
Permanent				0.104***	0.104***
				(0.019)	(0.019)
Other				-0.100***	-0.101***
				(0.029)	(0.029)
ISCO88 (Ref.: Menial Job)					
Managers				0.255***	0.256***
				(0.024)	(0.024)
Professionals				0.274***	0.274***
				(0.021)	(0.021)
Technicians and associate professionals				0.231***	0.232***
				(0.018)	(0.018)
Clerical support workers				0.163***	0.164***
				(0.020)	(0.020)
Service and sales workers				0.001	0.001
				(0.020)	(0.020)
Skilled agricultural, forestry and fishery workers				0.101	0.107
				(0.076)	(0.076)
Craft and related trades workers				0.140***	0.139***
				(0.018)	(0.018)
Plant and machine operators, and assemblers				0.101***	0.101***
				(0.019)	(0.019)
Firm Size (Ref.: Large)					
Small				-0.155***	-0.155***
				(0.009)	(0.009)
Medium				-0.037***	-0.037***
				(0.009)	(0.009)
NACE Industry (Ref.: Other)					
Manufacturing				0.096***	0.096***
				(0.016)	(0.016)
Agriculture				-0.137***	-0.141***
				(0.050)	(0.050)
Mining, Quarring, Energy, Water				0.123***	0.123***
				(0.030)	(0.030)
Chemicals/Pulp/Paper				0.108***	0.107***
				(0.018)	(0.018)
Construction				0.033*	0.032*
				(0.019)	(0.019)
Iron/Steel				0.113***	0.113***
				(0.019)	(0.019)
Textile/Apparel				-0.006	-0.004
				(0.039)	(0.040)
Wholesale/Retail				-0.050***	-0.050***
				(0.017)	(0.017)
Transportation/Communication				-0.009	-0.009
				(0.021)	(0.021)
Public Service				0.051***	0.051***
				(0.015)	(0.015)
Financials/Private Services				0.025	0.025
				(0.018)	(0.018)
Big Five Factor Openness					-0.001
					(0.004)
Big Five Factor Conscientiousness					0.004
					(0.005)

(Table continues on the next page)

Table 2.11: OLS Estimation Results: Gross Log Hourly Wage ($t+1$), controlling for General and Specific Training (Continued)

	(1)	(2)	(3)	(4)	(5)
Big Five Factor Extraversion					-0.005
					(0.004)
Big Five Factor Agreeableness					-0.008*
					(0.004)
Big Five Factor Neuroticism					-0.004
					(0.003)
Const.	2.589***	2.385***	2.314***	2.194***	2.257***
	(0.007)	(0.039)	(0.048)	(0.052)	(0.062)
Observations	11,355	11,355	11,355	11,355	11,355
$\overline{R}^2$	0.060	0.134	0.409	0.539	0.540

Source: Socio-Economic Panel (SOEP), data for years 1999 - 2008, version 33, SOEP, 2017, doi:10.5684/soep.v33, own calculations.
Notes: * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$. Standard errors are in parentheses and clustered on person-level.

Table 2.12: Logit Estimation Results: Training "Not at All Worth it" on LoC (std.) (Marginal Effects)

	(1)	(2)	(3)
	Full Sample	General Training	Specific Training
Locus of Control (std.)	0.002	-0.003	0.013
	(0.006)	(0.007)	(0.012)
General Training	-0.074***		
	(0.012)		
Control variables			
Locus of Control	✓	✓	✓
year, regional	✓	✓	✓
socio-demographics	✓	✓	✓
job, firm	✓	✓	✓
Big Five	✓	✓	✓
Observations	2,999	1,921	1,078

Source: Socio-Economic Panel (SOEP), data for years 1999 - 2008, version 33, SOEP, 2017, doi:10.5684/soep.v33, own calculations.
Notes: Standard errors are in parentheses and clustered on person-level. * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$.
The dependent variable is equal to 1 if the training was "not worth it at all". It is equal to 0 if training was "very much worth it", "a little worth it" or individuals "do not know yet". The number of observations is slightly lower than before because seven individuals did not answer this question. Column (1) considers all individuals who participated in either general or specific training. Column (2) only considers individuals who participated in general training. Column (3) only considers individuals who participated in specific training. Individuals who participated in both general and specific training within one cross-section are excluded from the regression.

Table 2.13: OLS Estimation Results: Course Characterstics on LoC (Dummy Median)

Dependent Variable: Course Characteristics	(1) General Training	(2) Specific Training
Total course duration (weeks)[b]	-0.104	-0.760
	(0.777)	(0.466)
Hours of Instruction every week	-0.576	1.027
	(0.644)	(0.701)
What was the purpose of this instruction?		
Introduction to a new job	-0.002	0.011
	(0.010)	(0.012)
Qualification for professional advancement	-0.010	-0.040*
	(0.020)	(0.021)
Adjustment to new demands in current job	0.006	0.025
	(0.020)	(0.026)
Other	0.020	0.014
	(0.014)	(0.023)
Did the course take place during working hours		
During Working Time	0.016	0.025
	(0.021)	(0.025)
Some Of Both	-0.001	-0.040**
	(0.016)	(0.018)
Outside Working Time	-0.017	0.017
	(0.018)	(0.021)
Did you receive a participation certificate?	0.027	0.012
	(0.019)	(0.028)
Who held the course:		
Employer	0.028	-0.027
	(0.023)	(0.028)
Private Institute	-0.007	0.009
	(0.019)	(0.018)
Did you receive financial support from your employer?		
Yes, From The Employer	-0.009	0.009
	(0.021)	(0.025)
Yes, From another Source	-0.001	0.013
	(0.011)	(0.010)
Dummy for no own Costs	-0.014	0.022
	(0.018)	(0.018)
Own Costs	-21.797	-2.932
	(21.062)	(12.508)
Looking back, was this further education worth it for you professionally?		
Very Much	-0.009	0.045*
	(0.024)	(0.024)
A Little	-0.008	-0.027
	(0.023)	(0.030)
Not At All	0.010	0.021
	(0.012)	(0.022)
Do Not Know Yet	0.007	-0.038**
	(0.014)	(0.018)
Control Variables		
Locus of Control	✓	✓
year, regional	✓	✓
socio-demographics	✓	✓
job, firm	✓	✓
Big Five	✓	✓
Observations[a]	1,925	1,081

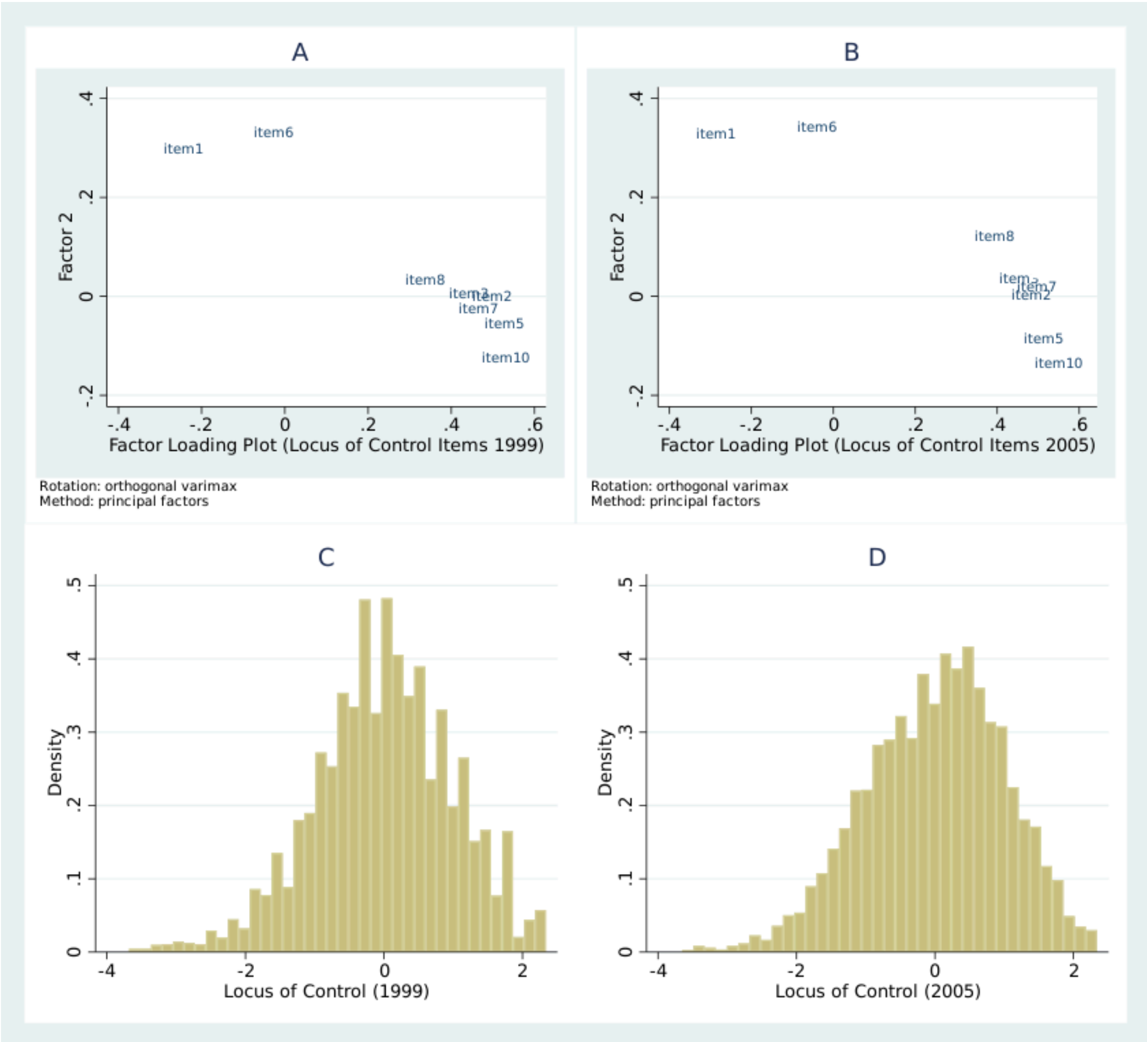
Source: Socio-Economic Panel (SOEP), data for years 1999 - 2008, version 33, SOEP, 2017, doi:10.5684/soep.v33, own calculations.
Notes: * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$.
Locus of Control was split at the median. The Table reports the coefficients of the locus of control dummy taken from regressions in which the presented survey question is the dependent variable and the individual characteristics (as in the main analysis) are controlled for. There is not enough variation in the variables "Correspondence Course" and "Purpose - Retraining for a different profession or job" to conduct a regression analysis.
[a] The number of observations of the presented survey question vary slightly due to item non-response. Individuals who participated in both general and specific training are excluded.
[b] Own calculation, based on information of the length (days, weeks, months) of each course.

Table 2.14: OLS Estimation Results: Participation in Training on LoC (Dummy Median)

	(1)	(2)	(3)	(4)	(5)
B. General Training					
Locus of Control (Dummy Median)	0.0683***	0.0660***	0.0414***	0.0285***	0.0226***
	(0.0072)	(0.0072)	(0.0071)	(0.0069)	(0.0071)
R^2	0.0082	0.0137	0.0562	0.0916	0.0936
Control Variables					
Locus of Control	✓	✓	✓	✓	✓
year, regional		✓	✓	✓	✓
socio-demographics			✓	✓	✓
job, firm				✓	✓
Big Five					✓
Observations	12,203	12,203	12,203	12,203	12,203

Source: Socio-Economic Panel (SOEP), data for years 1999-2008, version 33, SOEP, 2017, doi:10.5684/soep.v33, own calculations.
Notes: Standard errors are in parentheses and clustered on person-level. * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$.

Figure 2.4: Locus of Control: Factor Analysis and Distribution



Source: Socio-Economic Panel (SOEP), data for years 1999 - 2008, version 33, SOEP, 2017, doi: 10.5684/soep.v33, own illustration.
Notes: Figure 2 A. (B.) shows the loading plot of a factor analysis of the locus of control items of the year 1999 (2005). We identify items 1 and 6 as loading on Factor 2 (interpretable as internal factor) and items 2, 3, 5, 7, 8, 10 as loading on Factor 1 (interpretable as external factor). Item 4 and 9 are not loading on any of the two factors and were therefore neglected in the analysis.
Figure 2 C. and *2 D.* show the distribution of the continuous standardized locus of control index for the years 1999 and 2005, which is calculated by firstly reversing all external items and secondly by extracting a single factor by running a factor analysis for each year. Hence, higher scores reflect higher internality and lower scores reflect higher externality. The original item scale of the year 1999 was reversed (in order of higher scores reflecting higher internality) and was recoded in order to match the locus of control scale of the year 2005. The recoding is as follows: 2 to 3, 3 to 5 and 4 to 7.

Chapter 3

Risk Preferences and Training Investments*

Abstract

We analyze workers' risk preferences and training investments. Our conceptual framework differentiates between the investment risk and insurance mechanisms underpinning training decisions. Investment risk leads risk-averse workers to train less; they undertake more training if it insures them against future losses. We use the German Socio-Economic Panel (SOEP) to demonstrate that risk affinity is associated with more training, implying that, on average, investment risks dominate the insurance benefits of training. Crucially, this relationship is evident only for general training; there is no relationship between risk attitudes and specific training. Thus, consistent with our conceptual framework, risk preferences matter more when skills are transferable – and workers have a vested interest in training outcomes – than when they are not. Finally, we provide evidence that the insurance benefits of training are concentrated among workers with uncertain employment relationships or limited access to public insurance schemes.

3.1 Introduction

Human capital investments inevitably involve risk. Investment decisions depend not only on people's individual risk tolerance, but also on the nature of the risks they face and the way those risks drive potential investment returns. Investment risk is generated in the first

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instance by uncertainty about the future payoffs to newly acquired skills (see, e.g., Levhari and Weiss, 1974; Brown *et al.*, 2006), but may also stem from other sources such as people's uncertainty about their own ability (Shaw, 1996). Education, in particular, also provides a degree of labor market insurance – likely reducing risk – raising questions about whether people view schooling acquisition as a risky investment (Belzil and Leonardi, 2007, 2013). Empirically, attitudes toward risk seem to be very influential in education decisions (see Heckman and Montalto, 2018, for a review). Many studies find that risk aversion is linked to lower educational attainment (Brown *et al.*, 2006), though in some cases only weakly so (Belzil and Leonardi, 2007), while others find a positive relationship (Harrison *et al.*, 2007). Risk preferences also influence choices about enrolment in higher education (Hartlaub and Schneider, 2012; Heckman and Montalto, 2018), fields of study (De Paola and Gioia, 2012), and occupational choices (King, 1974).

Thus far, researchers asking whether human capital is an investment or a form of insurance have focused exclusively on formal education. Our research extends this literature by – for the first time – studying the question in the context of training that takes place on the job. This is an important contribution because of the key role that work-related training has in making internal labor markets more dynamic, improving firms' competitive position, ensuring that workers' skills remain up-to-date and transferable, and promoting social inclusion.[1] The ongoing structural change in the global labor market as a result of, e.g., digitalization, automation, and the dramatic increase in remote working in response to the COVID-19 pandemic has the potential to generate new opportunities for some workers, while leaving many others behind. Not surprisingly, promoting investments in work-related education and training is a key policy priority for national governments and international development agencies alike (OECD, 1996; European Commission, 2007). Success in achieving this goal relies on a better understanding of the way that uncertainty affects workers' training choices.

Our research contributes to this effort by estimating the effect of workers' risk preferences on their decisions to invest in work-related training. We begin by developing a

[1] There is evidence, for example, that training improves productivity at the firm level (e.g., Barrett and O'Connell, 2001). Training is positively associated with workers' wages (Lynch, 1992; Frazis and Loewenstein, 2005; Haelermans and Borghans, 2012), performance ratings (Bartel, 1995), promotion chances (Bishop, 1990), reemployment probabilities (Ok and Tergeist, 2003), and occupational position (Greenhalgh and Stewart, 1987).

conceptual framework that differentiates between the key investment and insurance mechanisms underpinning people's training decisions. Training is modeled as a choice made under uncertainty. Workers face uncertainty about the payoff to training which results in training being a risky investment. Besides that, training provides insurance against falls in future income that, for example, occur as a result of involuntary job loss or labor market downturns. We argue that the overall relationship between workers' risk preferences and their training choices depends on the relative strength of these two sources of underlying risk. To the extent that it is investment risk that dominates, risk-averse workers will undertake less training, and will engage in relatively more training whenever it has a large enough role in insuring them against future income losses.

Importantly, we take inspiration from Becker (1962) and are also mindful of the difference between training that is transferable to other employment contexts (i.e., general training) and training that is not (i.e., specific training). This is a key contribution of our research to the previous literature that considers the role of risk solely in the context of investments in education. While formal education is the quintessential example of general human capital, work-related training may constitute either general or specific human capital and often involves elements of both (see Acemoglu and Pischke, 1999a; Asplund, 2005; Frazis and Loewenstein, 2007, for reviews). The fundamental role of skill transferability in the allocation of training costs and returns, first identified by Becker (1962), leads us to expect that workers' risk preferences will be most relevant for their decisions to invest in general human capital. This insight results in our second key prediction. We expect risk preferences to play a larger role in general training decisions than in specific training decisions because the returns to specific training largely accrue to firms rather than workers.

We utilize data from the German Socio-Economic Panel (SOEP, 2019) to test our hypotheses empirically. We find that those with greater affinity for risk are more likely to invest in some type of work-related training. This positive relationship indicates that, on average, the investment risk of training generally dominates its insurance benefits. Importantly, we show that the link between risk preferences and training is driven by the positive association between risk tolerance and general training; there is no significant relationship between risk preferences and investments in specific training. Our results are not sensitive to the way we measure general vs. specific training or to the degree of autonomy that workers are likely to have over their training choices. Moreover, the pattern of job mobility following training indicates that our classification of training as either general or specific is likely to capture a meaningful distinction in skill transferability.

Thus, our key contribution is to demonstrate that, as expected, workers' attitudes toward risk play a larger role in those training decisions in which the returns accrue to them rather than firms; workers' risk attitudes play little role when they do not. **?** reach the same conclusion with respect to the role of locus of control in work-related training decisions. Taken together, our research provides new insights into the conceptual importance of skill transferability in human capital investment decisions like work-related training. Skill transferability gives people a vested interest in the outcomes of their choices. Consequently, their responses to investment returns will be stronger when skills are transferable – and the returns largely accrue to them – than when they are not.

Risk preferences matter, in particular, because they shape the way people trade off the utility costs associated with the uncertainty of investment returns against the insurance benefits that training may provide. Extending our main analysis, we empirically investigate the relative importance of these competing factors in labor market contexts in which one mechanism can reasonably be argued to dominate the other. Our results provide evidence that – consistent with our conceptual framework – the insurance motive for training is stronger in jobs with relatively stable wages, in non-permanent jobs, and among those who have recently experienced unemployment. These insights highlight the need to assess investments in employment-related training through the lens of the broader decision environment.

Finally, our research also makes a contribution by lending weight to a key debate regarding the measurement of risk preferences. Previous researchers have noted that attitudes toward risk are context-specific, raising questions about the capacity of more general measures of risk preferences to adequately capture risk-related behavior (see, e.g., Slovic, 1972; Weber *et al.*, 2002). We consider this issue and find that our domain-specific measure of career-related risk affinity is more predictive of people's training choices than is a measure of general risk affinity.

3.2 Theoretical Framework

Levhari and Weiss (1974) were the first to consider the role of risk in human capital investments using a simple two-period model in which earnings depend on the amount of time invested in human capital and on a random variable capturing the uncertainty of human capital returns. Similarly, Williams (1978) explicitly models the connection between risky human capital and risky asset investments. This focus on the risk underlying human capital investments has led researchers to investigate the links between individuals' risk attitudes and their investment choices. In particular, Shaw (1996) develops a theoretical model of the joint investment in financial wealth vs. human capital in which increasing risk aversion is predicted to decrease households' investments in risky human capital. Shaw does not, however, explicitly consider the nature of that human capital, i.e., whether it is best characterized as schooling or on-the-job training. To date, empirical studies of the issue largely focus on the effects of risk preferences on schooling decisions (see, e.g., Brown *et al.*, 2006; Belzil and Leonardi, 2007, 2013), typically finding a negative association between risk aversion and schooling investments.

3.2.1 Modeling Training Investments

We develop a stylized model of training investment in the face of uncertain returns. We assume that each worker decides at the beginning of a period whether or not to invest in training. In the absence of training, a worker earns wage w_0. The costs c of training T are known to the worker, while the returns from training are uncertain. Utility depends positively on income and the shape of this relationship depends on the risk aversion θ_i. We assume that workers' risk preferences are not observed by firms. A worker decides to invest in training if the expected returns from training exceed the costs.

In our stylised framework, we distinguish between two channels through which training may affect employment outcomes. First, training leads with probability p_w to an increase in wages of Δw; with probability $(1 - p_w)$ wages remain unchanged. Wage increases may occur, e.g., if training leads to future promotion, job change, or upward career mobility. In practice, there are many reasons for uncertainty about the returns to training including uncertainty about: (i) how quickly training investments become obsolete; (ii) one's own ability to benefit from training; (iii) firm-specific success; and (iv) the quality of the training (see, e.g., Levhari and Weiss, 1974; Williams, 1979; Shaw, 1996). This uncertainty implies that participation in training is a risky investment.

Second, training might act as an insurance mechanism by reducing the likelihood of future income losses. Workers lose their jobs with probability p_j. Training acts as partial insurance against this job loss. Workers who participate in training experience job loss with probability $p_{jT} = p_j - \Delta p_j$, with $p_j \geq \Delta p_j \geq 0$. If they lose their jobs, workers receive transfer payments b instead of the wage w_0.

Given this general framework, the expected values of training ($T = 1$) and no training ($T = 0$) conditional on risk aversion θ_i are given by:

$$\begin{aligned} V_i(T=1|\theta_i) &= (1-p_{jT})(1-p_w)u(w_0-c|\theta_i) + (1-p_{jT})p_w u(w_0-c+\Delta w|\theta_i) \\ &\quad + p_{jT}u(b-c|\theta_i) \qquad (3.1) \\ V_i(T=0|\theta_i) &= (1-p_j)u(w_0|\theta_i) + p_j u(b|\theta_i) \qquad (3.2) \end{aligned}$$

Worker i participates in training if the following inequality holds:

$$\begin{aligned} (1-p_{jT})(1-p_w)u(w_0-c|\theta_i) + (1-p_{jT})p_w u(w_0-c+\Delta w|\theta_i) + p_{jT}u(b-c|\theta_i) \\ > (1-p_j)u(w_0|\theta_i) + p_j u(b|\theta_i). \end{aligned}$$

There are no clear predictions about the role of risk aversion in the decision to participate in training in this general framework. Workers must trade-off the possibility that training will not result in a wage increase, leaving them out of pocket, against the potential need for the partial insurance against future job loss that training provides. The relationship between workers' risk preferences and their training choices will depend on the relative strength of the two sources of underlying uncertainty, p_w and p_j. Consequently, to clarify ideas, we first present two specific cases in which we alternatively shut down (i) the risk of job loss ($p_j = 0$) and (ii) the probability of experiencing a wage increase ($p_w = 0$), respectively. We then conduct some simulations in order to provide insights into the way that different parameters values affect the decision to participate in training and how this decision depends on the degree of risk aversion.

Our theoretical framework is static. The costs and potential returns of training are realized in the same period. In reality, however, some portion of the returns to training may only materialize in future periods, for example, in the form of an increased wage growth. If workers can borrow in the initial period to pay the costs of training, our approach is likely to be a good approximation of a dynamic process. In contrast, if workers face credit constraints and are not able to smooth their consumption, our framework may not fully capture the relationship between risk aversion and training decisions. Consequently, we consider the sensitivity of our results to this issue by simulating outcomes in a two-period model in Section 3.2.2 below.

Case 1 – Training solely as a risky investment: With $p_j = 0$ the expected value of training ($T = 1$) vs. no training ($T = 0$) conditional on risk aversion θ_i can be expressed as:

$$V_i(T = 1|\theta_i) = (1 - p_w)u(w_0 - c|\theta_i) + p_w u(w_0 - c + \Delta w|\theta_i) \tag{3.3}$$

$$V_i(T = 0|\theta_i) = u(w_0|\theta_i) \tag{3.4}$$

Worker i undertakes training if:

$$(1 - p_w)u(w_0 - c|\theta_i) + p_w u(w_0 - c + \Delta w|\theta_i) > u(w_0|\theta_i).$$

Undertaking training is potentially beneficial only if the associated future wage increase exceeds the cost of training, i.e., if $\Delta w - c > 0$. Whether or not a worker participates in training depends on the chances of receiving a future wage increase, the utility gain associated with this wage gain, and the utility loss associated with paying the costs of the training. The way these monetary costs and benefits are translated into worker utility is dictated by the shape of the utility function which depends on workers' degree of risk aversion (θ_i). Even if the expected monetary costs and benefits of training do not differ across workers, the expected utility gain from training will be smaller for a worker who is generally risk-averse than for a worker who is generally willing to take risks. This leads to the prediction that – if training is a risky investment with uncertain returns – the likelihood of undertaking training depends negatively on individual-specific risk aversion.

Case 2 – Training solely as an insurance against income loss: We now consider the case in which training solely acts as partial insurance against this job loss. The expected values of training ($T = 1$) and no training ($T = 0$) conditional on risk aversion θ_i are given by:

$$V_i(T = 1|\theta_i) = (1 - p_{jT})u(w_0 - c|\theta_i) + p_{jT}u(b - c|\theta_i) \quad (3.5)$$

$$V_i(T = 0|\theta_i) = (1 - p_j)u(w_0|\theta_i) + p_j u(b|\theta_i) \quad (3.6)$$

Worker i participates in training if the following inequality holds:

$$(1 - p_{jT})u(w_0 - c|\theta_i) + p_{jT}u(b - c|\theta_i) > (1 - p_j)u(w_0|\theta_i) + p_j u(b|\theta_i).$$

Workers undertake training if expected utility from training (given on the left) exceeds the expected utility from not receiving training (given on the right). In this case, uncertainty in the returns to training is captured through a differential in the probability of future job loss. Training reduces this probability by Δp_j, but involves cost c.

Given this framework, undertaking training reduces income in both possible states – working for wage w_0 or receiving transfer payments b – by training cost c. If we make the reasonable assumption that the probability of keeping one's job is greater than losing it, i.e., $p_j > 1 - p_j$, and unemployment benefits are less than wages, i.e., $w_0 > b$, the variance of the income given training is smaller than the variance given no training. This leads to the prediction that – if undertaking training reduces the probability of a negative income shock – the chances of participating in training depend positively on workers' degree of risk aversion θ_i.

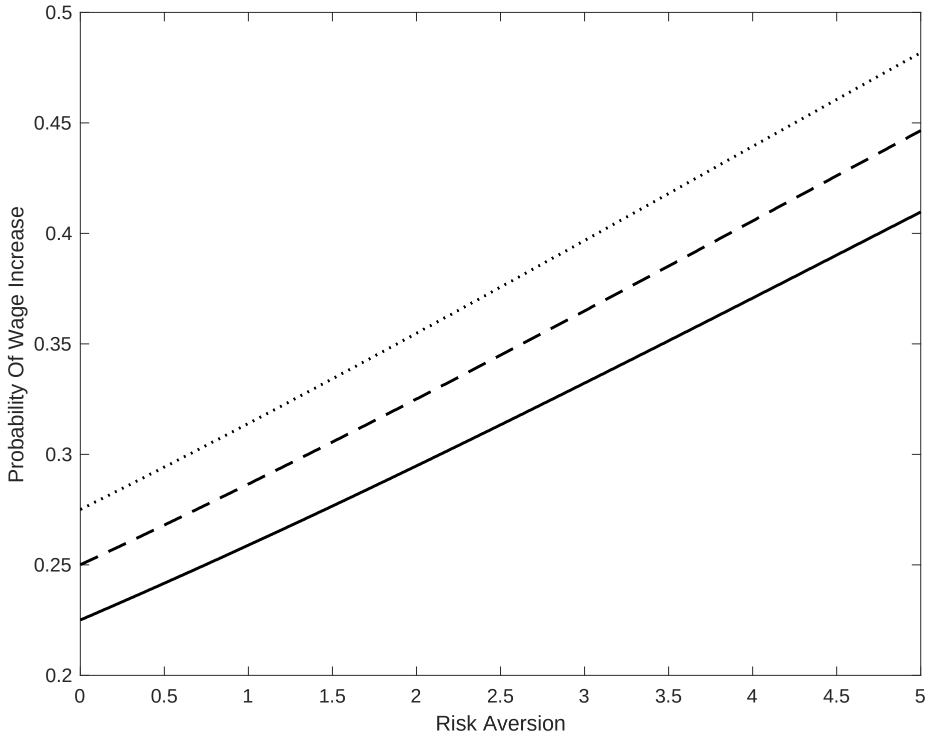
3.2.2 Simulations

We turn now to our simulation analysis which will provide additional insight into the relationship between workers' risk preferences and the other drivers of their training decisions. In this exercise, we assume a utility function with constant relative risk aversion (CRRA). Utility u is given by $u = \frac{y^{1-\theta}}{1-\theta}$. The level of consumption is given by y. We set the baseline wage (w_0) to one and the benefit level (b) to 0.6, which corresponds to the replacement rate of unemployment benefits in Germany. We consider three different levels of training costs: $c_1 = 0.09, c_2 = 0.10, c_3 = 0.11$.

First, we simulate results for Case 1 in which training is characterized solely by its investment returns. Here, training leads with probability p_w to a wage increase $\Delta_w = 0.4$.

We vary the probability p_w from 0.05 to 0.5, and the relative risk aversion parameter θ from 0 – which implies risk neutral agents – to 5. This range of risk aversion parameters corresponds to the range of values usually considered to be reasonable in the literature. For each value of risk aversion θ, we calculate the minimum probability of a post-training wage increase, p_w, which is required to provide workers with an incentive to invest in training. These threshold values are plotted in Figure 3.1. All values of p_w which are above the corresponding lines are consistent with training participation. We observe – as expected – that as workers become more risk-averse they will only invest in training if a post-training wage increase becomes more likely. Not surprisingly, this threshold depends positively on the costs of training.

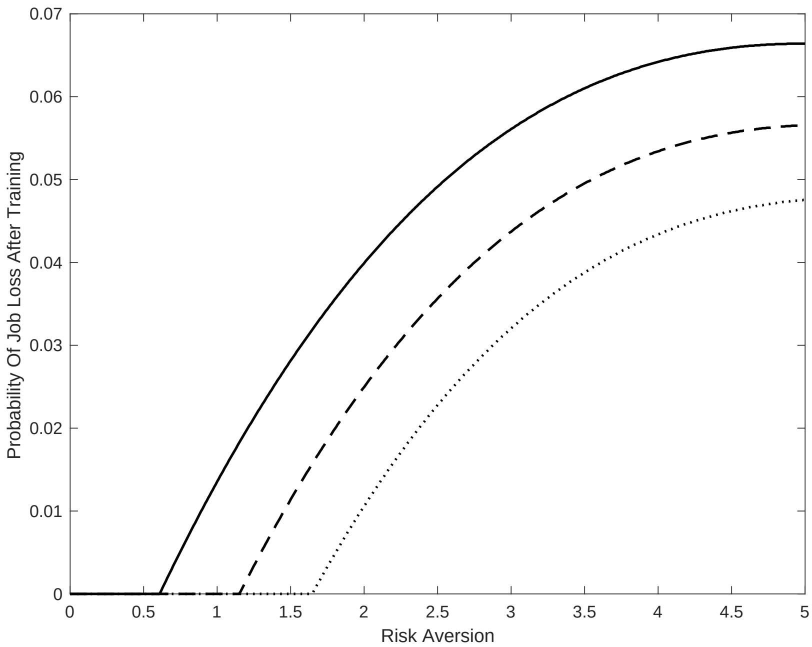
Figure 3.1: Simulations of Case 1 – Threshold Values for Probability of Wage Increase (p_w)



Source: Simulation results.
Notes: The figure shows the minimum values of the probability of a wage increase p_w (y-axis) needed to induce individuals to participate in training by risk aversion (x-axis). Values of p_w above the corresponding line go along with training participation. We set the baseline wage $w_0 = 1$, the benefit level $b = 0.6$, the probability of a job loss (if one is not trained) $p_j = 0$, the post-training probability of a job loss $p_{jT} = 0$, and the (potential) wage increase $\Delta_w = 0.4$. We consider three different levels of training costs: $c = 0.09$ (solid line), $c = 0.1$ (dashed line), and $c = 0.11$ (dotted line).

Second, we simulate results for case 2 in which training provides insurance by altering the probability of subsequent job loss. The probability of losing a job if one is not trained is set to $p_j = 0.2$. We vary the post-training probability of job loss, p_{jT}, from 0 to 0.18. We define for each level of risk aversion (θ) the maximum probability of post-training job loss that leads a worker to invest in training. The results are reported in Figure 3.2. All values of p_{jT} below the corresponding lines are consistent with training participation. For example, an individual with risk aversion parameter $\theta = 2.5$ and facing training costs of $c = 0.1$ would participate in training if the probability of entering unemployment after training is below 0.0357. As predicted, we observe a positive relationship between the maximum probability of post-training job loss needed to incentivize training participation and workers' degree of risk aversion θ. Again, the level of costs increases the thresholds values. Higher costs go along with a need for a larger reduction in the probability of entering unemployment to induce workers to participate in training.

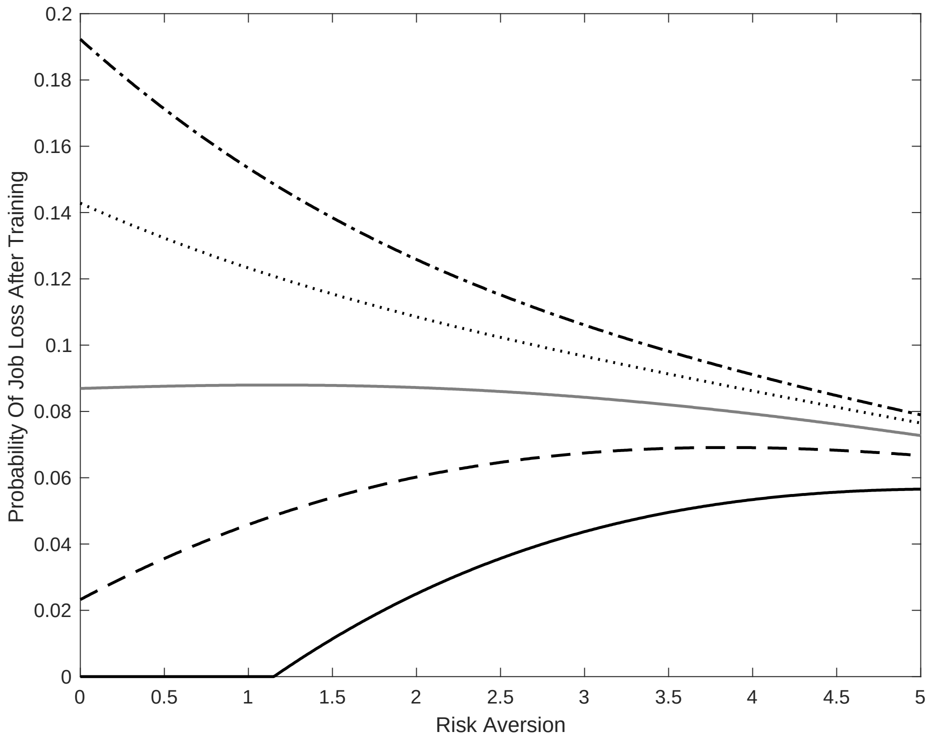
Figure 3.2: Simulations of Case 2 – Threshold Values for Probability of Job Loss after Training (p_{Tj})



Source: Simulation results.
Notes: The figure shows the maximum values of post-training probability of a job loss p_{jT} (y-axis) needed to induce individuals to participate in training by risk aversion (x-axis). Values of p_{jT} below the corresponding line go along with training participation. We set the baseline wage $w_0 = 1$, the benefit level $b = 0.6$, the probability of a job loss (if one is not trained) $p_j = 0.2$, probability of a wage increase $p_w = 0$, and the (potential) wage increase $\Delta_w = 0$. We consider three different levels of training costs: $c = 0.09$ (solid line), $c = 0.1$ (dashed line), and $c = 0.11$ (dotted line).

Third, we investigate what happens in the more general case when training affects both the probability of entering unemployment and the probability of experiencing a wage increase. We focus first on how training decisions vary with the probability of job loss. The cost of training is set to $c = 0.1$, while the probability of getting a wage increase after training is set to $p_w = 0.3$. The wage gain associated with training is increased in four equal steps from $\Delta_w = 0$ to $\Delta_w = 0.4$. For each of these four possible wage gains, we show the relationship between risk aversion and the maximum probability of post-training job loss that is consistent with individuals being willing to train in Figure 3.3. As in Case 2, we find that when there is no wage gain associated with training, i.e., $\Delta_w = 0$, there is a positive relationship between risk aversion and the maximum probability of job loss (p_{jT}) that separates those who train from those who do not. This positive relationship continues to hold with $\Delta_w = 0.1$, and it vanishes with $\Delta_w = 0.2$. For $\Delta_w = 0.3$ and $\Delta_w = 0.4$ we observe a negative relationship between the maximum level of p_{jT} and risk aversion. Here, workers with higher risk aversion have a lower tendency to invest in training due to the increased variability in the returns. For workers with a relatively high level of risk aversion, the benefits due to a reduction in the job loss probability have to be relatively large to make a training investment attractive. For this set of parameter values, we also observe a positive relationship between the level of risk aversion and the minimum probability p_w that leads to an investment in training.

Figure 3.3: Simulations of Case 3 – Threshold Values for Probability of Wage Increase (p_w) Depending on Potential Wage Increase (Δ_w)

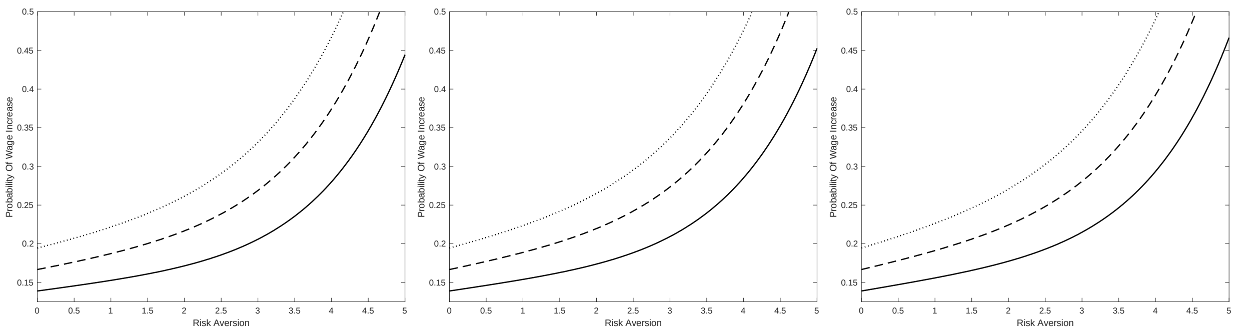


Source: Simulation results.
Notes: The figure shows the maximum values of the post-training probability of a job loss p_{jT} (y-axis) needed to induce individuals to participate in training by risk aversion (x-axis). Values of p_{jT} below the corresponding line go along with training participation. We set the baseline wage $w_0 = 1$, the benefit level $b = 0.6$, the probability of a job loss (if one is not trained) $p_j = 0.2$, the probability of a wage increase $p_w = 0.3$, and the training costs $c = 0.1$. We consider five different levels of (potential) wage increases: $\Delta_w = 0$ (solid line), $\Delta_w = 0.1$ (dashed line), $\Delta_w = 0.2$ (solid grey line), $\Delta_w = 0.3$ (dotted line), $\Delta_w = 0.4$ (dash-dotted line).

In our framework, we assume that there are two potential post-training wages, w_0 and $w_0 + \Delta_w$. We investigate how sensitive our results are to the specification of potential wage growth. In this exercise, we set the job loss probability without training to $p_j = 0.2$, which is reduced to $p_{jT} = 0.1$ after training. We choose three different specifications for the potential wage growth after training. First, we assume that the wage increase corresponds to 0.4 – our baseline specification, see panel A of Figure 3.4. Second, we assume two potential wage gains $\Delta_{w1} = 0.3$ and $\Delta_{w2} = 0.5$, both occurring with a probability equal to $p_w/2$ (panel B). And finally, we assume four potential wage gains ($\Delta_{w1} = 0.2$, $\Delta_{w2} = 0.3$, $\Delta_{w3} = 0.5$ $\Delta_{w4} = 0.6$), all occurring with a probability equal to $p_w/4$ (panel C). This implies that the expected wage growth after training is the same across all specifications, while its variance is increasing. Figure 3.4 displays the minimum probability of experiencing a wage increase after training p_w which is required to give workers an incentive to undertake training. We observe that an increase in the variance of the wage returns, i.e., moving from panel A to panel C in Figure 3.4, results in a slightly steeper increase in p_w as risk aversion increases, while this value is as expected the same for risk-neutral agents. Most importantly, the relationships depicted in the three panels are virtually identical. This is also true when we consider the threshold values for the probability of experiencing a job loss (see Appendix Figure 3.7). This gives us confidence that our decision to assume a fixed wage increase – rather than considering a distribution of potential wage increases – is not the primary factor driving agents' behavior.

Figure 3.4: Simulations with Different Assumptions about the Variance of the Wage Increase (Δ_w) – Threshold Values for Probability of Wage Increase (p_w)

A - $\Delta_w = 0.4$ B - $\Delta_{w1} = 0.3, \Delta_{w2} = 0.5$ C - $\Delta_{w1} = 0.2, \Delta_{w2} = 0.3, \Delta_{w3} = 0.5, \Delta_{w4} = 0.6$



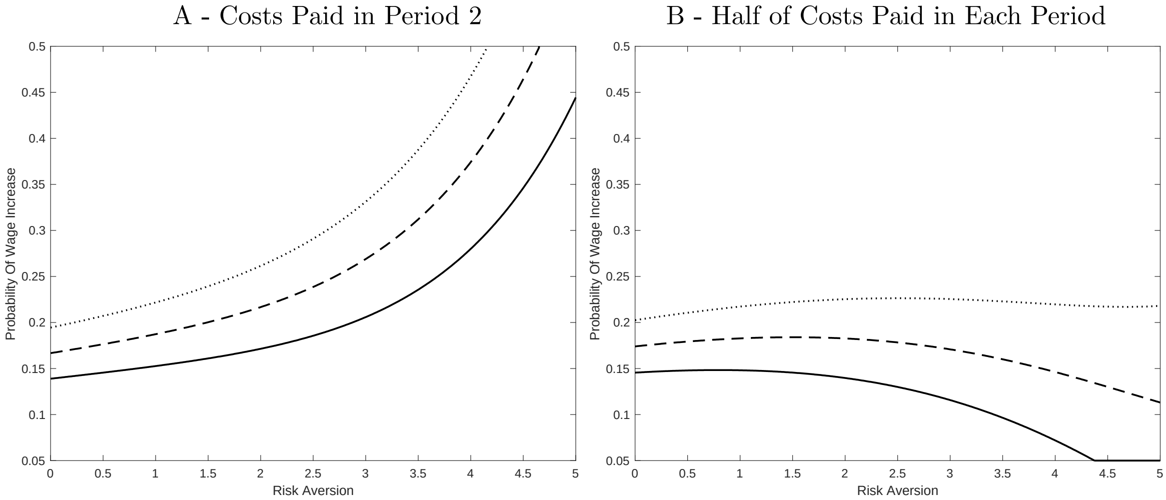
Source: Simulation results.
Notes: The figure shows the minimum values of the probability of a wage increase p_w (y-axis) needed to induce individuals to participate in training by risk aversion (x-axis). Values of p_w above the corresponding line go along with training participation. We set the baseline wage $w_0 = 1$, the benefit level $b = 0.6$, the probability of a job loss (if one is not trained) $p_j = 0.2$, the post-training probability of a job loss $p_{jT} = 0.1$, and the expected wage growth $\mathbb{E}(\Delta_w) = 0.4$. We consider three different levels of training costs: $c = 0.09$ (solid line), $c = 0.1$ (dashed line), and $c = 0.11$ (dotted line). Panel A: we set the (potential) wage increase $\Delta_w = 0.4$. Panel B: we allow for two (potential) wage changes $\Delta_{w1} = 0.3$ and $\Delta_{w2} = 0.5$, each occurring with probability $p_w/2$. Panel C: we allow for four (potential) wage changes $\Delta_{w1} = 0.2, \Delta_{w2} = 0.3, \Delta_{w3} = 0.5$, and $\Delta_{w4} = 0.6$, each occurring with probability $p_w/4$.

Finally, we consider a two-period model. Workers invest in training in period 1, while the training pays off in period 2 in terms of potential wage gains and reduced unemployment risk. We set the discount factor to 0.95, which is within the range of standard values used in the literature.[2] Our results are reported in Figure 3.5. We first assume that workers pay the costs of training in period 2 (see panel A) and find results that are similar to those in

[2]Our results do not change if we use alternative values like for example 0.92 or 0.98.

our static baseline model. Second, we assume that half of training costs are paid in period 1, and the other half is paid in period 2 (panel B). Here, the relationship between the threshold value for the probability of getting a wage increase and risk aversion depends on the level of costs, and it is potentially non-monotonic (first increasing and then decreasing). In Figure 3.8 in the Appendix, we present the relationship between the maximum probability p_{Tj} leading still to training participation and the level of risk aversion. As in our static baseline model, we find a negative relationship between these parameters.

Figure 3.5: Simulations for a Two Period Model – Threshold Values for Probability of Wage Increase (p_w)



Source: Simulation results.
Notes: The figure shows the minimum values of the probability of a wage increase p_w (y-axis) needed to induce individuals to participate in training by risk aversion (x-axis). Values of p_w above the corresponding line go along with training participation. We set the baseline wage $w_0 = 1$, the benefit level $b = 0.6$, the probability of a job loss (if one is not trained) $p_j = 0.2$, the post-training probability of a job loss $p_{jT} = 0.1$, and the (potential) wage increase $\Delta_w = 0.4$. We consider three different levels of training costs: $c = 0.09$ (solid line), $c = 0.1$ (dashed line), and $c = 0.11$ (dotted line). Individuals decide to participate in training in period 1, which leads to a potential increase in wages and a reduction in unemployment probability in period 2. Panel A: the costs are paid in period 2. Panel B: we assume that individuals pay half of the costs in each period.

Taken together, the simulations of our static baseline model lead us to expect a negative relationship between the level of risk aversion and training participation if training is mainly considered to be a risky investment. In a dynamic framework, the results are sensitive to the timing of the payment of training costs. Moreover, the relationship between the level of risk aversion and training participation may be ambiguous in some cases. However, an overall negative relationship between risk aversion and training participation indicates that workers primarily consider training to be a risky investment – rather than an insurance mechanism – which may have a payoff in the form of future wage increases.

3.2.3 General vs. Specific Training

One of the key distinctions between work-related training and formal education is the range of contexts in which any newly acquired skills are productive. Some training is like formal education in that it results in skills that are broadly applicable; other types of training have limited applicability beyond the current context. In his seminal work, Becker (1962) demonstrates that this degree of skill transferability drives the way that the costs and benefits of training are shared between workers and firms. Firms receive all benefits and pay all costs when training is "perfectly specific" (i.e., raises productivity only in the current firm). Workers receive all benefits and pay all costs when training is "perfectly general" (i.e., fully transferable across firms). Most training naturally falls between these two extremes, including some components which may be specific to the current employer as well as other components which increase productivity both inside and outside the current firm. Moreover, imperfect competition may allow firms to earn rents by paying post-training wages that are lower than workers' post-training productivity. The consequence is that there are a wide variety of circumstances in which firms may find it profitable to pay – at least in part – for training that is general (see Acemoglu and Pischke, 1999a,b; Caliendo *et al.*, 2022, for reviews).

The key insights of our theoretical framework remain unchanged in the face of these extensions to the Becker (1962) model, however, so long as wages continue to depend positively on worker productivity. The returns to training fundamentally depend on the cost-benefit-sharing rule. Workers undertaking general training face investment risk because they largely both pay and receive the benefits of training. In contrast, specific training poses little investment risk for workers because they neither pay the costs nor receive the benefits of the training they undertake. Consequently, the role of risk preferences in training decisions depends on the transferability of the skills to be acquired. We expect the decision to invest in general training to depend on workers' level of risk aversion, however, the relationship between risk aversion and participation in specific training is likely to be less pronounced.

3.3 Data

3.3.1 Estimation Sample

We utilize data from the German Socio-Economic Panel (SOEP, 2019) which is an annual representative household panel survey. In 1984, approximately 12,000 individuals living in 6,000 households were surveyed. Subsequently, the SOEP sample has periodically been extended to include samples of those living in the former German Democratic Republic or minority groups (e.g., migrants). In 2018, approximately 30,000 individuals from 15,000 households were surveyed (Goebel *et al.*, 2019). The SOEP data provide us with rich information about respondents' socioeconomic background, labor market behavior, and economic preferences.

The years 2004 and 2008 are of particular interest for our analysis because detailed information on training activities and risk attitudes are available in these years. We pool data from these two waves and make a number of sample restrictions. Specifically, we restrict our analysis to the working-age population between the ages of 25 and 60 who were employed at the time of training. We exclude individuals who are self-employed at the time of the interview as well as respondents with missing data for the risk attitudes measure, the training measure, or any other control variables.[3] Our final sample includes 3,806 individuals from the year 2004, and 5,790 from the year 2008 which results in an overall estimation sample of 9,596 observations.[4] For our empirical analysis, we first exploit the panel structure of the SOEP to impute necessary information (see Section 3.3.3), afterwards we pool the years 2004 and 2008 and control for time effects.

3.3.2 Training Measures

In 2004 and 2008, SOEP respondents under the age of 65 were asked whether they had engaged in any courses for further professional education in the last three years. If so, they were then asked detailed questions about the timing, duration, and costs of the three most

[3]The Supplementary Appendix 3.7 contains an extensive data section 3.7.1 with more information. Table 3.13 provides an overview of the degree to which sample restrictions reduce our sample size. A comparison of our final estimation sample with our population of interest for selected control variables is provided in Table 3.14. There are very few significant differences in the two samples leaving us confident that we do not have an issue with selective non-response.

[4]Specifically, we observe 1,459 individuals only in 2004, and 3,443 only in 2008, while 2,347 are observed in both years and are included in the sample twice.

recent courses they had undertaken. As we have information about training start dates, we can identify those respondents who participated in at least one training course in the 12 months prior to the interview date. We define these individuals to be training participants.[5]

Our conceptual framework suggests that the effect of risk preferences on training participation depends on the extent to which any acquired skills are transferable across jobs, i.e., whether the training is of general or specific nature. The information provided in 2004 and 2008 about skill transferability allows us to distinguish between general and specific training using responses to the following question: "To what extent could you use the newly acquired skills if you got a new job in a different company?". Survey participants respond by indicating: "Not at all", "Only to a limited extent", "For the most part", or "Completely".

Following Becker (1962), we define specific training to be training that is "Not at all" or "Only to a limited extent" transferable outside the company; general training is training that can be transferred "For the most part" or "Completely". Overall, 1,493 respondents report having participated only in general training within the last year, while 827 respondents report participating in specific training only. In addition, 168 respondents report participating in both types of training within the preceding 12 months. This provides us with a total of 2,488 observations which are classified as training participants and 7,108 observations which are classified as non-participants. In Section 3.4.2.2, we consider the robustness of our results to alternative definitions of general and specific training and the context in which training choices are made.

Detailed information regarding the nature of the training courses undertaken can be found in Table 3.7 in the Appendix. General training is more likely to take place in private institutes and for the purpose of "qualification for professional advancement", while specific training is more likely to be organized by the current employer and for the purpose of "adjustments to new demands in the current job". There is clearly, however, a wide variety of contexts in which training occurs. Interestingly, approximately 19 percent of those participating in specific training believe that the training they received was not worth it professionally; this is true for only 8 percent of those participating in general training.

[5] Overall, training information is available in the SOEP in the years 2000, 2004, 2008, and 2014-2019. We do not utilize the years 2000 and 2014-2019 because we do not have information on attitudes toward risk in 2000 or the transferability of training in 2014-2019.

3.3.3 Risk Preferences

Beginning in 2004, the SOEP survey adopted several new approaches to measuring risk preferences. First, respondents are asked to make a general assessment of their willingness to take risks by answering the following question: "How willing are you to take risks, in general?" Respondents answer using an 11-point Likert scale that ranges from "not at all willing to take risks" to "very willing to take risks". This measure of general risk preferences is available in 2004, 2006, 2008, and every year since. Second, in 2004, 2009, and 2014, respondents are asked about their willingness to take risks in six different domains. Specifically, people were asked: "How would you rate your willingness to take risks in the following areas? How is it while driving? ... in financial matters? ... during leisure and sports? ... in your occupational career? ... with your health? ... with your faith in other people?" Respondents rate their willingness to take risks in each domain on a scale from 0 to 10.[6]

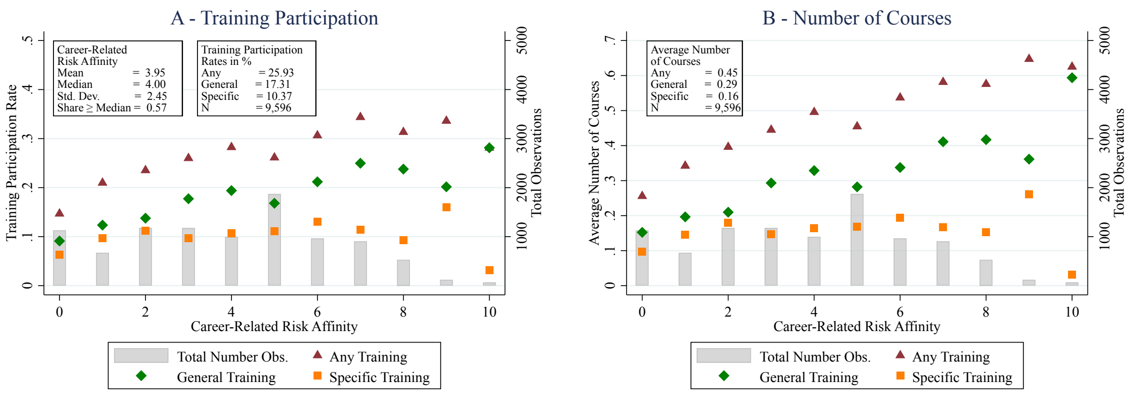
Dohmen *et al.* (2011) conduct an in-depth analysis of the predictive power of SOEP's general and domain-specific risk attitude measures. They find that general risk preference are able to predict a wide range of behaviors across domains indicating that there is a stable, underlying risk trait. Within each domain, however, the relevant domain-specific risk attitude measure is a better predictor of behavior, suggesting that the context is important in how risk preferences are expressed. Consequently, a growing number of studies focus their analyses on domain-specific risk attitudes when analyzing people's choices (see, e.g., Hanoch *et al.*, 2006; van der Pol and Ruggeri, 2008; Barseghyan *et al.*, 2011; Budria *et al.*, 2013). Given our interest in employment-related training investments, we do the same, focusing our attention on the relationship between training investments and people's career-related risk preferences. In Section 3.4.2.3, we consider the sensitivity of our results to the choice of risk attitude measure.

Specifically, we create a continuous measure of 2004 career-related risk affinity that is increasing in the willingness to take risks. We maximize our estimation sample by using our

[6]The 2004 SOEP also includes a hypothetical, i.e., unincentivized, lottery question. Specifically, respondents are asked to nominate how much of a 100,000 Euro endowment they would invest in a lottery with a 50-50 chance of doubling or losing half of the invested amount. Dohmen *et al.* (2011) find that this measure predicts behavior only in the financial domain.

2004 measure of career-related risk affinity in both 2004 and 2008.[7] Summary statistics are provided in the left text box in Figure 3.6, panel A. The average career-related risk affinity in our sample is 3.95, while the median is 4.

Figure 3.6: Training Investment by Career-Related Risk Affinity



Source: Socio-Economic Panel (SOEP), data for years 2004, 2008, version 35, SOEP, 2019, doi:10.5684/soep.v35, own calculations.
Notes: Panel A: The figure shows the training participation rates for any training type, general and specific training by career-related risk affinity (left y-axis). The question asked in the survey is "How would you rate your willingness to take risks in your occupational career?". Respondents can answer on an 11-point Likert scale ranging from "not at all willing to take risks (0)" to "very willing to take risks (10)". Additionally, the distribution of the career-related risk affinity is depicted with the grey bars (right y-axis). The left box presents the mean, median and standard deviation of the career-related risk affinity measure, as well as the share of individuals whose self-reported career-related risk attitude is equal to or greater than the median. The right box presents the training participation rates for overall, general, and specific training as well as the overall number of individuals in the sample.
Panel B: The figure shows the average number of courses for any training type, general and specific training by career-related risk affinity (left y-axis). The number of courses is capped at 3 because we only know the type of training for the three most recent courses. Additionally, the distribution of the career-related risk affinity is depicted with the grey bars (right y-axis). The box presents the average number of courses for overall, general, and specific training as well as as the overall number of individuals in the sample.

While participation in some form of training is on average 26 percent, the likelihood of participating in training varies notably by risk affinity. It is approximately 15 percent for those who report that they are not at all willing to take risks in their careers and is more than 30 percent among those who rate their willingness to take career-related risks as a six or higher. Participation rates are higher for general training than for specific training irrespective of people's risk attitudes. Consistent with our conceptual framework, participation rates for any and general training increase with risk affinity, while participation in specific training appears to be less sensitive to risk attitudes. The same is true if we look at

[7]In the robustness section 3.4.2.4, we replicate our main analysis for the years 2004 and 2008 separately. When looking at 2004 only, we practically forgo the imputation of the risk attitude. An overview of the timing of our main variables is depicted in Figure 3.9.

the intensive training margin, e.g., the number of courses (capped at three)[8], in Figure 3.6, panel B. We see the average number of courses for any and general training increase with risk affinity, but not for specific training.

3.3.4 Control Variables

Our choice of control variables is informed by the literature on the determinants of training participation. First, multiple socio-demographic factors have been found to influence the probability of undertaking training. Older and less educated workers, for example, are less likely to receive training (Oosterbeek, 1996; Lynch and Black, 1998; Bassanini *et al.*, 2007; Maximiano, 2012). Many studies suggest that men are more likely to receive training than are women (Lynch, 1992; Dieckhoff and Steiber, 2011; Fitzenberger and Muehler, 2015), though other studies find that the gender gap in training either favors women (Simpson and Stroh, 2002) or disappears entirely once occupational characteristics are controlled (Oosterbeek, 1996). Second, both occupational and firm characteristics influence training decisions. The probability of training increases with experience (Lynch, 1992) and is higher for workers with a permanent (Oosterbeek, 1996) or full-time contract (Leuven and Oosterbeek, 1999) or who are union members (Lynch, 1992; Booth *et al.*, 2003). Investment rates differ by labor market sector (Oosterbeek, 1998) and are higher in larger firms (Lynch and Black, 1998; Maximiano, 2012). Finally, evidence suggests that personality traits such as locus of control (Caliendo *et al.*, 2022) affect the incidence of training investments.

Given this background, our estimation models control for a number of factors including: (i) socio-demographic characteristics (i.e., age, gender, marital status, number of children, disabilities, migration background, home ownership status, highest educational degree and vocational training, employment and unemployment experience, and real net household income); (ii) regional-specific variables (i.e., regional state dummies, local unemployment rates, and regional GDP); (iii) job-related characteristics (i.e., employment status, occupational position, contract type, tenure, trade union and trade association membership, and ISCO88 occupation); (iv) firm-specific characteristics (i.e., firm size and NACE industry)[9];

[8]The number of courses are capped at three because we only know the type of training for the three most recent courses.

[9]Our occupational classification is based on the International Standard Classification of Occupations 88

and (v) personality traits (i.e., Big Five traits and locus of control).[10] Descriptive statistics for our control variables are provided by training status in Table 3.8 in the Appendix.[11]

3.4 Results

3.4.1 Estimation Strategy

Conceptually, risk attitudes influence the decision to invest in work-related training both because the returns to training are uncertain and because training may provide a degree of insurance against future income shocks. The former leads us to expect a positive relationship between risk affinity and participation in training; the latter leads us to expect a negative relationship (see Section 3.2). Which effect dominates then becomes an empirical question which we investigate here. Irrespective of whether risk affinity is associated with more or less training, we expect the relationship to be stronger in the case of general training because workers have a vested interest in training outcomes.

We analyze the relationship between risk affinity and three separate training outcomes, any training, general training, and specific training. Specifically, our three outcome variables are indicators for participation in the previous 12 months (extensive training margin) in: (i) any type of training T^A; (ii) general training T^G; or (iii) specific training T^S. We pool observations from 2004 and 2008 and estimate the following logit model:

$$P(T^j)_{it} = \frac{\exp(\alpha_0 + \alpha_1 Risk_{i0} + \boldsymbol{X'_{it}\alpha_2})}{1 + \exp(\alpha_0 + \alpha_1 Risk_{i0} + \boldsymbol{X'_{it}\alpha_2})} \quad (3.7)$$

where i indicates individuals, t captures time, and $j \in \{A, G, S\}$ references the type of training (i.e., any, general, or specific). The main independent variable of interest is *Risk*, i.e., career-related risk affinity, which we standardize in order to facilitate interpretation and

(ISCO88) which categorizes occupations into 10 groups. We drop "soldiers" as they are not included in our sample and focus on the remaining 9 occupations (see Table 3.8). We aggregated industries into 12 categories based on the classification system NACE ("Nomenclature statistique des Activités Economiques dans la Communauté Européenne") used by the European Union (see Table 3.8).

[10]Unfortunately, information on trade union and association membership, as well as the Big Five and locus of control are not all available in the years 2004 and 2008. Hence, we take the years from the most recent year available (if possible). Consequently, we impute the missing information on trade union and association membership status from 2003 to 2004 and 2007 to 2008, Big Five traits are imputed from 2005 to 2004 and 2008, and locus of control is imputed from 1999 to 2004 and 2005 to 2008. Excluding the imputed controls slightly increases coefficients, but does not change our main conclusions (see Table 3.15 in the Supplementary Appendix).

[11]Further details on the definition of our control variables are available in the Supplementary Appendix 3.7.2.

make our results more comparable to other studies. The parameter α_1 captures the effect of the career-related risk affinity on the probability of participating in training. We include a rich set of control variables in the vector $\boldsymbol{X_{it}}$ capturing (i) socio-demographic; (ii) region-specific, (iii) job-related, and (iv) firm-specific characteristics as well as (v) personality traits as detailed in Section 3.3.4. When examining the relationship between risk affinity and the intensive training margin (duration and hours per week), we use an OLS regression with the same set of covariates. To account for some individuals appearing in the sample twice, we cluster the standard errors at the individual level.

Unfortunately, we lack exogenous variation in risk affinity; indeed it is difficult to imagine the experiment that would result in a substantial and sustained shift in people's risk preference. Consequently, we regard our estimates as providing descriptive rather than causal evidence on the role of risk attitudes in training decisions.

3.4.2 Risk Affinity and Training Investments

3.4.2.1 The Incidence and Duration of Training

The estimated association between career-related risk affinity and investments in work-related training are shown in Table 3.1. The results reported are the average marginal effects corresponding to the logit estimation of equation (3.7) in the case of training participation (the extensive training margin). Our preferred specification focuses on a continuous measure of risk affinity (see column 1), while results from a discrete indicator for being in the top half of the risk-affinity distribution are shown in column (2). In columns (3)–(6), we report estimates of the association between risk affinity and various measures of training intensity (the intensive training margin), reporting OLS coefficients which are also interpreted as average marginal effects. The three panels of Table 3.1 correspond to the three outcomes that we consider: (i) any training (panel A); (ii) general training (panel B); and (iii) specific training (panel C).

Consider first the estimated effects of risk affinity on the incidence of training in our preferred specification which includes all controls (column 1).[12] We find that having a greater affinity for risk is associated with a significantly higher likelihood of undertaking any training in the previous 12 months. A one standard deviation (SD) increase in career-

[12]Full estimations results are available in Table 3.9 in the Appendix.

related risk affinity, i.e., a 2.5-points increase on the 11-point Likert scale, is associated with a probability of any training participation that is 2.2 percentage points (p.p.) (almost 8.5 percent) higher.

Table 3.1: Training Investments and Career-Related Risk Affinity
(Logit Average Marginal Effects and OLS Coefficients)

	Participation		Number of Courses	Duration (in Weeks)	Hours (per Week)
	(1)	(2)	(3)	(4)	(5)
A. Training					
Career-Related Risk Affinity (std.)	0.022***		0.042***	0.133*	0.429***
	(0.005)		(0.010)	(0.074)	(0.100)
Career-Related Risk Seeking (Indicator)		0.033***			
		(0.010)			
Average of Dependent Variable	25.93	21.41	0.45	0.82	3.83
Effect in %	8.48	15.41	9.33	16.22	11.20
Pseudo-R^2 / $\overline{R^2}$	0.13	0.13	0.12	0.01	0.09
B. General Training					
Career-Related Risk Affinity (std.)	0.022***		0.039***	0.133*	0.406***
	(0.004)		(0.008)	(0.071)	(0.085)
Career-Related Risk Seeking (Indicator)		0.034***			
		(0.008)			
Average of Dependent Variable	17.31	13.39	0.29	0.66	2.51
Effect in %	12.71	25.39	13.45	20.15	16.18
Pseudo-R^2 / $\overline{R^2}$	0.11	0.11	0.08	0.01	0.06
C. Specific Training					
Career-Related Risk Affinity (std.)	0.003		0.003	0.000	0.022
	(0.003)		(0.006)	(0.022)	(0.060)
Career-Related Risk Seeking (Indicator)		0.007			
		(0.007)			
Average of Dependent Variable	10.37	9.20	0.16	0.16	1.33
Effect in %	2.89	7.61	1.88	0.00	1.65
Pseudo-R^2 / $\overline{R^2}$	0.10	0.10	0.05	-0.00	0.05
Controls	✓	✓	✓	✓	✓
Observations	9,596	9,596	9,596	9,577	9,387

Source: Socio-Economic Panel (SOEP), data for years 2004, 2008, version 35, SOEP, 2019, doi:10.5684/soep.v35, own calculations.
Notes: The table displays the average marginal effects estimated based on logit estimations (columns 1-2) and coefficients estimated based on OLS estimation (columns 3-6). The dependent variables are indicated in the column headers and below. Panels refer to training type: any (panel A), general (panel B), specific (panel C). The main explanatory variable of interest is the standardized career-related risk affinity measured in 2004 (except in column 2, see below). All regressions include the full set of control variables. For each regression, we display the (unconditional) average of the dependent variable ("Average of Dependent Variable"), the average effect in % (in relation to the unconditional participation rate) of the main explanatory variable ("Effect in %"), and the Pseudo-R^2 (logit regressions) or $\overline{R^2}$ (OLS regressions). Standard errors are in parentheses and clustered on person-level. * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$.
(1) Logit regression with an indicator dependent variable indicating participation in training. Full linear specification. Detailed estimation results available in Table 3.9 in the Appendix.
(2) Logit regression with an indicator dependent variable indicating participation in training. Career-related risk seeking measured in 2004 is an indicator that takes on the value one if the continuous measure of career-related risk affinity is equal to or greater than the median (4 on the non-standardized scale). Here, the average of the dependent variable refers to the unconditional average of the dependent variable for the reference group.
(3) OLS regression with a dependent variable indicating the number of courses of the last year, capped at 3 as we only know the type (general vs. specific) for the 3 most recent courses.
(4) OLS regression with a dependent variable indicating the overall duration of the most recent course in weeks (own calculation, based on information of the length (days, weeks, months) of each course).
(5) OLS regression with a dependent variable indicating the hours of instructions per weeks of the most recent course.

Becker (1962) was the first to recognize the fundamental importance of skill transferability in the way net training returns are shared between firms and workers. In essence, greater skill transferability results in more opportunities for future job change, allowing workers to capture a larger share of the returns to training. Once we distinguish between general (panel B) and specific training (panel C), it becomes evident that the relationship between risk affinity and training overall is driven mainly by general training. The 2.2 p.p. increase in general training that is associated with a 1 SD increase in risk affinity is of the same magnitude as that for training overall and translates into an effect size of roughly 12.7 percent. On average, those with a risk affinity in the top half of the distribution are 3.4 p.p. (25.4 percent) more likely than those in the bottom half of the distribution to invest in general training (see column 2). In contrast, the estimated effect of risk affinity on specific training, is small and statistically insignificant.

Risk affinity is also positively related to the intensity of work-related training. Specifically, greater risk tolerance is positively and significantly related to the number of training courses undertaken (column 3).[13] As before, the overall training effect is driven by general training. The same is true when we instead consider either the duration of training in weeks (column 4) or the hours of instruction per week in the most recent course (column 5).

Taken together, our results indicate that a greater affinity for career-related risk is associated with greater investments in work-related training. Thus, on average, the uncertainty around the returns to training may play a more important role in people's training decisions than does any insurance that training might provide. Consistent with our expectations, this relationship is driven by training that is largely transferable and gives workers a vested interest in training outcomes. Workers' risk attitudes are not significantly related to their decision to invest in work-related training that is specific to their current job and firm.

3.4.2.2 The Distinction Between General and Specific Training

Our dichotomy between general and specific training is based on respondents' views about the extent to which the skills they acquire would also be useful in a new job in another firm. We expect workers' risk preferences to be more salient for investments in general training because enhanced skill transferability gives them more vested interest in whether training is

[13] Our data only allow us to distinguish general vs. specific training for the first three training events. Estimating the model on this subsample of training events may result in an underestimate of the overall effect of risk affinity.

successful. Given this, we focus our attention on assessing whether our measures of general vs. specific training, in fact, capture a meaningful difference in the extent to which skills can be transferred. We proceed along two lines. First, we consider the generalizability of our results to alternative measures of general vs. specific training events. Second, we turn to investigating two conceptual issues: (i) the potential role of worker autonomy, and (ii) the pattern of job mobility following training.

The take-away message is that workers' self-reports of skill transferability appear to be a sensible basis for distinguishing between general and specific training. Specifically, our conclusions are robust to a range of measurement issues, suggesting that we are capturing a meaningful distinction in the type of training that people undertake. Consistent with our conceptual framework, our results are also relatively stronger in training situations where workers are likely to have more agency. Finally, the pattern of job mobility after training is consistent with the premise that our distinction between general vs. specific training captures a meaningful distinction in skill transferability.

Measurement Issues: The dichotomy between general and specific training has proven to be a useful construct for understanding the consequences of training for workers and firms. Many researchers, however, argue that training is seldom entirely specific. Lazear (2009), for example, views all skills as general, arguing that it is only the skill mix and the weights attached to particular skills that are specific to each employer. This ambiguity makes the method used to empirically distinguish between general and specific training an important issue.

We first investigate the robustness of our findings to the threshold we use to differentiate between training that is specific rather than general. We first redefine specific training as skills perceived to be "not at all" transferable to jobs in other firms; all other responses indicate general training. We find virtually no difference in the estimated relationship between risk affinity and training participation (see column 2 of Table 3.2). We then consider an even starker distinction in skill transferability: training is general only if the skills acquired are "completely" transferable and is specific when the skills are "not at all" transferable. As all other training events are dropped from analysis, this allows us to differentiate between the extremes of the transferability of skills. Although the effect of risk attitudes on training is somewhat weaker, our general conclusions remain the same, risk affinity is associated with an increase in training that is general rather than specific (see column 3).

Table 3.2: Training Participation and Career-Related Risk Affinity by Training Definition (Logit Average Marginal Effects)

	Baseline (1)	Transferable vs. Not (2)	Completely vs. Not (3)	Training Worth It (4)	Most Recent Course (5)	Exclude Both Types (6)
A. Training						
Career-Related Risk Affinity (std.)	0.022***	0.022***	0.014***	0.020***	0.022***	0.020***
	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)
Participation Rate	25.93	25.93	10.32	23.64	25.93	24.61
Effect in %	8.48	8.48	13.57	8.46	8.48	8.13
Pseudo-R^2	0.13	0.13	0.12	0.14	0.13	0.13
B. General Training						
Career-Related Risk Affinity (std.)	0.022***	0.020***	0.011***	0.021***	0.020***	0.020***
	(0.004)	(0.005)	(0.003)	(0.004)	(0.004)	(0.004)
Participation Rate	17.31	23.77	7.71	16.45	16.41	15.84
Effect in %	12.71	8.41	14.27	12.77	12.19	12.63
Pseudo-R^2	0.11	0.12	0.12	0.12	0.11	0.10
C. Specific Training						
Career-Related Risk Affinity (std.)	0.003	0.003	0.003	0.002	0.001	0.000
	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Participation Rate	10.37	2.96	2.71	8.84	9.51	8.77
Effect in %	2.89	10.14	11.07	2.26	1.05	0.00
Pseudo-R^2	0.10	0.12	0.14	0.11	0.09	0.09
Controls	✓	✓	✓	✓	✓	✓
Observations	9,596	9,596	7,926	9,308	9,596	9,428

Source: Socio-Economic Panel (SOEP), data for years 2004, 2008, version 35, SOEP, 2019, doi:10.5684/soep.v35, own calculations.
Notes: The table displays the average marginal effects estimated based on logit estimations. The dependent variables are dummies indicating participation in any training (panel A), general training (panel B), and specific training (panel C). The main explanatory variable of interest is the standardized career-related risk affinity measured in 2004. All regressions include the full set of control variables. For each regression, we display the (unconditional) average of the dependent variable ("Participation Rate"), the average effect in % (in relation to the unconditional participation rate) of the main explanatory variable ("Effect in %"), and the Pseudo-R^2. Standard errors are in parentheses and clustered on person-level. * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$.
(1) Main results from column (1) in Table 3.1.
(2) Changing definition of general and specific training (general=completely, to a large extent, only to a limited extent; specific=not at all).
(3) Changing definition of general and specific training (general=completely; specific=not at all).
(4) Exclude those who say 'training not worth it'.
(5) Only consider the most recent training course of each year.
(6) Exclude individuals who participated in both general and specific training in the same year.

It is also possible that our measure of specific training captures training that respondents regard as not useful at all, rather than training that is simply not transferable across jobs. If so, this might account for the disparity that we observe in the response of general vs. specific training investments to workers' risk attitudes. We investigate this issue by excluding all respondents who report that "training was not worth it" from the analysis. We find no evidence that our results are being driven by perceptions of the usefulness of training (see column 4).

Finally, we consider the potential for our results to be driven by workers undertaking both specific and general training. In particular, there are 168 people who participate in both general and specific training within the same 12 month period. As such, these individuals contribute to identifying the effects of risk affinity on both general and specific training. We investigate the importance of this issue by first, focusing only on their single most recent training (column 5) and second, by dropping them from the sample (column 6). Neither substantively alters our conclusions.

Table 3.3: Training Participation and Career-Related Risk-Affinity by Training Context
(Logit Average Marginal Effects)

	Baseline (1)	(Partially) Paid by Employee (2)	(Partially) Outside Working Time (3)
A. Training			
Career-Related Risk Affinity (std.)	0.022***	0.004**	0.005*
	(0.005)	(0.002)	(0.003)
Participation Rate	25.93	2.95	8.44
Effect in %	8.48	13.56	5.92
Pseudo-R^2	0.13	0.14	0.11
B. General Training			
Career-Related Risk Affinity (std.)	0.022***	0.004**	0.006**
	(0.004)	(0.002)	(0.003)
Participation Rate	17.31	2.27	6.11
Effect in %	12.71	17.62	9.82
Pseudo-R^2	0.11	0.14	0.12
C. Specific Training			
Career-Related Risk Affinity (std.)	0.003	0.001	0.000
	(0.003)	(0.001)	(0.002)
Participation Rate	10.37	0.80	2.60
Effect in %	2.89	12.50	0.00
Pseudo-R^2	0.10	0.18	0.08
Controls	✓	✓	✓
Observations	9,596	8,902	9,583

Source: Socio-Economic Panel (SOEP), data for years 2004, 2008, version 35, SOEP, 2019, doi:10.5684/soep.v35, own calculations.
Notes: The table displays the average marginal effects estimated based on logit estimations. The dependent variables are dummies indicating participation in any training (panel A), general training (panel B), and specific training (panel C). The main explanatory variable of interest is the standardized career-related risk affinity measured in 2004. All regressions include the full set of control variables. For each regression, we display the (unconditional) average of the dependent variable ("Participation Rate"), the average effect in % (in relation to the unconditional participation rate) of the main explanatory variable ("Effect in %"), and the Pseudo-R^2. Standard errors are in parentheses and clustered on person-level. * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$.
(1) Main results from column (1) in Table 3.1.
(2) Changing definition of general and specific training (general=mainly transferable and (partially) paid by the employee; specific=mainly not transferable and (partially) paid by the employee). Training is considered to be (partially) paid by the employee, if she did not indicate that she had no own costs.
(3) Changing definition of general and specific training (general=mainly transferable and took place (partially) outside of working time; specific=mainly not transferable and took place (partially) outside of working time.

Worker Autonomy: Our conceptual framework views training decisions as a joint initiative of workers and firms rather than a sole mandate of the latter (see Section 3.2). Unfortunately, our data do not allow us to separately identify the nature of training (i.e., general vs. specific) as well as who initiated it. However, roughly 35 percent of those undertaking any training in 2014 indicate that their "most important course" of the previous year was obligatory. In contrast, 39 percent agreed to participate in optional training, while 26 percent initiated training themselves.[14] This leaves us confident that, on balance, much of the training participation we observe in our estimation sample is optional as well.

We nevertheless investigate this issue further by conducting an analysis of a subset of training events in which workers are more likely to have had some autonomy; i.e., (i) those that they at least partially pay for, and (ii) those taking place (at least partially) outside of regular working hours. The results are reported in columns (2) and (3) of Table 3.3, respectively. Although the estimated marginal effects are smaller in magnitude, they are larger in relative terms. Importantly, our overall conclusion is unchanged: risk affinity is associated with a positive and significant effect on overall and general training participation, but a small and insignificant effect on specific training.

Subsequent Job Mobility: Job mobility following training is expected to be higher if the skills obtained are more transferable (i.e., general) than if they are not (i.e., specific). Consequently, to the extent that our measures of general vs. specific training capture a difference in skill transferability – as intended – we would expect to see that job changes are more frequent following general rather than specific training events.

We investigate this issue by considering people's job status in $t + 1$.[15] We find that training participants are more likely than other workers to remain in their current position between t and $t + 1$ (see Table 3.4). This relationship between training and job retention is much stronger for specific training (3.6 p.p.) than it is for general training (1.8 p.p.). Those receiving specific training are also significantly less likely to leave the labor market or become self-employed. Both results are consistent with the proposition that the skills generated by specific training are relatively more valuable in the current firm. Conversely, although neither general nor specific training is related to overall job change, general train-

[14] These results come from 2014 when SOEP included a question on the initiation of training, but did not, unfortunately, ask about the transferability of training implying that we cannot differentiate between general and specific training.

[15] Descriptive statistics by training status are reported in Table 3.16 in the Supplementary Appendix.

ing is associated with a larger reduction in the chances of becoming unemployed in $t+1$, suggesting that those receiving general training may be more employable generally. Taken together, these results provide us with confidence that our categorization of training as either general or specific is likely to capture a meaningful distinction in skill transferability.

Table 3.4: Future Job Status, Training Participation, and Career-Related Risk-Affinity (Logit Average Marginal Effects)

	Job Stayers between t and $t+1$ (1)	Job Change between t and $t+1$ (2)	Unemployed in $t+1$ (3)	Other in $t+1$ (4)
Career-Related Risk Affinity (std.)	-0.007**	0.003**	-0.002	0.006**
	(0.003)	(0.002)	(0.002)	(0.002)
General Training	0.018**	0.001	-0.017***	-0.004
	(0.008)	(0.004)	(0.005)	(0.006)
Specific Training	0.036***	-0.006	-0.011*	-0.020***
	(0.010)	(0.004)	(0.007)	(0.006)
Average of Dependent Variable	90.82	1.90	3.24	4.04
Average of Dependent Variable (No Training)	89.52	2.02	4.02	4.44
Effect of Risk Attitude in %	-0.77	15.79	-6.17	14.85
Effect of General Training in %	2.01	4.95	-42.29	-9.01
Effect of Specific Training in %	4.02	-29.70	-27.36	-45.05
Pseudo-R^2	0.12	0.13	0.24	0.09
Controls	✓	✓	✓	✓
Observations	8,613	8,613	8,613	8,613

Source: Socio-Economic Panel (SOEP), data for years 2004, 2008, version 35, SOEP, 2019, doi:10.5684/soep.v35, own calculations.
Notes: The table displays the average marginal effects estimated based on logit estimations. The dependent variables are highlighted in the column header and below. The main explanatory variables of interest are the standardized career-related risk affinity measured in 2004 and the dummies indicating participation in general and specific training. All regressions include the full set of control variables. For each regression, we display the (unconditional) average of the dependent variable ("Average of the Dependent Variable"), the (unconditional) average of the dependent variable for non-training participants ("No Training"), the average effect in % (in relation to the unconditional participation rate of the sample for the risk preference, and of the reference group of non-participants for the two training indicators) of the three main explanatory variables ("Effect in %"), and the Pseudo-R^2. Standard errors are in parentheses and clustered on person-level. * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$. For the averages of the dependent variables, we compare non-training participants with general and specific training participants, respectively. Results of mean comparison tests are indicated by asterisks in the rows "Average of the Dependent Variable (General Training)" and "Average of the Dependent Variable (Specific Training)", respectively.
(1) Dependent variable: Indicator that takes on the value one if the individual stayed with the current employer between t and $t+1$.
(2) Dependent variable: Indicator that takes on the value one if the individual changed employers between t and $t+1$.
(3) Dependent variable: Indicator that takes on the value one if the individual is unemployed in $t+1$.
(4) Dependent variable: Indicator that takes on the value one if the individual has a different status in $t+1$, e.g. self-employed or left the labor force.

3.4.2.3 The Choice of Risk Attitude Measure

Previous studies have utilized different approaches to measuring people's risk preferences. The use of incentivized lottery questions has gained a lot of traction in experimental studies (e.g., Eckel and Grossman, 2002; Holt and Laury, 2002; Crosetto and Filippin, 2013). The costs associated with incentivizing responses makes these measures impractical for large-scale observational studies. Consequently, survey-based measures of risk attitudes have also been developed. These measures are typically not incentivized, leaving them vulnerable to selection effects, strategic choices, and inattention (see Camerer and Hogarth, 1999). At the same time, they have the important advantage of allowing risk preferences to be measured on a much broader scale and subsequently studied in the context of real world outcomes (e.g., Barsky *et al.*, 1997; Donkers *et al.*, 2001; Dohmen *et al.*, 2011).

The SOEP includes measures of both domain-specific and general risk preferences (see Section 3.3.3). The correlation between career-related and general risk affinity is 0.44 which is highly significant (p-value = 0.000). At the same time, while clearly related, the two measures are not completely overlapping. A Kolmogorov-Smirnov test indicates that the distribution of career-related and general risk preferences (shown in Figure 3.10) are significantly different. Interestingly, people perceive themselves to be significantly more risk-averse with respect to their occupational career than in general (p-value = 0.000).

Thus far, our analysis has centered on the relationship between work-related training and people's affinity for career-related risk. We turn now to consider the sensitivity of our results to this choice. Specifically, we replicate our main results (see Table 3.1) focusing instead on people's affinity for risk in general (see Appendix Table 3.10). General risk affinity is not significantly related to participation in either specific training or training overall, while a one SD increase in general risk affinity is associated with a 0.7 p.p. increase in general training.

Thus, our main conclusions are unaffected by the measure of risk affinity we employ. At the same time, general risk affinity has an effect size that is less than half that associated with career-related risk affinity reinforcing that investment choices are likely to be better understood through the lens of context-specific rather than general risk attitude measures.

3.4.2.4 Robustness Analysis

We turn now to consider the robustness of our conclusions to some key modeling decisions that we have made. First, people's risk attitudes influence their educational and occupational choices (King, 1974; De Paola and Gioia, 2012; Hartlaub and Schneider, 2012; Heckman and Montalto, 2018). Consequently, including these variables as controls in our model may moderate the estimated effect of risk affinity on training participation. We consider this issue by re-estimating equation (3.7), excluding controls for highest educational degree, occupational position, ISCO-occupation, and NACE-sector classification in order to avoid the influence of these potentially endogenous factors. The results are reported in column (2) of Table 3.5. Irrespective of the training outcome we consider, effect sizes are moderately higher as expected. At the same time, our overall conclusion remains the same; risk affinity plays a significant role for general, but not specific, training.

Second, the Global Financial Crisis which occurred in 2007-2008 may have had reduced people's appetite for making risky investments. We consider this issue by replicating our analysis for training that took place in 2004 before the crisis began (see column 3). We find that the overall association between training and career-related risk affinity is, in fact, somewhat smaller in the pooled sample than in 2004. However, in both cases, we continue to find that results are driven by general training; we do not find a significant relationship between risk affinity and specific training. Note that in this specification, our measure of risk affinity is not imputed. The overall stable results suggest that the imputation of our risk attitude measure from 2004 to 2008 does not drive our conclusions.

Third, we investigate the potential for reverse causality to bias our results. Specifically, career-related risk affinity was measured at the 2004 interview, while our training measures capture training events in the 12 months prior to the 2004 and 2008 interviews. To address this issue, we re-estimate equation (3.7) using only 2008 training information in combination with our 2004 measure of risk affinity, which is pre-determined. Despite the decrease in sample size, the effect size and statistical significance remains almost unchanged (see column 4). The effect of risk affinity is estimated to be 1.7 p.p. in the case of any training and 2.1 p.p. in the case of general training. We find no effect of career-related risk affinity on specific work-related training.

Table 3.5: Robustness: Training Participation and Career-Related Risk Affinity (Logit Average Marginal Effects)

	Baseline	Exogenous Controls	Year 2004		Year 2008	
	(1)	(2)	(3)	(4)	(5)	(6)
A. Training						
Career-Related Risk Affinity (std.)	0.022***	0.029***	0.028***	0.017***	0.010*	0.018***
	(0.005)	(0.005)	(0.007)	(0.006)	(0.006)	(0.006)
General Training 2004					0.166***	
					(0.013)	
Specific Training 2004					0.164***	
					(0.016)	
Patience (std.)						0.009
						(0.006)
Participation Rate	25.93	25.93	22.91	27.91	27.91	27.94
Effect in %	8.48	11.18	12.22	6.09	3.58	6.44
Pseudo-R^2	0.13	0.08	0.15	0.13	0.16	0.13
B. General Training						
Career-Related Risk Affinity (std.)	0.022***	0.027***	0.024***	0.021***	0.015***	0.021***
	(0.004)	(0.004)	(0.006)	(0.005)	(0.005)	(0.005)
General Training 2004					0.141***	
					(0.011)	
Specific Training 2004					0.053***	
					(0.015)	
Patience (std.)						0.010*
						(0.005)
Participation Rate	17.31	17.31	14.90	18.89	18.89	18.91
Effect in %	12.71	15.60	16.11	11.12	7.94	11.11
Pseudo-R^2	0.11	0.07	0.13	0.11	0.13	0.11
C. Specific Training						
Career-Related Risk Affinity (std.)	0.003	0.005	0.007	0.000	-0.001	0.000
	(0.003)	(0.003)	(0.005)	(0.004)	(0.004)	(0.004)
General Training 2004					0.026***	
					(0.010)	
Specific Training 2004					0.097***	
					(0.010)	
Patience (std.)						-0.001
						(0.004)
Participation Rate	10.37	10.37	9.33	11.05	11.05	11.07
Effect in %	2.89	4.82	7.50	0.00	-0.90	0.00
Pseudo-R^2	0.10	0.06	0.11	0.10	0.12	0.10
Controls	✓	✓	✓	✓	✓	✓
Observations	9,596	9,596	3,806	5,790	5,790	5,784

Source: Socio-Economic Panel (SOEP), data for years 2004, 2008, version 35, SOEP, 2019, doi:10.5684/soep.v35, own calculations.
Notes: The table displays the average marginal effects estimated based on logit estimations. The dependent variables are dummies indicating participation in any training (panel A), general training (panel B), and specific training (panel C). The main explanatory variable of interest is the standardized career-related risk affinity measured in 2004. All regressions include the full set of control variables (except in column 2, see below). For each regression, we display the (unconditional) average of the dependent variable ("Participation Rate"), the average effect in % (in relation to the unconditional participation rate) of the main explanatory variable ("Effect in %"), and the Pseudo-R^2. Standard errors are in parentheses and clustered on person-level. * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$.
(1) Main results from column (1) in Table 3.1.
(2) Excluding potentially endogenous variables (highest educational degree, occupational position, ISCO88, NACE). Remaining job and firm control variables are: employment status, contract type, tenure, member trade union/association, firm size.
(3) Only year 2004 with career-related risk affinity (std.) measured in 2004.
(4) Only year 2008 with career-related risk affinity (std.) measured in 2004.
(5) Only year 2008 with career-related risk affinity (std.) measured in 2004. Additionally control for general and specific training participation in 2004.
(6) Only year 2008 with career-related risk affinity (std.) measured in 2004. Additionally control for standardized time preferences (patience) measured in 2008.

Fourth, we account for the possibility that previous training investments have an impact on future training investments. Specifically, we again focus only on training events that were reported in 2008, controlling for participation in general and specific training in 2004 (see column 5). The estimated coefficient falls to 1 p.p. (3.6 percent) for training overall, suggesting that training investments may indeed be linked over time. Still, our key conclusion remains the same; we find a positive and significant effect of risk affinity on participation in general training participation, but no effect on specific training.

Finally, we consider the importance of time preferences in the context of training investments (column 6). As some returns to training may not be immediate, it is possible that impatient individuals are less willing to participate in training. If the riskiness and delay in returns to training are correlated, our results may reflect this colinearity. The 2008 SOEP, for the first time, includes a measure of patience, which we proxy as a measure of time preferences. Using our 2008 sample, we re-estimate our model controlling for time preferences. The results are given in column (6). We find that patience is significantly related to general training. Specifically, a one SD increase in patience is associated with a 5.3 percent increase in the likelihood of participating in general training. Our results suggest that patience is not significantly related to specific training. A comparison of the results in columns (4) and (6) reveals that controlling for patience has virtually no effect on the estimated effect of risk affinity, suggesting that risk and time preferences have effects on training that are largely orthogonal.

Taken together, these results give us confidence that our overall conclusions are extremely robust.

3.4.3 The Investment vs. Insurance Benefits of Training

Risk preferences influence training investment decisions in part because the returns to training are uncertain. At the same time, risk preferences also determine the extent to which workers value the insurance against future income shocks that training might provide. The former leads us to expect a positive relationship between risk affinity and training; the latter leads us to expect the opposite (Section 3.2). Our empirical results indicate that, across our sample as a whole, the uncertainty around the returns to training is a more important driver of people's training decisions than is the potential insurance that training might provide (see Table 3.1).

Table 3.6: Training Participation and Career-Related Risk Affinity by Employment Situations (Logit Average Marginal Effects)

	Baseline	Wage Variance		Contract Type		Unemployed in the last three Years	
		Low	High	Permanent	Non-Perm.	No	Yes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. Training							
Career-Related Risk Affinity (std.)	0.022***	0.005	0.029***	0.022***	0.008	0.023***	0.003
	(0.005)	(0.007)	(0.006)	(0.005)	(0.012)	(0.005)	(0.012)
Participation Rate	25.93	16.61	30.29	26.80	19.78	26.96	16.73
Effect in %	8.48	3.01	9.57	8.21	4.04	8.53	1.79
Pseudo-R^2	0.13	0.13	0.12	0.13	0.21	0.13	0.21
B. General Training							
Career-Related Risk Affinity (std.)	0.022***	0.007	0.028***	0.023***	0.010	0.023***	0.007
	(0.004)	(0.006)	(0.005)	(0.005)	(0.010)	(0.004)	(0.010)
Participation Rate	17.31	10.80	20.32	17.86	13.44	17.85	12.32
Effect in %	12.71	6.48	13.78	12.88	7.44	12.89	5.68
Pseudo-R^2	0.11	0.14	0.09	0.11	0.19	0.11	0.22
C. Specific Training							
Career-Related Risk Affinity (std.)	0.003	0.000	0.005	0.002	0.006	0.003	0.003
	(0.003)	(0.005)	(0.004)	(0.004)	(0.008)	(0.004)	(0.009)
Participation Rate	10.37	6.73	12.10	10.68	8.18	10.96	5.41
Effect in %	2.89	0.00	4.13	1.87	7.33	2.74	5.55
Pseudo-R^2	0.10	0.11	0.09	0.09	0.21	0.09	0.26
Controls	✓	✓	✓	✓	✓	✓	✓
Observations	9,596	2,944	6,569	8,398	1,198	8,589	998

Source: Socio-Economic Panel (SOEP), data for years 2004, 2008, version 35, SOEP, 2019, doi:10.5684/soep.v35, own calculations.
Notes: The table displays the average marginal effects estimated based on logit estimations. The dependent variables are dummies indicating participation in any training (panel A), general training (panel B), and specific training (panel C). The main explanatory variable of interest is the standardized career-related risk affinity measured in 2004. All regressions include the full set of control variables. For each regression, we display the (unconditional) average of the dependent variable ("Participation Rate"), the average effect in % (in relation to the unconditional participation rate) of the main explanatory variable ("Effect in %") and the Pseudo-R^2. Standard errors are in parentheses and clustered on person-level. * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$.
(1) Main results from column (1) in Table 3.1.
(2/3) The regression only includes sectors with a low wage variance in column (2), only high variance in column (3). We define industries to have a "low (high) wage variance" when the wage variance is below (exceeds) the median wage variance (80.3). Descriptives of hourly wages by sector and the classification into high/low wage variance sector are available in Table 3.12 in the Appendix.
(4/5) The regression only includes individuals with a permanent contract in column (4), and a non-permanent contract in column (5).
(6/7) The regression only includes individuals who have not been unemployed in the last three years in column (6), and who have been unemployed in column (7).

In what follows, we expand on this key result by conducting a series of ancillary analyses designed to disentangle the two potential mechanisms – risky returns and insurance benefits – that underpin the relationship between risk attitudes and training investments. Our strategy will be to make more detailed comparisons of training in sub-sectors of the labor market in which it is reasonable to argue that one mechanism is likely to dominate the other.[16] Specifically, we differentiate between workers: (i) facing high vs. low wage variability; (ii)

[16] Descriptive statistics for the sub-groups can be found in Appendix Table 3.11.

with permanent vs. temporary contracts; and (iii) with and without recent unemployment experience.

In particular, wage variability is linked to the investment risks associated with training. In labor market sectors with limited wage variance, the variability in training returns – and hence the risks – will also be low. Investment risks will be higher in sectors with less predictable and highly variable wages. Thus, everything else equal, we expect the positive relationship between risk affinity and training to be stronger in the latter case than in the former. We investigate this proposition by re-estimating our model of training participation separately for workers employed in high vs. low wage variance industries.[17] Results are presented in columns (2) and (3) of Table 3.6 and we find that, in high-variance industries, career-related risk affinity is associated with a significant increase in the chances that workers undertake any (2.9 p.p.) or general (2.8 p.p) training. In contrast, there is no relationship between risk affinity and training in industries with low wage variance.

We also consider how the employment relationship itself shapes the relationship between attitudes and training investments. Specifically, while the vast majority (87 percent) of workers in our sample have a permanent employment contract, many workers (13 percent) have a non-permanent contract. Workers in temporary jobs are likely to place a larger value on the potential insurance benefits of training. In this case, the insurance benefits of training will be at odds with the costs associated with uncertain training returns. This leads us to expect that – on balance – there will be a weaker relationship between risk affinity and training for temporary workers than there is for permanent workers who place less weight on training's insurance benefits.

Estimating our model separately for permanent and temporary workers confirms this intuition. A one SD increase in risk affinity leads to a 2.2 p.p. (8.2 percent) increase in the chance that workers with permanent contracts undertake any training (see column 4). As before, this is driven solely by their participation in general rather than specific training.

[17]This distinction is based on the gross hourly wages of all SOEP respondents employed in 2000–2008. For this sample, we calculate mean wages and wage variances for each sector, which are presented in Appendix Table 3.12. From the 12 sector wages, we identify the median wage variance (80.3). We define industries to have a "high wage variance" (highlighted in bold) when the wage variance exceeds the median variance (80.3); "low wage variance" sectors have wage variances less than the median wage variance. Results are stable when defining sectors as "high wage variance" if their wage variance is above the 75% percentile (see Table 3.17 in the Supplementary Appendix). We focus on sectors due to their impact on wage dispersion (see, e.g., Card *et al.*, 2013; Fitzenberger *et al.*, 2013; Baumgarten *et al.*, 2020), for instance via trade unions and wage agreements (Saniter, 2007), or sector-specific minimum wages (Caliendo *et al.*, 2019b).

In contrast, there is no relationship between the risk attitudes and the training decisions of workers in temporary employment situations. This is consistent with their risk preferences having two opposing effects; risk affinity reduces the utility costs associated with uncertain investment returns, but reduces the utility benefits from the insurance training provides. For permanent workers who need less insurance against job loss, risk affinity primarily operates by reducing the utility cost of the uncertainty around training returns.

Finally, we consider how the relationship between risk preferences and training varies by whether or not workers have been unemployed in the past three years. Our motivation for this distinction is two-fold. First, workers with recent unemployment experience are most likely entitled to fewer unemployment benefits than are workers continuously employed.[18] Second, previous unemployment is a strong predictor for future unemployment. For both reasons, we expect that the insurance motive for training will be stronger for workers who have been unemployed in the previous three years. Like temporary workers, those recently unemployed experience two opposing influences; risk affinity reduces both the costs of uncertain training returns and the benefits of any insurance training provides. Consequently, we expect the relationship between risk preferences and training outcomes to be weaker for them than for continuously employed colleagues who have greater access to the public unemployment insurance system.

We re-estimate our results separately by workers' unemployment histories and present the results in columns (6) and (7) of Table 3.6. As expected, risk affinity is positively associated with the chances that continuously employed workers participate in any work-related training. This effect on overall training is driven solely by the relationship between risk preferences and general training. Each one SD increase in risk affinity is linked to a 12.9 percent (2.3 p.p.) increase in the likelihood that a continuously employed worker undertakes general training. In contrast, risk affinity has no significant effect on the chances that recently unemployed workers participate in training.[19]

[18] In our study period, the length of unemployment benefit entitlement depends on the months worked in the last 5/7 years and age. For example, a 35-year old who had worked 12 (24) months in the last seven years was entitled to 6 (12) months of unemployment benefits in 2003/2004. This period rose proportionally to the number of months in employment (and had several age discontinuities). Once a claim was made, it could only be renewed with new employment spells. The system was changed during the *Hartz* reforms in 2005, but the mentioned principle remained in place (see Caliendo and Hogenacker, 2012, for a short summary).

[19] Our estimates are very similar if we consider recent unemployment in either the previous year only or over the previous two years (see Table 3.18 in the Supplementary Appendix).

Taken together, our results indicate that the strength of the relationship between risk preferences and general training varies in ways that are consistent with the relative weight that workers are likely to place on the costs of uncertain investment returns and the insurance benefits of training. Uncertainty costs are largely ubiquitous; the insurance benefits of training, however, are likely to be concentrated among workers with uncertain employment relationships or more limited access to public insurance schemes. This tends to dampen the influence that risk affinity has in promoting their training investments. Importantly, to the extent that there is a significant relationship between risk affinity and training, this is driven entirely by general training. There is no evidence in any of the labor market sectors we consider that risk preferences are significantly related to investments in specific training.

3.5 Conclusions

Work-related training has become an imperative for many workers at the coalface of structural labor market change. Their investment decisions hinge not only on their tolerance for risk, but also on the way that uncertainty shapes their investment returns. Uncertainty about future payoffs no doubt increases risk. Like other types of human capital, however, training also has the potential to insure people against future job loss, reducing uncertainty and decreasing risk. A better understanding of the way that workers negotiate these tradeoffs is instrumental in meeting strategic objectives to expand the take-up of work-related education and training (see OECD, 1996; European Commission, 2007).

We address these issues by analyzing the role that risk preferences have in workers' decisions to invest in work-related training. This is an important extension of the previous literature that considers the role of risk solely in the context of investments in education. Our conceptual framework is novel in two regards. First, it differentiates between the competing investment and insurance mechanisms underpinning training investment decisions. To the extent that investment risks dominate, we expect risk-averse workers to undertake less training. Risk-averse workers are expected to undertake more training whenever the predominate role of training is in insuring them against future income losses. Second, we distinguish between general training that is transferable to other employment contexts and specific training that is not. Skill transferability has a fundamental role in the allocation of investment costs and returns (see Becker, 1962). This leads us to expect that risk preferences will be less important in decisions about specific rather than general training since the returns to specific training largely accrue to firms rather than to workers.

Thus, in the end, the relationship between risk preferences and training investments is an empirical question which we put to the data. Our estimates indicate that there is a positive association between risk affinity and training investments which is extremely robust to sample selection, variable definition, and model specification. This implies that, across the labor market as a whole, the uncertainty surrounding the return to training is more important in people's training decisions than are any insurance benefits that training might provide. Any insurance benefits of training appear to be concentrated among workers with uncertain employment relationships or more limited access to public insurance schemes.

Our results lead us to several key conclusions. First, there is value in distinguishing between the utility costs associated with uncertain investment returns and the insurance benefits of training. Doing so allows us to begin to identify when workers' risk affinity will lead to increased work-related training and when training investments are likely to be prompted by workers' risk aversion. A willingness to take risks is more likely to drive training decisions when workers' are unsure about either their own ability to benefit from training or the quality and enduring value of training itself, for example. In contrast, risk aversion is more relevant in underpinning the training investments of workers who value the employment insurance they cannot access through ongoing employment relationships or the social safety net. Future research which extends our results for the German labor market to other employment contexts would be particularly valuable in shedding light on these issues.

Second, skill transferability ultimately drives the allocation of training costs and benefits, and by extension, the extent to which workers have a vested interest in the investment decisions being made. Risk preferences matter more for general training because workers are more likely to both pay the costs and receive the benefits of training that is transferable to other contexts. Importantly, these insights about workers' differential responsiveness to investments in general vs. specific training extend beyond their risk preferences to their perceptions of control (Caliendo *et al.*, 2022). Our belief is that other key economic preferences (e.g., impatience, time consistency), personality traits, and cognitive biases may also have a more important influence on investments in general as opposed to specific work-related training. Research investigating this supposition would be extremely useful in advancing our conceptual understanding of work-related education and training.

Finally, we conclude that risk preferences matter for training investments. In one sense, this is hardly surprising given the extensive evidence that people's willingness to take risks underpins not only the human capital investments they make, but also has consequences for their labor market and health outcomes, addictive behavior, financial decisions, and migration choices (e.g., Shaw, 1996; see Schildberg-Hörisch, 2018, for a review). Despite this, the previous literature is silent about the role of risk preferences in work-related training investments. We are the first to investigate this issue. The insights we have gained are particularly apparent when we consider stated preferences for career-related risk. Although our substantive conclusions are unaffected, stated preferences for risk in general have an effect size that is less than half that associated with career-related risk affinity. This points to the benefits of context-specific rather than general measures of risk affinity in understanding how workers respond to uncertainty in the labor market.

Despite these insights, at least two key issues remain unaddressed. The first is that the nature of risk almost certainly differs between general and specific training. Our data prevent us from investigating this issue directly. Yet, the insurance value of training, for example, quite naturally depends on the nature of that training. Training which is specific to a particular firm or occupation is unlikely to provide much insurance against employment loss following widespread labor market down turns. This implies that the trade-off between investment risk and insurance benefit associated with the training decision is dependent on the degree of skill transferability. Developing an understanding of the differences in the risks associated with general and specific training – and the consequences of those differences for training decisions – awaits future examination of contexts in which the returns risks and insurance benefits of training not only vary, but also can be identified.

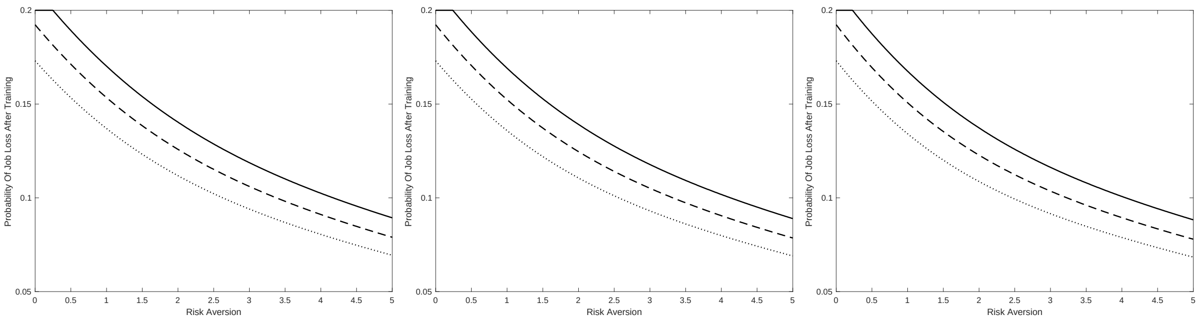
The second issue is whether attitudes toward risk can shed light on the apparent under-investment in training among certain groups of workers. Researchers often find, e.g., that female, less-skilled, and older workers tend to receive less training than their otherwise similar co-workers (Oosterbeek, 1996; Leuven and Oosterbeek, 1999; Mitsakis, 2019). Risk preferences can also differ across labor market groups. Women, for example, seem to make safer, more risk-averse choices (see, e.g., Hersch, 1996; Jianakoplos and Bernasek, 1998; Halek and Eisenhauer, 2001; Eckel and Grossman, 2008), while demographic evidence on risk attitudes indicates that people also become more risk-averse as they grow older (see, e.g., Halek and Eisenhauer, 2001; Dohmen *et al.*, 2011). Whether or not these disparities in risk affinity are linked to the differential training investments observed in the literature is an open question.

Future research which addressed these, and other, important related issues would be valuable in developing policy levers that target work-related training. Understanding the tension between the uncertain returns and insurance mechanisms inherent in training investments, for example, might open the door for policy interventions in which the private risks of training are publicly insured. However future training policy unfolds, it is crucial that policymakers are mindful of the way that skill transferability mediates the training risks that workers face. The sources of underlying risk fundamentally depend on the nature of the training workers undertake and the share of the training returns they receive.

3.6 Appendix

Figure 3.7: Simulations with Different Assumptions about Δ_w – Threshold Values for Probability of Job Loss after Training (p_{Tj})

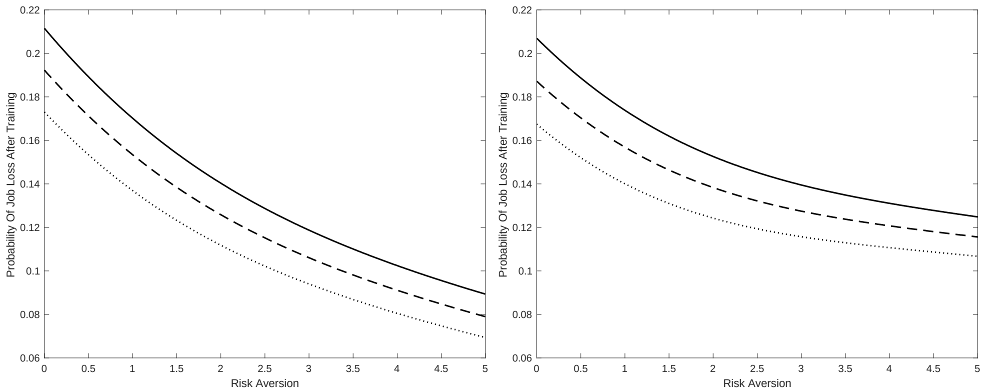
A - $\Delta_w = 0.4$ B - $\Delta_{w1} = 0.3, \Delta_{w2} = 0.5$ C - $\Delta_{w1} = 0.2, \Delta_{w2} = 0.3, \Delta_{w3} = 0.5, \Delta_{w4} = 0.6$



Source: Simulation results.
Notes: The figure shows the maximum values of the probability of a wage increase p_{jT} (y-axis) needed to induce individuals to participate in training by risk aversion (x-axis). Values of p_{jT} below the corresponding line go along with training participation. We set the baseline wage $w_0 = 1$, the benefit level $b = 0.6$, the probability of a job loss (if one is not trained) $p_j = 0.2$, the probability of a wage increase $p_w = 0.3$, and the expected wage growth $\mathbb{E}(\Delta_w) = 0.4$. We consider three different levels of training costs: $c = 0.09$ (solid line), $c = 0.1$ (dashed line), and $c = 0.11$ (dotted line). Panel A: we set the (potential) wage increase $\Delta_w = 0.4$. Panel B: we allow for two (potential) wage changes $\Delta_{w1} = 0.3$ and $\Delta_{w2} = 0.5$, each occurring with probability $p_w/2 = 0.15$. Panel C: we allow for four (potential) wage changes $\Delta_{w1} = 0.2, \Delta_{w2} = 0.3, \Delta_{w3} = 0.5$, and $\Delta_{w4} = 0.6$, each occurring with probability $p_w/4 = 0.075$.

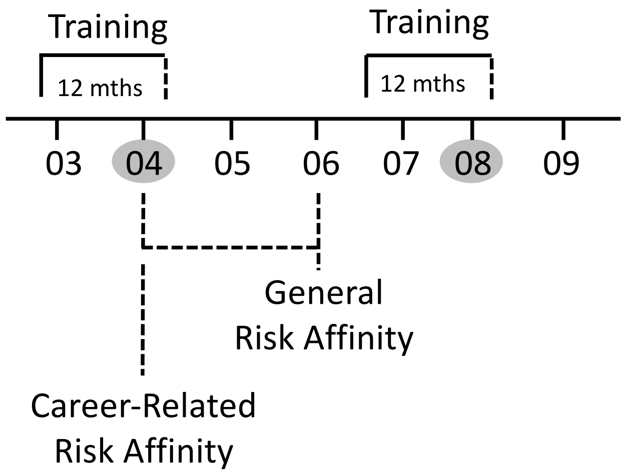
Figure 3.8: Simulations for a Two Period Model – Threshold Values for Probability of Job Loss after Training (p_{Tj})

A - Costs Paid in Period 2 B - Half of Costs Paid in Each Period



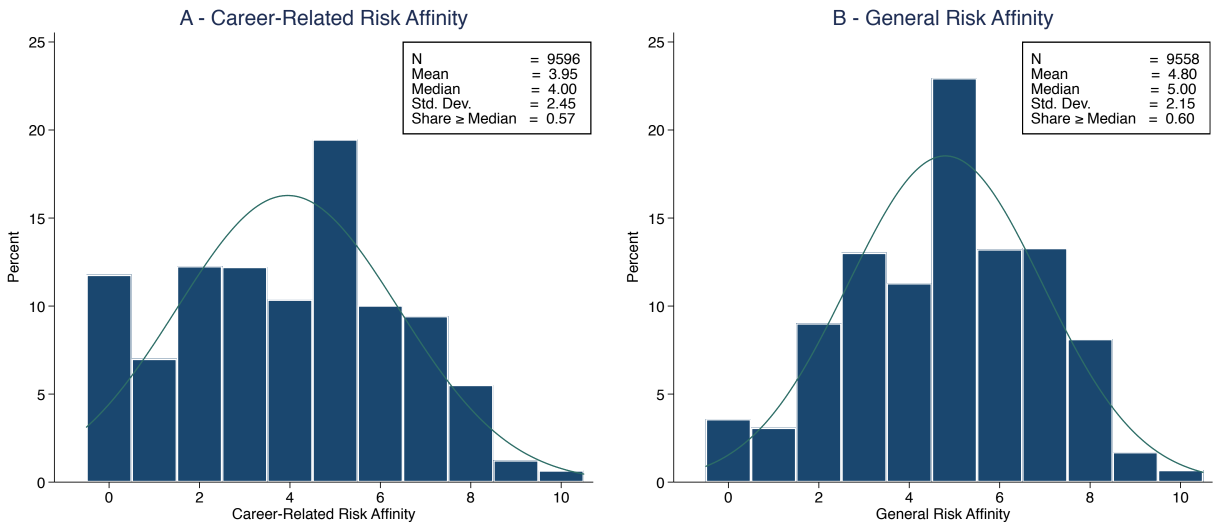
Source: Simulation results.
Notes: The figure shows the maximum values of the post-training probability of a job loss p_{jT} (y-axis) needed to induce individuals to participate in training by risk aversion (x-axis). Values of p_{jT} below the corresponding line go along with training participation. We set the baseline wage $w_0 = 1$, the benefit level $b = 0.6$, the probability of a job loss (if one is not trained) $p_j = 0.2$, the probability of a wage increase $p_w = 0.1$, and the (potential) wage increase $\Delta_w = 0.4$. We consider three different levels of training costs: $c = 0.09$ (solid line), $c = 0.1$ (dashed line), and $c = 0.11$ (dotted line). Individuals decide to participate in training in period 1, which leads to a potential increase in wages and a reduction in unemployment probability in period 2. Panel A: the costs are paid in period 2. Panel B: we assume that individuals pay half of the costs in each period.

Figure 3.9: Description of the Data Structure



Source: Own illustration.
Notes: The figure gives an overview of the available years and timing of the main variable measurements. We use the data from the years 2004 and 2008 in our analysis as they include relevant information about training participation. The variable measuring the participation in training refers to the three years prior to the interview. We define individuals as training participants if they report participation in training within the 12 months prior to the date of interview. Career-related risk affinity is available in the year 2004 and is imputed to 2008. The general risk affinity measure is available in 2004, 2006 and 2008. We utilize the 2004 measurement in 2004 and impute the information from 2006 to 2008.

Figure 3.10: Distribution of Career-Related Risk Affinity and General Risk Affinity



Source: Socio-Economic Panel (SOEP), data for years 2004, 2008, version 35, SOEP, 2019, doi:10.5684/soep.v35, own calculations.
Notes: Figure A shows the distribution of the career-related risk affinity for the years 2004 and 2008. Career-related risk affinity is available in 2004 and is imputed to 2008. Figure B shows the distribution of the general risk affinity. It is available in 2004 and 2006 and is imputed from 2006 to 2008.
The two boxes present the number of individuals available, the mean, the median, the standard deviation and the share of individuals whose self-reported risk attitude is equal to or greater than the median for the career-related and general risk attitude, respectively.
Comparing the means of the two measures with a t-test yields a p-value of 0.000, indicating a significant difference. Additionally, the Kolmogorov-Smirnov test with a p-value of 0.000 indicates that the variables follow different distributions. Finally, the correlation between the two measures is 0.44 and is significantly different from zero with a p-value of 0.000.

Table 3.7: Summary Statistics for Course Characteristics

	General Training (1)	Specific Training (2)
A. Transferability of Skills		
To what extent could you use the newly acquired skills if you got a new job in a different company?[a]		
Not at all	0.00	0.27
Limited	0.00	0.73
To a large extent	0.56	0.00
Completely	0.44	0.00
B. Further Course Characteristics		
Total course duration (weeks)[b]	4.07	1.63***
Hours of instruction every week	16.26	15.18*
Correspondence course	0.03	0.04
What was the purpose of this instruction?		
Retraining for a different profession or job	0.01	0.00*
Introduction to a new job	0.04	0.05*
Qualification for professional advancement	0.24	0.14***
Adjustment to new demands in current job	0.75	0.78*
Other	0.11	0.13
Did the course take place during working hours?		
During working time	0.66	0.76***
Some of both	0.12	0.10
Outside working time	0.21	0.13***
Did you receive a participation certificate?	0.80	0.65***
Who held the course?		
Employer	0.44	0.63***
Private institute	0.18	0.10***
Did you receive financial support from your employer?		
Yes, from the employer	0.72	0.75
Yes, from another source	0.01	0.00*
Dummy for no own costs	0.84	0.90***
Own costs	682.05	262.31***
Looking back, was this further education worth it for you professionally?		
Very much	0.42	0.18***
A little	0.38	0.53***
Not at all	0.08	0.19***
Do not know yet	0.11	0.10
Observations[a]	1,493	827

Source: Socio-Economic Panel (SOEP), data for years 2004, 2008, version 35, SOEP, 2019, doi:10.5684/soep.v35, own calculations.
Notes: The table shows mean values of course characteristics by skill transferability of the courses (general versus specific training). Results of mean comparison tests are indicated by asterisks. The test compared general training participants to specific training participants. * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$.
[a] The numbers of observations of the presented survey questions vary slightly due to item non-response. The 168 individuals who participated in both general and specific training within one cross-section have been excluded from the descriptives. In case individuals participated in more than one course (of the same type) within one cross-section, we took the information available of the most recent course.
[b] Own calculation, based on information of the length (days, weeks, months) of each course.

Table 3.8: Summary Statistics for Explanatory Variables

	No Training (1)	General Training (2)	Specific Training (3)
Observations[a]	7,108	1,493	827
Share of estimation sample[a]	0.74	0.16	0.09
Career-Related Risk Affinity[b]	3.79	4.55***	4.12***
Socio-Economic Variables			
Age[b]	43.15	42.06***	43.98**
Female	0.50	0.47	0.45**
Married	0.70	0.67**	0.71
Number of Children[b]	0.64	0.67	0.59
Disabled	0.07	0.05**	0.06
Migration Background			
No Migration Background	0.82	0.90***	0.92***
Direct Migration Background	0.14	0.06***	0.06***
Indirect Migration Background	0.04	0.03	0.02***
Owner of House or Dwelling	0.54	0.59***	0.61***
Highest Educational Degree			
No, Other Degree, Hauptschule	0.37	0.16***	0.16***
Realschule	0.34	0.31*	0.36
Abitur or Fachhochschule	0.09	0.13***	0.08
University or College	0.20	0.40***	0.40***
Vocational Training			
No Vocational Training	0.20	0.21	0.17**
Apprenticeship	0.53	0.41***	0.43***
Vocational School	0.27	0.37***	0.40***
Work Experience (FT + PT) (in Years)[b]	20.36	19.12***	21.24**
Unemployment Experience (in Years)[b]	0.74	0.43***	0.35***
Real Net HH Income Last Month of 2 Years Ago (in 1000 €)[b]	3.06	3.39***	3.34***
Regional Information			
Region			
West Germany	0.33	0.34	0.32
East Germany	0.26	0.27	0.32***
South Germany	0.28	0.25**	0.23***
North Germany	0.11	0.11	0.11
City States	0.05	0.07***	0.06
Unemployment Rate in Region[b]	9.34	9.23	9.72**
GDP in 1,000 € in Region[b]	28.88	29.76***	28.47
Job-Specific Characteristics			
Employment Status			
Full-Time	0.71	0.79***	0.80***
Part-Time	0.22	0.19**	0.19*
Other	0.07	0.02***	0.01***
Occupational Position			
White-collar Worker	0.55	0.74***	0.66***
Blue-collar Worker	0.40	0.13***	0.16***
Civil Servant	0.05	0.12***	0.18***
Contract Type			
Permanent	0.86	0.91***	0.91***
Temporary	0.07	0.06	0.04***
Other	0.07	0.03***	0.05**
Tenure (in years)[b]	11.49	11.83	14.60***
Member Trade Union	0.17	0.20**	0.25***
Member Trade Association	0.06	0.13***	0.11***
ISCO88			
Managers	0.05	0.09***	0.06
Professionals	0.13	0.29***	0.27***
Technicians and Associate Professionals	0.22	0.30***	0.32***
Clerical Support Workers	0.13	0.10***	0.12
Service and Sales Workers	0.11	0.08***	0.08***
Skilled Agricultural, Forestry and Fishery Workers	0.01	0.00	0.00
Craft and Related Trades Workers	0.15	0.09***	0.09***
Plant and Machine Operators, and Assemblers	0.10	0.03***	0.03***
Menial Jobs	0.09	0.01***	0.02***
Firm-Specific Characteristics			
Firm Size			

(Table continues on the next page)

Table 3.8: Summary Statistics for Explanatory Variables (Continued)

	(1)	(2)	(3)
Small	0.57	0.48***	0.36***
Medium	0.21	0.24**	0.26***
Large	0.21	0.28***	0.37***
NACE Industry			
Manufacturing	0.12	0.13	0.10
Agriculture	0.01	0.01	0.01
Mining, Quarrying, Energy, Water	0.01	0.02	0.03***
Chemicals, Pulp, Paper	0.07	0.05***	0.05*
Construction	0.07	0.04***	0.03***
Iron, Steel	0.06	0.03***	0.04**
Textile, Apparel	0.01	0.00***	0.00***
Wholesale, Retail	0.14	0.08***	0.07***
Transportation, Communication	0.06	0.04***	0.06
Public Service	0.27	0.44***	0.46***
Financials, Private Services	0.13	0.14	0.12
Other	0.05	0.03**	0.03*
Personality Characterstics			
Big Five Factor Openness[b]	4.44	4.68***	4.58***
Big Five Factor Conscientiousness[b]	6.04	6.03	5.94***
Big Five Factor Extraversion[b]	4.83	4.98***	4.83
Big Five Factor Agreeableness[b]	5.43	5.43	5.31***
Big Five Factor Neuroticism[b]	3.92	3.76***	3.85*
Locus of Control[c,b]	4.38	4.57***	4.42*

Source: Socio-Economic Panel (SOEP), data for years 2004, 2008, version 35, SOEP, 2019, doi:10.5684/soep.v35, own calculations.

* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

Notes: The table shows mean values of explanatory variables by training status. Results of mean comparison tests are indicated by asterisks. The test compared non-training participants to general (compare column 2) and specific training (compare column 3) participants. The summary statistics in columns (2) and (3) refer to those people who exclusively participate in general or specific training.

[a] The number of non-training, general, and specific training participants does not add up to the estimation sample size as 168 people participate in both general and specific training within one cross-section which are excluded from the descriptives.

[b] Denotes continuous variable.

[c] The locus of control index in the descriptives table is the average sum over all internal and reversed external items.

Table 3.9: Detailed Results: Participation in Training by Training Type (Logit Average Marginal Effects)

	Training (1)	General Training (2)	Specific Training (3)
Career-Related Risk Affinity (std.)	0.0216***	0.0219***	0.0030
	(0.0048)	(0.0042)	(0.0035)
Age	-0.0024*	-0.0032***	0.0008
	(0.0013)	(0.0012)	(0.0009)
Female	-0.0094	-0.0005	-0.0066
	(0.0114)	(0.0100)	(0.0082)
Married	-0.0022	-0.0090	0.0025
	(0.0110)	(0.0097)	(0.0080)
Number of Children	0.0063	0.0082*	0.0016
	(0.0056)	(0.0048)	(0.0041)
Disabled	-0.0065	-0.0042	-0.0094
	(0.0193)	(0.0177)	(0.0139)
Migration Background (Ref.: None)			
Direct Migration Background	-0.0441**	-0.0377**	-0.0173
	(0.0184)	(0.0164)	(0.0146)
Indirect Migration Background	-0.0338	-0.0059	-0.0274
	(0.0264)	(0.0216)	(0.0206)
Owner of House or Dwelling	0.0101	0.0073	-0.0013
	(0.0100)	(0.0090)	(0.0072)
Highest Educational Degree (Ref.: No, Other Degree, Hauptschule)			
Realsch	0.0512***	0.0264**	0.0352***
	(0.0139)	(0.0126)	(0.0105)
Abitur or Fachhochschule	0.0389**	0.0401**	0.0051
	(0.0186)	(0.0159)	(0.0145)
University or College	0.1045***	0.0576***	0.0572***
	(0.0176)	(0.0156)	(0.0128)
Vocational Education (Ref.: None)			
Apprenticeship	0.0683***	0.0336***	0.0484***
	(0.0141)	(0.0121)	(0.0104)
Vocational School	0.0977***	0.0524***	0.0542***
	(0.0142)	(0.0123)	(0.0103)
Work Experience (FT + PT) (in Years)	0.0001	0.0009	-0.0013
	(0.0013)	(0.0012)	(0.0009)
Unemployment Experience (in Years)	-0.0054	0.0004	-0.0069**
	(0.0042)	(0.0037)	(0.0035)
Log of Real Net HH Income Last Month of 2 Years Ago (in €)	-0.0083	0.0058	-0.0107
	(0.0108)	(0.0095)	(0.0079)
Region (Ref.: West Germany)			
East Germany	0.0230	0.0103	0.0177
	(0.0213)	(0.0186)	(0.0155)
South Germany	-0.0345**	-0.0255**	-0.0158
	(0.0141)	(0.0121)	(0.0105)
North Germany	-0.0040	0.0022	-0.0027
	(0.0157)	(0.0141)	(0.0113)
City States	0.0222	0.0265	-0.0054
	(0.0214)	(0.0189)	(0.0155)
Unemployment Rate in Region	-0.0054**	-0.0038*	-0.0026
	(0.0025)	(0.0022)	(0.0019)
Log of GDP € in Region	-0.0013	0.0239	-0.0169
	(0.0256)	(0.0223)	(0.0193)
Dummy for year 2008	0.0228**	0.0192**	0.0063
	(0.0110)	(0.0098)	(0.0082)
Employment Status (Ref.: Other)			
Full-Time	0.1260***	0.0822***	0.0814***
	(0.0302)	(0.0267)	(0.0276)
Part-Time	0.0987***	0.0612**	0.0744***
	(0.0299)	(0.0264)	(0.0277)
Occupational Position (Ref.: Civil Servant)			
White-collar Worker	-0.0412**	0.0011	-0.0296**
	(0.0177)	(0.0148)	(0.0116)
Blue-collar Worker	-0.1638***	-0.1058***	-0.0702***
	(0.0245)	(0.0219)	(0.0175)

(Table continues on the next page)

Table 3.9: Detailed Results: Participation in Training by Training Type (Continued) (Logit Average Marginal Effects)

	(1)	(2)	(3)
Contract Type (Ref.: Permanent)			
Temporary	-0.0513***	-0.0307*	-0.0192
	(0.0194)	(0.0164)	(0.0147)
Other	-0.0648***	-0.0529***	-0.0107
	(0.0227)	(0.0205)	(0.0154)
Tenure (in Years)	0.0003	-0.0005	0.0009**
	(0.0006)	(0.0006)	(0.0005)
Member Trade Union	0.0347***	0.0218**	0.0094
	(0.0119)	(0.0104)	(0.0082)
Member Trade Association	0.0430***	0.0432***	0.0032
	(0.0154)	(0.0129)	(0.0110)
ISCO88 (Ref.: Menial Jobs)			
Managers	0.1938***	0.1777***	0.0555**
	(0.0335)	(0.0332)	(0.0251)
Professionals	0.1980***	0.1765***	0.0739***
	(0.0311)	(0.0318)	(0.0230)
Technicians and Associate Professionals	0.1701***	0.1440***	0.0671***
	(0.0296)	(0.0306)	(0.0222)
Clerical Support Workers	0.1235***	0.1044***	0.0569**
	(0.0312)	(0.0319)	(0.0229)
Service and Sales Workers	0.1609***	0.1379***	0.0585**
	(0.0311)	(0.0321)	(0.0232)
Skilled Agricultural, Forestry and Fishery Workers	0.1231	0.1240	0.0243
	(0.0824)	(0.0769)	(0.0663)
Craft and Related Trades Workers	0.1819***	0.1677***	0.0645***
	(0.0308)	(0.0316)	(0.0223)
Plant and Machine Operators, and Assemblers	0.0725**	0.0791**	0.0065
	(0.0353)	(0.0359)	(0.0264)
Firm Size (Ref.: Large)			
Small	-0.0683***	-0.0201**	-0.0619***
	(0.0111)	(0.0098)	(0.0080)
Medium	-0.0244**	-0.0077	-0.0238***
	(0.0124)	(0.0110)	(0.0084)
NACE Industry (Ref.: Other)			
Manufacturing	0.0499**	0.0482**	0.0119
	(0.0247)	(0.0222)	(0.0186)
Agriculture	0.1011*	0.0253	0.0877*
	(0.0597)	(0.0492)	(0.0460)
Mining, Quarring, Energy, Water	0.0769*	0.0353	0.0603**
	(0.0399)	(0.0374)	(0.0259)
Chemicals, Pulp, Paper	0.0076	-0.0016	0.0099
	(0.0290)	(0.0261)	(0.0219)
Construction	-0.0083	-0.0003	-0.0158
	(0.0308)	(0.0275)	(0.0247)
Iron, Steel	-0.0065	-0.0117	0.0111
	(0.0310)	(0.0279)	(0.0229)
Textile, Apparel	-0.3127**	-0.1842*	
	(0.1221)	(0.0974)	
Wholesale, Retail	-0.0448*	-0.0333	-0.0170
	(0.0258)	(0.0235)	(0.0196)
Transportation, Communication	0.0185	-0.0004	0.0248
	(0.0299)	(0.0275)	(0.0213)
Public Service	0.0670***	0.0459**	0.0327*
	(0.0225)	(0.0202)	(0.0172)
Financials, Private Services	0.0393	0.0254	0.0165
	(0.0243)	(0.0220)	(0.0184)
Big Five Factor Openness	0.0098**	0.0058	0.0023
	(0.0045)	(0.0039)	(0.0033)
Big Five Factor Conscientiousness	-0.0011	0.0045	-0.0068*
	(0.0059)	(0.0053)	(0.0040)
Big Five Factor Extraversion	0.0017	0.0044	-0.0017
	(0.0047)	(0.0041)	(0.0034)
Big Five Factor Agreeableness	-0.0022	0.0042	-0.0055
	(0.0051)	(0.0046)	(0.0036)

(Table continues on the next page)

Table 3.9: Detailed Results: Participation in Training by Training Type (Continued) (Logit Average Marginal Effects)

	(1)	(2)	(3)
Big Five Factor Neuroticism	0.0002	0.0008	-0.0017
	(0.0042)	(0.0037)	(0.0030)
Locus of Control (std.)	0.0148***	0.0189***	-0.0002
	(0.0048)	(0.0043)	(0.0034)
Observations	9596	9596	9596
Pseudo-R^2	0.132	0.112	0.096

Source: Socio-Economic Panel (SOEP), data for years 2004, 2008, version 35, SOEP, 2019, doi:10.5684/soep.v35, own calculations.
Notes: The table displays the average marginal effects estimated based on logit estimations corresponding to column (1) of Table 3.1. The dependent variables are dummies indicating participation in any training (column 1), general training (column 2), and specific training (column 3). The main explanatory variable of interest is the standardized career-related risk affinity measured in 2004. All regressions include the full set of control variables. For each regression, we display the Pseudo-R^2. Standard errors are in parentheses and clustered on person-level. * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$.

Table 3.10: Training Investments and General Risk Affinity
(Logit Average Marginal Effects and OLS Coefficients)

	Participation		Number of Courses	Duration (in Weeks)	Hours (per Week)
	(1)	(2)	(3)	(4)	(5)
A. Training					
General Risk Affinity (std.)	0.003		0.006	0.155*	0.184*
	(0.005)		(0.009)	(0.080)	(0.098)
General Risk-Seeking (Indicator)		0.001			
		(0.009)			
Average of Dependent Variable	25.93	24.53	0.45	0.82	3.83
Effect in %	1.16	0.41	1.33	18.90	4.80
Pseudo-R^2 / $\overline{R^2}$	0.13	0.13	0.12	0.01	0.09
B. General Training					
General Risk Affinity (std.)	0.007*		0.013*	0.110	0.186**
	(0.004)		(0.007)	(0.072)	(0.085)
General Risk-Seeking (Indicator)		0.009			
		(0.008)			
Average of Dependent Variable	17.31	15.56	0.29	0.66	2.51
Effect in %	4.04	5.78	4.48	16.67	7.41
Pseudo-R^2 / $\overline{R^2}$	0.11	0.11	0.07	0.01	0.05
C. Specific Training					
General Risk Affinity (std.)	-0.002		-0.007	0.045	-0.002
	(0.003)		(0.006)	(0.034)	(0.058)
General Risk-Seeking (Indicator)		-0.007			
		(0.007)			
Average of Dependent Variable	10.37	10.54	0.16	0.16	1.33
Effect in %	-1.93	-6.64	-4.38	28.12	-0.15
Pseudo-R^2 / $\overline{R^2}$	0.10	0.10	0.05	0.00	0.05
Controls	✓	✓	✓	✓	✓
Observations	9,558	9,558	9,558	9,539	9,349

Source: Socio-Economic Panel (SOEP), data for years 2004, 2008, version 35, SOEP, 2019, doi:10.5684/soep.v35, own calculations.
Notes: The table displays the average marginal effects estimated based on logit estimations (columns 1-2) and coefficients estimated based on OLS estimation (columns 3-6). The dependent variables are indicated in the column headers and below. Panels refer to training type: any (panel A), general (panel B), specific (panel C). The main explanatory variable of interest is the standardized general risk affinity measured in 2004 and 2006 (except in column 2, see below). All regressions include the full set of control variables. For each regression, we display the (unconditional) average of the dependent variable ("Average of Dependent Variable"), the average effect in % (in relation to the unconditional participation rate) of the main explanatory variable ("Effect in %"), and the Pseudo-R^2 (logit regressions) or $\overline{R^2}$ (OLS regressions). Standard errors are in parentheses and clustered on person-level. * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$.
(1) Logit regression with a dummy dependent variable indicating participation in training. Full linear specification.
(2) Logit regression with a dummy dependent variable indicating participation in training. General risk seeking measured in 2004 and 2006 is a dummy that takes on the value one if the continuous measure of general risk affinity is equal to or greater than the median (5 on the non-standardized scale). Here, the average of the dependent variable refers to the unconditional average of the dependent variable for the reference group.
(3) OLS regression with a dependent variable indicating the number of courses of the last year, capped at 3 as we only know the type (general vs. specific) for the 3 most recent courses.
(4) OLS regression with a dependent variable indicating the overall duration of the most recent course in weeks (own calculation, based on information of the length (days, weeks, months) of each course).
(5) OLS regression with a dependent variable indicating the hours of instructions per weeks of the most recent course.

Table 3.11: Summary Statistics for Risk Attitude and Training Participation by Employment Situations

	Baseline	Wage Variance		Contract Type		Unemployed in the last three years	
		Low	High	Permanent	Non-Perm.	No	Yes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Risk Attitudes							
Career-Related Risk Affinity							
Mean	3.95	3.97	3.94	3.95	3.99	3.90	4.41***
Median	4.00	4.00	4.00	4.00	4.00	4.00	5.00
Share $\geq$ Median	0.57	0.57	0.57	0.56	0.59	0.56	0.65***
General Risk Affinity	4.80	4.91	4.75***	4.79	4.84	4.76	5.11***
Training							
Any Training	0.26	0.17	0.30***	0.27	0.20***	0.27	0.17***
General Training	0.17	0.11	0.20***	0.18	0.13***	0.18	0.12***
Specific Training	0.10	0.07	0.12***	0.11	0.08***	0.11	0.05***
Observations	9,596	2,944	6,569	8,398	1,198	8,589	998

Source: Socio-Economic Panel (SOEP), data for years 2004, 2008, version 35, SOEP, 2019, doi:10.5684/soep.v35, own calculations.
Notes: The tables shows mean values of the main risk attitude and training participation variables by subgroups. The subgroups correspond to those analyzed in Table 3.6. The number of observations for the presented general risk affinity vary slightly due to item non-response. Results of mean comparison tests are indicated by asterisks (except for the median career-related risk affinity). The test compares the corresponding two subgroups, respectively: high and low wage variance (compare column 3), permanent and non-permanent contracts (compare column 5), and not unemployed and unemployed in the last three years (compare column 7). * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$.
(1) Full sample as in column (1) in Table 3.1.
(2/3) The averages only includes sectors with a low wage variance in column (2), only high variance in column (3). We define industries to have a "low (high) wage variance" when the wage variance is below (exceeds) the median wage variance (80.3). Descriptives of hourly wages by sector and the classification into high/low wage variance sector are available in Table 3.12 in the Appendix.
(4/5) The averages only includes individuals with a permanent contract in column (4), and a non-permanent contract in column (5).
(6/7) The averages only includes individuals who have not been unemployed in the last three years in column (6), and who have been unemployed in column (7).

Table 3.12: Summary Statistics for Hourly Wages by Industry (2000-2008)

	Observations	Mean	Variance	Min	Max
	(1)	(2)	(3)	(4)	(5)
NACE Industry					
Manufacturing	9,171	17.45	**128.56**	0.48	673.25
Agriculture	846	10.78	69.67	0.24	184.57
Mining, Quarrying, Energy, Water	1,095	19.01	**84.52**	2.00	159.48
Chemicals, Pulp, Paper	4,327	17.18	**92.74**	0.70	178.94
Construction	4,885	13.62	43.48	0.91	176.83
Iron, Steel	4,001	15.87	48.60	0.98	150.36
Textile, Apparel	572	12.95	73.31	3.05	142.71
Wholesale, Retail	8,999	12.23	64.19	0.34	235.35
Transportation, Communication	4,081	14.85	76.01	1.45	110.75
Public Service	23,583	16.48	**143.49**	0.35	838.12
Financials, Private Services	9,046	15.90	**279.77**	0.33	1,165.75
Other	3,703	13.71	**165.34**	0.77	489.63

Source: Socio-Economic Panel (SOEP), data for years 2000-2008, version 35, SOEP, 2019, doi:10.5684/soep.v35, own calculations.
Notes: The table shows descriptives of hourly wages by sector and displays the number of observations (column 1), mean (column 2), variance (column 3), minimum (column 4) and maximum value (column 5). From the 12 sectors, we calculate the median wage variance which is equal to 80.3. Variances greater than or equal to the median variance are highlighted in bold. The corresponding sectors are categorized as "high wage variance" sectors.

3.7 Supplementary Appendix

3.7.1 Sample Information

In this Data Appendix, we provide additional information regarding the utilized data sample. We first demonstrate the sample size effects of our filtering rules and the resulting sample size by year. Afterwards we provide some additional brief information about the final sample and our training participants.

Sample Loss: Our population of interest is the working population aged 25-60. Table 3.13 provides an overview of how our control variable restrictions filter our overall sample size. The first row indicates the number of individuals of our population of interest in the years 2004 and 2008 in the SOEP. Importantly, we condition here on the individuals being observed in all other necessary years from which we impute control variables.[20] This excludes individuals who did not provide answers in control variables because they were not asked the question, rather than choosing not to provide an answer. Overall, roughly 12,000 individuals are available for our analysis. In the following, we exclude those individuals who have a missing in any of the control variables. Most individuals are lost due to socio-economic information, followed by the personality traits. Nevertheless, we lose overall only about 3,000 observations, leaving us with a final estimation sample of 9,596 individuals.

Table 3.13: Sample Loss due to Item Non-Response

	2004 (1)	2008 (2)	All (3)
Employed Population aged 25-60	4,881	7,365	12,246
Explanatory Variable Missing			
Socio-Economic Info Missing	-419	-641	-1,060
Job Info Missing	-173	-442	-615
Firm Info Missing	-27	-57	-84
Personality Info Missing	-422	-284	-706
Risk Attitude Missing	-34	-151	-185
Estimation Sample	3,806	5,790	9,596

Source: Socio-Economic Panel (SOEP), data for years 2004, 2008, version 35, SOEP, 2019, doi:10.5684/soep.v35, own calculations. *Notes:* The table shows the number of available individuals of our population of interest, namely the employed working population aged 25-60 (row 1). This sample conditions on individuals being observed in all necessary years for the imputed control variables. It further shows the number of individuals who are excluded from the sample due to item non-response in the various groups of control variables, as well as the final estimation sample.

Sample Comparison: We are interested in checking whether there is any selection due to item non-response. Hence, we compare the population of interested presented in row (1) of Table 3.13 with our final estimation sample. In Table 3.14, we present a select few variables, which are missing in only very few observations. There is no difference between the two samples. Consequently, we are confident that our sample does not suffer from selection.

[20]For more information, see the control variable Appendix 3.7.2. In 2004, individuals are required to be observed additionally in 1999, 2003, and 2005. In 2008, individuals are required to be observed additionally in 2005 and 2007.

Table 3.14: Sample Comparison: Summary Statistics for Explanatory Variables

	Population of Interest (1)	Final Sample (2)
Key Variables		
Year 2008	0.60	0.60
Female	0.49	0.49
Age[a]	42.67	43.02***
Highest Educational Degree		
No, Other Degree, Hauptschule	0.31	0.31
Realschule	0.34	0.33
Abitur or Fachhochschule	0.10	0.10
University or College	0.25	0.26
Migration Background		
No Migration Background	0.84	0.85
Direct Migration Background	0.12	0.12
Indirect Migration Background	0.04	0.03
Region		
West Germany	0.33	0.33
East Germany	0.26	0.27
South Germany	0.27	0.27
North Germany	0.11	0.11
City States	0.06	0.05
Unemployment Rate in Region[a]	9.33	9.34
GDP in 1,000 € in Region[a]	10.24	10.24
Tenure[a]	11.52	11.83**
Employment Status		
Full-Time	0.73	0.73
Part-Time	0.21	0.21
Other	0.06	0.06*
Firm Size		
Small	0.54	0.54
Medium	0.22	0.22
Large	0.24	0.24
NACE Industry		
Manufacturing	0.12	0.12
Agriculture	0.01	0.01
Mining, Quarrying, Energy, Water	0.01	0.01
Chemicals, Pulp, Paper	0.06	0.06
Construction	0.06	0.06
Iron, Steel	0.05	0.05
Textile, Apparel	0.01	0.01
Wholesale, Retail	0.12	0.12
Transportation, Communication	0.05	0.06
Public Service	0.31	0.31
Financials, Private Services	0.12	0.13
Other	0.04	0.04
Observations	12,246	9,596

Source: Socio-Economic Panel (SOEP), data for years 2004, 2008, version 35, SOEP, 2019, doi:10.5684/soep.v35, own calculations.
Notes: This table presents mean values of a subset of the explanatory variables and compares them between the population of interest (column 1) and the final sample used in the analysis (column 2). The presented variables barely or do not have any missings in column (1). Result of mean comparison tests are indicated by asterisks. The test compared the mean of the two samples for each variable. * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$.
[a] Denotes continuous variable.

Final Sample: Overall, there are 2,347 individuals who meet all are criteria in both years, and are thus included in our sample in both years. Additionally, 1,459 individuals are included in our sample only in the year 2004 and 3,443 individuals only in 2008. Thus, when

we only consider the year 2004 (2008), we have 3,806 (5,790) individuals in our sample. If in turn, we pool the two years, our estimation sample amounts to 9,596 individuals.
Training Participants: In our sample, there are overall 2,488 training participants. Of these, 1,493 respondents report having participated only in general training within the last year, while 827 respondents report participating only in specific training. An additional 168 respondents report participating in both types of training within the preceding 12 months. This provides us with a total of 2,488 observations which are classified as training participants and 7,108 observations which are classified as non-participants. The descriptive statistics for the most recent course are reported in Table 3.7). Our dependent variable for general training takes on the value 1 if any of the training courses in the last year were identified as general. If any of the courses are of a specific nature, the dependent variable for specific training is coded as 1. This means, both dependent variables are equal to 1 for the 168 individuals who participated in both types of training.

3.7.2 Control Variables

In the following, we provide in more detail how our control variables are defined:
Socio-Demographic Characteristics

- Age is a continuous measure which indicates the age of the individuals in years.
- Female is a dummy that takes on the value of one if the individual is female and zero otherwise. In the years included in this study, the SOEP does not include the gender "divers".
- Marital status is a dummy that takes on the value of one if the individual is married and zero otherwise.
- Number of children is a continuous measure which indicates the number of children under the age of 17 years that live in the household.
- Disabled is dummy that takes on the value one if the individual has a disability and zero otherwise.
- Migration background includes three dummies which take on the value one if the individual has (i) no migration background, (ii) a direct migration background, or (iii) an indirect migration background, and zero otherwise. "No migration background" is the reference category.
- Home ownership status is a dummy that takes on the value one if the individual is an owner of a house or a dwelling and is zero otherwise.
- Highest educational degree are four dummies which take on the value of one if the individuals has acquired as their highest educational degree (i) no degree/other degree/Hauptschul-degree, (ii) Realschul-degree, (iii) Abitur or Fachhochschul-degree, or (iv) a university or college degree, and zero otherwise. "No degree/other degree/Hauptschul-degree" is the reference category.
- Vocational training are three dummies which take on the value of one if the individual has (additionally to their education degree) (i) received no vocational education, (ii) participated in an apprenticeship, or (iii) visited a vocational school. "No vocational education" is the reference category.

- Employment experience is a continuous measure which indicates the employment experience of full and part time jobs in years.
- Unemployment experience is a continuous measure which indicates the unemployment experience in years.
- Real net household income is a continuous measure which indicates the real net household income of the previous month of two years ago in 1,000 Euro. In the regression analysis, the log is taken of this variable to prevent potential biases due to outliers.

Regional-Specific Variables

- Regional state dummies are five dummies which take on the value of one if an individual lives in the (i) centre west, (ii) east, (iii) south, or (iv) north of Germany and is zero otherwise. "Centre west" is the reference category.
- Local unemployment rates is a continuous measure which indicates the regional share of unemployed in the labor force in %.
- Regional GDP is a continuous measure that indicates the regional GDP in 1,000 Euros. In the regression analysis, the log is taken of this variable to prevent potential biases due to outliers.

Job-Related Characteristics

- Employment status are three dummies which take on the value of one if the individual is employed (i) full time, (ii) part time, or (iii) other and is zero otherwise. "Other" is the reference category.
- Occupational position are three dummies which take on the value of one if the individual is in a (i) civil servant, (ii) white-collar, or (iii) blue-collar position and is zero otherwise. "Civil servant" is the reference category.
- Contract type are three dummies which take on the value of one if the individual has a (i) permanent, (ii) temporary, or (iii) other contract type and is zero otherwise. "Permanent" is the reference category.
- Tenure is a continuous measure which indicates the tenure in years of the individual in the current position.
- Trade union membership is a dummy which takes on the value of one if the individual is a member of a trade union and zero otherwise. As this information is not available in 2004 and 2008, we impute the information from the previous year (i.e., from 2003 to 2004 and from 2007 to 2008).
- Trade association membership is a dummy which takes on the value of one if the individual is a member of a trade association and zero otherwise. As this information is not available in 2004 and 2008, we impute the information from the previous year (i.e., from 2003 to 2004 and from 2007 to 2008).
- ISCO88 occupation refers to the occupational classification which is based on the International Standard Classification of Occupations 88 (ISCO88). We drop the category "soldiers" as they are not included in our sample and focus on the remaining 9

occupations. Hence, there are 9 dummies which take on the value of one if the individual is grouped into the category of (i) managers, (ii) professionals, (iii) technicians and associate professionals, (iv) clerical support workers, (v) service and sales workers, (vi) skilled agricultural, forestry and fishery workers, (vii) craft and related trades workers, (viii) plant and machine operators, and assemblers, or (ix) menial jobs, and is zero otherwise. “Menial jobs” is the reference category.

Firm-Specific Characteristics

- Firm size are three dummies which take on the value of one if the individual is employed in a firm with (i) less than 200 workers (small), (ii) between 200 and 2,000 workers (medium), (iii) more than 2,000 workers (large). “Large” is the reference category.

- NACE industry refers to the industry classification which is basedbased on the classification system NACE (‘Nomenclature statistiqe des Activités Economiques dans la Communauté Européenne”) used by the European Union. We aggregate the intustries into 12 categories. Hence there are 12 dummies which take on the value of one if the individual works in the industry of (i) manufacturing, (ii) agriculture, (iii) mining, quarrying, energy, water, (iv) chemicals, pulp, paper, (v) construction, (vi) iron, steel, (vii) textile, apparel, (viii) wholesale, reail, (ix) transportation, communication, (x) public service, (xi) financials, private services, or (xii) other and is zero otherwise. “Other” is the reference category.

Personality Traits

- Big Five personality traits are five continuous measures that indicate the level of openness, conscientiousness, extraversion, agreeableness, neuroticism of an individual. All of these measures are based on three self-assessment questions each which are reverse coded (if needed) and then averaged. In the SOEP, information on the Big Five traits is available in the years 2005, 2009, 2013, 2017, and 2019. We attempt to only impute information from previous years (i.e., before training takes place), thus, we impute the information from 2005 to 2008. However, because 2005 is the earliest year in which the Big Five were elicited, we also take this information and impute it to 2004.

- Locus of control is a continuous measure which indicates where an individual believes the control over her life lives. High values indicate an internal locus of control (i.e., the individuals believes to hold control herself), low values indicate an external locus of control (i.e., she believes that the control over her life lies externally, e.g., with luck, faith or other people). This measure is based on 8 self-assessment questions which are reverse coded (if needed) and then combined to one measure based on a factor analysis. This scale has additionally been standardized. In the SOEP, information on locus of control is available in the years 1999, 2005, 2010, and 2015. In order to only impute information from previous years (i.e., before training takes place), we impute the information from 1999 to 2004 and from 2005 to 2008.

3.7.3 Supplementary Tables

Table 3.15: Robustness: Training Participation and Career-Related Risk Affinity without Imputed Controls
(Logit Average Marginal Effects)

	All Controls (1)	Exclude Imputed Controls (2)
A. Training		
Career-Related Risk Affinity (std.)	0.022***	0.025***
	(0.005)	(0.005)
Participation Rate	25.93	25.93
Effect in %	8.48	9.64
Pseudo-R^2	0.13	0.13
B. General Training		
Career-Related Risk Affinity (std.)	0.022***	0.025***
	(0.004)	(0.004)
Participation Rate	17.31	17.31
Effect in %	12.71	14.44
Pseudo-R^2	0.11	0.11
C. Specific Training		
Career-Related Risk Affinity (std.)	0.003	0.004
	(0.003)	(0.003)
Participation Rate	10.37	10.37
Effect in %	2.89	3.86
Pseudo-R^2	0.10	0.09
Main Controls	✓	✓
Imputed Controls	✓	
Observations	9,596	9,596

Source: Socio-Economic Panel (SOEP), data for years 2004, 2008, version 35, SOEP, 2019, doi:10.5684/soep.v35, own calculations.
Notes: The table displays the average marginal effects estimated based on logit estimations. The dependent variables are dummies indicating participation in any training (panel A), general training (panel B), and specific training (panel C). The main explanatory variable of interest is the standardized career-related risk affinity measured in 2004. For each regression, we display the (unconditional) average of the dependent variable ("Participation Rate"), the average effect in % (in relation to the unconditional participation rate) of the main explanatory variable ("Effect in %"), and the Pseudo-R^2. Standard errors are in parentheses and clustered on person-level. * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$.
(1) Full specification with all control variables. Compare Table 3.1, column 1.
(2) Exclude the imputed control variables (trade union and association membership, the Big Five personality traits, locus of control).

Table 3.16: Summary Statistics for Future Job Status by Training Status

	No Training (1)	General Training (2)	Specific Training (3)
Job Status			
Job Stayers between t and $t+1$	0.90	0.93***	0.96***
Job Changers between t and $t+1$	0.02	0.02	0.01***
Unemployed in $t+1$	0.04	0.01***	0.01***
Other in $t+1$	0.04	0.04	0.02***
Observations	6,347	1,350	765

Source: Socio-Economic Panel (SOEP), data for years 2004, 2008, version 35, SOEP, 2019, doi:10.5684/soep.v35, own calculations.
Notes: The table shows mean values of the future job status by training status. Results of mean comparison tests are indicated by asterisks. The test compared non-training participants to general (compare column 2) and specific training (compare column 3) participants. The summary statistics in columns (2) and (3) refer to those people who exclusively participate in general or specific training.

Table 3.17: Robustness: Training Participation and Career-Related Risk Affinity by Wage Variance
(Logit Average Marginal Effects)

	Baseline	Wage Variance			
		Low	High (above 50%)	Low	High (above 75%)
	(1)	(2)	(3)	(4)	(5)
A. Training					
Career-Related Risk Affinity (std.)	0.022***	0.005	0.029***	0.008	0.030***
	(0.005)	(0.007)	(0.006)	(0.007)	(0.007)
Participation Rate	25.93	16.61	30.29	17.82	31.23
Effect in %	8.48	3.01	9.57	4.49	9.61
Pseudo-R^2	0.13	0.13	0.12	0.15	0.11
B. General Training					
Career-Related Risk Affinity (std.)	0.022***	0.007	0.028***	0.009	0.030***
	(0.004)	(0.006)	(0.005)	(0.006)	(0.006)
Participation Rate	17.31	10.80	20.32	11.47	21.09
Effect in %	12.71	6.48	13.78	7.85	14.22
Pseudo-R^2	0.11	0.15	0.09	0.15	0.09
C. Specific Training					
Career-Related Risk Affinity (std.)	0.003	0.001	0.005	-0.000	0.006
	(0.003)	(0.005)	(0.004)	(0.005)	(0.005)
Participation Rate	10.37	6.73	12.10	7.38	12.36
Effect in %	2.89	1.49	4.13	0.00	4.85
Pseudo-R^2	0.10	0.13	0.09	0.14	0.08
Controls	✓	✓	✓	✓	✓
Observations	9,596	2,944	6,569	3,670	5,843

Source: Socio-Economic Panel (SOEP), data for years 2004, 2008, version 35, SOEP, 2019, doi:10.5684/soep.v35, own calculations.
Notes: The table displays the average marginal effects estimated based on logit estimations. The dependent variables are dummies indicating participation in any training (panel A), general training (panel B), and specific training (panel C). The main explanatory variable of interest is the standardized career-related risk affinity measured in 2004. All regressions include the full set of control variables. For each regression, we display the (unconditional) average of the dependent variable ("Participation Rate"), the average effect in % (in relation to the unconditional participation rate) of the main explanatory variable ("Effect in %"), and the Pseudo-R^2. Standard errors are in parentheses and clustered on person-level. * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$.
(1) Main results from column (1) in Table 3.1.
(2/3) The regression only includes sectors with a low wage variance in column (2), only high variance in column (3). We define industries to have a "low (high) wage variance" when the wage variance is below (exceeds) the median wage variance (80.3). Descriptives of hourly wages by sector and the classification into high/low wage variance sector are available in Table 3.12 in the Appendix.
(4/5) The regression only includes sectors with a low wage variance in column (4), only high variance in column (5). We define industries to have a "low (high) wage variance" when the wage variance is below (exceeds) the 75% percentile wage variance (136.03). Descriptives of hourly wages by sector and the classification into high/low wage variance sector are available in Table 3.12 in the Appendix.

Table 3.18: Robustness: Training Participation and Career-Related Risk Affinity by Unemployment Experience
(Logit Average Marginal Effects)

	Baseline	Unemployed					
		In $t-1$		In $t-1$ or $t-2$		In $t-1$, $t-2$ or $t-3$	
		No	Yes	No	Yes	No	Yes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. Training							
Career-Related Risk Affinity (std.)	0.022***	0.023***	0.001	0.022***	0.009	0.023***	0.003
	(0.005)	(0.005)	(0.014)	(0.005)	(0.013)	(0.005)	(0.012)
Participation Rate	25.93	26.61	12.94	26.81	15.61	26.96	16.73
Effect in %	8.48	8.64	0.77	8.21	5.77	8.53	1.79
Pseudo-R^2	0.13	0.13	0.35	0.13	0.28	0.13	0.21
B. General Training							
Career-Related Risk Affinity (std.)	0.022***	0.023***	0.008	0.023***	0.011	0.023***	0.007
	(0.004)	(0.004)	(0.014)	(0.004)	(0.011)	(0.004)	(0.010)
Participation Rate	17.31	17.73	9.39	17.83	11.24	17.85	12.32
Effect in %	12.71	12.97	8.52	12.90	9.79	12.89	5.68
Pseudo-R^2	0.11	0.11	0.28	0.11	0.29	0.11	0.22
C. Specific Training							
Career-Related Risk Affinity (std.)	0.003	0.003	-0.012	0.003	0.002	0.003	0.003
	(0.003)	(0.004)	(0.010)	(0.004)	(0.009)	(0.004)	(0.009)
Participation Rate	10.37	10.67	4.59	10.79	5.42	10.96	5.41
Effect in %	2.89	2.81	-26.14	2.78	3.69	2.74	5.55
Pseudo-R^2	0.10	0.09	0.43	0.09	0.32	0.09	0.26
Controls	✓	✓	✓	✓	✓	✓	✓
Observations	9,596	9,117	479	8,840	756	8,589	998

Source: Socio-Economic Panel (SOEP), data for years 2004, 2008, version 35, SOEP, 2019, doi:10.5684/soep.v35, own calculations.

Notes: The table displays the average marginal effects estimated based on logit estimations. The dependent variables are dummies indicating participation in any training (panel A), general training (panel B), and specific training (panel C). The main explanatory variable of interest is the standardized career-related risk affinity measured in 2004. All regressions include the full set of control variables. For each regression, we display the (unconditional) average of the dependent variable ("Participation Rate"), the average effect in % (in relation to the unconditional participation rate) of the main explanatory variable ("Effect in %") and the Pseudo-R^2. Standard errors are in parentheses and clustered on person-level. * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$.

(1) Main results from column (1) in Table 3.1.

(2/3) The regression only includes individuals who have not been unemployed in the last years in column (2), and who have been unemployed in column (3).

(4/5) The regression only includes individuals who have not been unemployed in the last two years in column (4), and who have been unemployed in column (5).

(6/7) The regression only includes individuals who have not been unemployed in the last three years in column (6), and who have been unemployed in column (7).

Chapter 4

Job Satisfaction and Training Investments*

Abstract

Job satisfaction has been found to impact behavioral choices at the workplace. Since levels of satisfaction are not guaranteed to remain high, understanding the consequences of job dissatisfaction is essential. Hence, I analyze the relationship between a worker's job satisfaction and her training investments. Based on my theoretical model, I expect a U-shaped relationship if dissatisfied workers attempt to improve the situation or plan to quit. In contrast, there is an overall positive relationship if dissatisfied workers neglect their duties. Using logit regressions with the Household, Income and Labour Dynamics in Australia (HILDA) survey I find tentative evidence that there is on average an overall positive relationship with a 1 standard deviation increase in job satisfaction being associated with a 1.5% increased likelihood of participating in training. A closer inspection of the reasons for training as well as quit intentions reveals some hints of a U-shaped relationship. My results highlight the importance of considering the source of dissatisfaction as there are heterogeneous effects along different job satisfaction facets.

4.1 Introduction

Workers are constantly faced with continuous changes in the labor market, such as technological advancements. Additionally, quick or unexpected changes (such as those brought upon firms and workers in the COVID-19 pandemic) require workers to rapidly adapt to

*This chapter is currently submitted at the journal *Education Economics*.

new circumstances. In the wake of such changes, regularly assessing the need for an update of skills is required. Training has been recognized to be an effective tool in the battle of the ever-changing labor market: Multiple studies find that workers who participate in training also experience wage increases (see e.g. Frazis and Loewenstein, 2005; Leuven and Oosterbeek, 2008; Melero, 2010; Haelermans and Borghans, 2012). Similarly, firms also profit from their workers' training because it is associated with a productivity increase on the firm level (Dearden *et al.*, 2006; Konings and Vanormelingen, 2015). In addition, there is a series of non-pecuniary returns to training that the worker can benefit from. Training participation has been found to have a positive relationship with job performance (Bartel, 1995), the chance of receiving a promotion (Bishop, 1990; Pergamit and Veum, 1999; Melero, 2010), and the chances of re-employment in case the worker has been laid off (Ok and Tergeist, 2003), and a negative relationship with the risk of a job loss (Büchel and Pannenberg, 2004). Finally, burgeoning studies suggest that training participation can have a positive impact on job satisfaction (Georgellis and Lange, 2007; Jones *et al.*, 2009; Burgard and Görlitz, 2014). Overall, training reveals to be a pertinent tool for workers in their attempts to increase the security of their job and induce the desired advances in their career. Consequently, a series of studies aim to understand which traits or characteristics result in a lower willingness to participate in training, for instance firm characteristics, socio-demographics, or personality traits (see e.g. Lynch and Black, 1998; Weaver and Habibov, 2017; Caliendo *et al.*, 2022). I contribute to the literature by investigating the relationship between job satisfaction and training investments, in an attempt to understand whether job satisfaction contributes to a worker's willingness to develop in unison with the labor market.

Job satisfaction is an important attitude, which economists widely interpret as the (net) utility from working (see e.g. Verhofstadt *et al.*, 2003; Burgard and Görlitz, 2014). Psychologists have put multiple definitions forward of which some focus on the job itself, others on the sum of job-related factors, and, finally, some that consider the difference in expected and actual gains (for an overview see Tsai *et al.*, 2007). Verhofstadt *et al.* (2003) summarize four reasons for the importance of analyzing job satisfaction: (i) the humanitarian perspective of treating all individuals with respect; (ii) job satisfaction constitutes a valuable proxy of utility at work; (iii) the quality of the organizational functioning of the firm can be captured in the job satisfaction; and finally (iv) job satisfaction influences the behavioral choices of the worker which can impact the organizational functioning of the firm.

There is a plethora of studies examining this last aspect on how job satisfaction influences behavioral choices as workers usually do not continuously exhibit high levels of job satisfaction (Rusbult *et al.*, 1988). Consequently, it is of great value to understand which behavior results from high levels of dissatisfaction. Unsatisfied workers are found to react in either of the following four categories: exit (quit their job), loyalty (bear the unsatisfaction), voice (take action to improve the dissatisfactory situation), or neglect (disregard duties) (Farrell, 1983; Jodlbauer *et al.*, 2012). Most noteworthy, job dissatisfaction is a profound predictor of both quit intention as well as subsequent labor turnover (see e.g. Spencer and Steers, 1981; Lance, 1988; Clark *et al.*, 1998; Boswell *et al.*, 2005; Singh and Loncar, 2010; Chen *et al.*, 2011). On the other hand, increased levels of job satisfaction have been found to be associated with higher levels of performance (Judge *et al.*, 2001) and job motivation (Kinicki *et al.*, 2002). Overall, Clark *et al.* (1998) point out that satisfied workers are expected to "behave in a way that will enable them to keep [their job], that is, work harder or shirk less" (p. 499). In this vein, there are some studies considering job satisfaction in the context of training courses: Ensour *et al.* (2018) analyze the effect on training motivation and find an association between higher levels of job satisfaction and higher levels of training motivation. Similarly, job satisfaction has been found to be positively related to the commitment to learning new skills during training (Tsai *et al.*, 2007) as well as the willingness to transfer these new skills into the work environment after completing the training course (Jodlbauer *et al.*, 2012).

The aim of this study is to contribute to this strand of literature by analyzing how the job satisfaction of a worker influences her decision to invest into training. To the best of my knowledge, no study specifically considers the impact on actual training participation. I strive to close this gap by presenting a theoretical model in which workers decide whether to invest into training based on potential returns and the costs of training. I hypothesize that increased levels of job satisfaction lead to a higher probability of training participation. However, low levels of satisfaction (i.e. high levels of dissatisfaction) can result in two different scenarios: Highly dissatisfied workers may react with the exit or voice channel (i.e.

quit or improve the situation) which may increase the probability of training participation, as training may improve the chances of getting a new position or improve the unsatisfactory situation. Inversely, the neglect reaction may lead to a lower likelihood of training participation, as the worker may be less willing to invest into work-related training.

I turn to representative Australian data to test which channel dominates. An extensive investigation of the functional form lends support to the second scenario, in which the neglect channel dominates: There appears to be an overall positive relationship between job satisfaction and training participation as a one standard deviation increase in job satisfaction is associated with a 1.5% increase in the probability of participating in training. However, due to a limited number of highly unsatisfied workers in the sample, strong conclusions are difficult. In an attempt to enhance the analysis of the rather unsatisfied workers, I further examine the potential channels by considering different purposes of training, quit intentions and different facets of the job satisfaction. My findings suggest that for overall job satisfaction the neglect channel dominates the voice channel more strongly than the exit channel. However, once considering different facets of the job satisfaction the voice channel gains dominance for some of the facets (e.g. the satisfaction with pay), highlighting the importance of the origin of the dissatisfaction.

The remainder of this paper is structured as follows: Section 4.2 introduces the theoretical framework and hypotheses. The utilized data is introduced in Section 4.3, followed by the empirical strategy, main results and robustness in Section 4.4. A thorough investigation of the potential channels is presented in Section 4.5. Section 4.6 concludes.

4.2 Theoretical Framework

In this chapter, I discuss the theoretical framework of the training investment decision. I assume that the worker and the firm jointly decide upon training participation of the worker.[1] Training takes place if it results in a non-negative return for both the worker and the firm and positive returns for at least one of the involved parties. The possible

[1]In this model, I consider only training that is optional. It is to be expected that workers are not involved in the decision process of mandatory training. Hence, the worker's job satisfaction is unlikely to influence the participation decision of mandatory training. Smith *et al.* (2019) find in their study for Australia that at least 50% of the surveyed employers offered some form of optional training. Much of the mandatory training is arranged for the introduction of the job or for health and safety training. These statistics suggest that a large portion of training is undertaken optionally. In Section 4.4.3, I discuss the issue of mandatory training in the context of the empirical analysis.

returns for the firms are the increase in the worker's productivity and with that an increase in revenues. For the worker, potential returns to training are more varied: In addition to monetary returns, workers may for example seek an improvement in their performance, opportunities for new responsibilities (either by expanding their horizon, paving the way for promotions, or qualifying for different jobs) or to secure their current position. In the following model, I incorporate both monetary and non-monetary returns in the investment decision.

I assume a perfectly competitive market with output prices normalized to one. Both the workers and the firms are risk-neutral[2] and have no liquidity constraints. While the firms aim at maximizing their expected discounted profit, workers aim at maximizing their expected utility for both monetary and non-monetary benefits. The model consists of two periods ($t = 0, 1$). In $t = 0$, the worker's productivity equals her marginal revenue product (mP_L). In this period, the worker i and firm f jointly decide whether the worker should participate in training. This is the case if training yields a positive return for at least one of the two without resulting in a negative return for the other.

Training comes at the cost of C which is shared by the worker and firm according to the exogenous cost-sharing rule α, such that the worker pays αC and the firm $(1 - \alpha)C$. For the worker, it is possible that αC includes time costs in case the training does not take place (exclusively) during working hours. The costs of training are constant across workers and known prior to the investment decision in $t = 0$.

When the worker participates in training ($T_i = 1$, otherwise $T_i = 0$), two types of returns emerge. First, the productivity of the worker increases by K. This return is shared by the worker and the firm depending on the degree of transferability of the training course γ, such that the worker receives γK and the firm $(1 - \gamma)K$ in monetary returns. Following Becker (1962), for "perfectly general" training ($\gamma = 1$), all newly acquired skills are also applicable in other firms, while "perfectly specific" training ($\gamma = 0$) only provides skills that are of interest for the current firm. As a result, for general (specific) training the worker (firm) reaps all of the monetary returns of training, while for transferable training the returns are shared. Because I additionally consider non-monetary returns (see below) which are

[2]Considering risk-averse workers does not change the predictions of the model; it merely increases the complexity of the model.

not shared with the firm, not all returns depend on the transferability of skills (e.g. the opportunity to increase the job security). Consequently, the distinction is not pivotal in this analysis. However, I return to this notion in Section 4.4.3.

Additionally, workers have the opportunity to receive non-monetary returns b_i which are always non-negative. These returns cover a wide spectrum of possible non-monetary returns and vary across workers: which returns the worker intends to reap depends on her characteristics and the current situation she is in, e.g. which career goals she is striving for or whether she currently has difficulties with specific tasks. The factors influencing the potential non-monetary returns are summarized as x_i.[3]

One of these factors is the worker's job satisfaction JS_i. Job satisfaction is often (and in the utilized data here) measured by asking individuals to rate their satisfaction on a scale from "Totally dissatisfied" (e.g. 0) to "Totally satisfied" (e.g. 10). Thus, the scale is increasing in job satisfaction, or inversely, decreasing in job dissatisfaction. Hence, an individual ranked on the far right (left) of the scale is satisfied with all (no) aspects of the job. All other values represent a combination of satisfaction with some and dissatisfaction with other aspects of the job. Hence, it is useful to categorize the non-monetary returns in two types: those that arise from a point of satisfaction ($b_{1i} \geq 0$) and those that emerge in a state of dissatisfaction ($b_{2i} \geq 0$). Examples of b_{1i} are opportunities to gain new responsibilities or to manifest career advances.[4] Similarly, workers who enjoy their job may seek to improve their skills generally or simply secure themselves from future job losses. On the other hand, b_{2i} includes returns which can help workers change factors of the job they are not satisfied with. For instance, if a worker is dissatisfied as she finds a certain task too difficult, she could engage in training to learn how to perform the task more easily. This reflects the voice reaction to dissatisfaction as this person would seek ways to improve the current situation. Additionally, training participation may help a worker qualify for a different job or position. If the dissatisfaction of a worker results in an intention to quit, i.e. the exit

[3]It is possible to consider potential non-monetary returns for the firm as well: the firm may be interested in increasing the job satisfaction of their workers, may intend to groom a certain worker for another position, or may seek to retain workers by providing training courses they desire. It would be easy to incorporate such benefits in the model as well. However, since I focus on the worker's perspective, I exclude such benefits to simplify the model and leave this discussion for future work.

[4]Note that the utility of career advances does not reflect potential wage increases associated with this advancement: monetary returns are already captured in K. Rather, this could, for instance, reflect pride about achieving the promotion or excitement about the new responsibilities.

reaction, training holds the potential return of increasing the probability of receiving a new job.[5] While the returns b_{1i} and b_{2i} arise independently of each other, they can be similar and yet are distinct due to the point of view of the worker. For instance, both include a type of performance increase. In b_{1i} this may reflect the bonus of being able to perform a task in a new creative or more efficient way. In contrast, the gain in b_{2i} may instead merely arise from learning how to conduct a task in the first place. Importantly, for any given training course, it is unlikely that *all* non-monetary returns will arise as the returns depend on the workers' current situation as well as the type of training. This, however, does not preclude the opportunity of reaping benefits from both b_{1i} and b_{2i} from one training course, as a worker can be satisfied with some and dissatisfied with other aspects of the job.

In sum, the non-monetary returns of training can be depicted as

$$b_i(JS_i, x_i) \quad = \quad b_{1i}(JS_i, x_i) + b_{2i}(JS_i, x_i) \tag{4.1}$$

where $b_{1i}(JS_i, x_i)$ is increasing in JS_i and $b_{2i}(JS_i, x_i)$ is decreasing in JS_i (as it is increasing in dissatisfaction). As a consequence, there is a U-shaped relationship between b_i and JS_i.

Finally, as discussed above, the costs of training are constant across all workers and the cost-sharing rule of α is implemented. However, the decision problem of the worker may include an additional non-monetary cost $\tilde{c}_i$. These additional costs can arise in various ways. For instance, they may represent dismay about spending additional time on work-related issues if training takes place outside of regular working hours. A lower willingness to invest such additional time for work is an example of the neglect reaction to dissatisfaction. Alternatively, a worker may dislike training for it requires her to exert effort to learn new skills and subsequently transfer them to the job. In sum, it captures the lack of training and transfer motivation. Consequently, this additional cost depends again on the characteristics and situation of the worker, and, importantly, on the job satisfaction $\tilde{c}_i(JS_i, x_i)$. Following the literature, these costs are decreasing in JS_i as training and transfer motivation increase in job satisfaction (Ensour *et al.*, 2018; Jodlbauer *et al.*, 2012).

With these returns and costs of training, the firm and the worker will jointly decide

[5]It is worth noting that it is also possible to gain non-monetary returns from specific training that is useful for the exit reaction. For instance, participating in any type of training - including specific training - could be seen as a signal for potential future employers that the worker is willing to learn and develop and willing to invest in firm-specific training. Nevertheless, I return to the notion of general vs. specific training in Section 4.4.3.

whether the worker should participate in the training course. This is the case if at least one of the two parties gains positive returns without causing costs to the other. The net present values of training for the worker ($V_i(T_i = 1)$) and the firm ($V_f(T_i = 1)$) are equal to

$$V_i(T_i = 1) = \gamma K + b_{1i}(JS_i, x_i) + b_{2i}(JS_i, x_i) - (1+\rho)\alpha C - \tilde{c}_i(JS_i, x_i) \quad (4.2)$$

$$V_f(T_i = 1) = (1-\gamma)K - (1+\rho)(1-\alpha)C \quad (4.3)$$

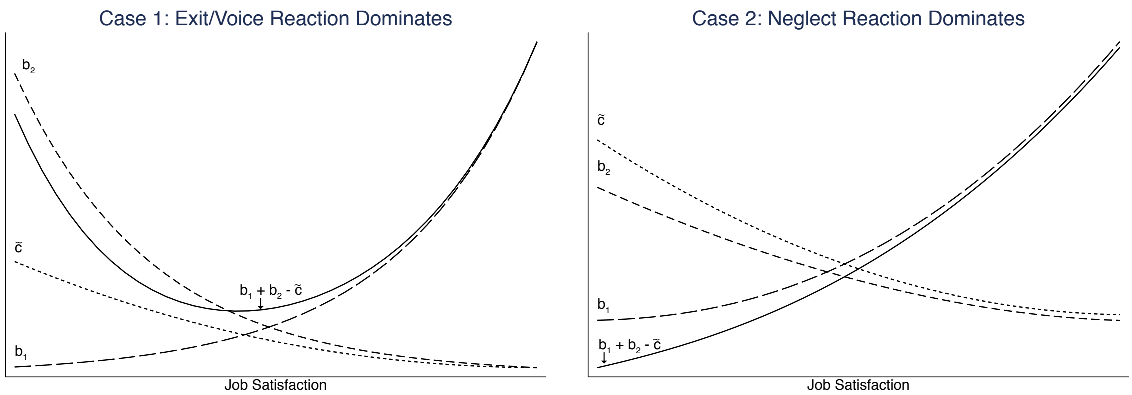
with the discount rate ρ.

It is apparent that the worker's decision to invest depends on her job satisfaction, while the firm's decision does not. However, it is not clear, in which direction the job satisfaction influences the worker's decision:

$$\frac{\partial V_i(T_i = 1)}{\partial JS_i} = \underbrace{\frac{\partial b_{1i}(JS_i, x_i)}{\partial JS_i}}_{>0} + \underbrace{\frac{\partial b_{2i}(JS_i, x_i)}{\partial JS_i}}_{<0} - \underbrace{\frac{\partial \tilde{c}_i(JS_i, x_i)}{\partial JS_i}}_{>0} \quad (4.4)$$

A graphical illustration of the relationship between job satisfaction and the non-monetary returns and costs are depicted in Figure 4.1.

Figure 4.1: Graphical Illustration of the Theoretical Model



Source: Own illustration.
Notes: Both graphs depict illustrations of the non-monetary returns and costs to training. b_1 are the benefits that arise from a point of job satisfaction and b_2 those that arise from a state of job dissatisfaction. $\tilde{c}$ are the non-monetary costs of training.
In Case 1, the benefits of training b_2 outweigh the costs of training $\tilde{c}$ on the left hand side. Here, the exit/voice reaction dominates the neglect reaction resulting in an overall U-shaped relationship between job satisfaction and the net value of training.
In Case 2, the costs $\tilde{c}$ outweigh the benefits b_2, such that the neglect channel dominates. This results in an overall positive relationship between job satisfaction and the net value of training.

As discussed above, the reverse effects of JS_i on b_{1i} and b_{2i} result in a U-shaped relationship between JS_i and b_i, while there is a negative relationship between JS_i and the costs $\tilde{c}_i$. The effect of JS_i on the net value of training V_i corresponds to the effect on the costs subtracted from the effect on the benefits. This combination amplifies the positive effect of JS_i on the far right side of the scale. For the workers on the far left of the scale, however, two potential scenarios arise: In the first case, the effect of JS_i on the benefits of training b_{2i} outweighs the effect on the costs $\tilde{c}_i$. This corresponds to the exit/voice reaction of dissatisfaction. In this case, there is an overall U-shaped relationship between JS_i and V_i (see case 1 of Figure 4.1). In contrast, the second case reflects the neglect reaction: If the effect on the costs outweighs the effect on the benefits, an overall positive relationship between JS_i and V_i emerges (case 2 of Figure 4.1).[6]

From a theoretical point of view, it is unclear which of these channels reveals to be dominant. Consequently, I turn to an empirical analysis in an attempt to descriptively identify the relationship between job satisfaction and training investments. Subsequently, I attempt to shed some light on the channels driving the relationship.

4.3 Data

4.3.1 Estimation Sample

For the empirical analysis, I utilize data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey. Since 2001, this household-based panel survey is conducted annually and covers information about economic and personal well-being, labor market dynamics and family life. In 2018, roughly 18,000 individuals from about 10,000 households were surveyed (Watson and Wooden, 2021). This dataset is especially suitable for this analysis, as it not only includes the basic necessary information on training and satisfaction across many years, but also because more in-depth analyses are possible with detailed information on the training courses and satisfaction facets.[7]

[6]Note that I do not further consider the loyalty reaction to dissatisfaction. As Farrell (1983) argues, the loyalty reaction is a rather calculated and/or transitory reaction. These individuals might believe that the dissatisfactory situation will be resolved somehow by someone. Meanwhile, they are willing to bear the dissatisfactory situation and remain loyal to their firm. The effect on training participation is unclear as these individuals may be willing to participate if the firm asks for this, but may still have high costs of participating.

[7]In other datasets, such as the Socio-Economic Panel (SOEP) in Germany, only few years provide the above mentioned information, or the detailed information is not provided at all. Other surveys, such as

In order to control for the recent training history, I restrict my sample to the years 2004-2019 and pool this data.[8] Further, I only consider the working-age population between the ages of 25 and 60. Workers are required to be employed and I exclude self-employed individuals. Finally, I drop observations for which information in the main or control variables are missing. These restrictions result in an estimation sample of 63,647 observations with 9,339 distinct individuals.

4.3.2 Training Measures

Since 2003, individuals are asked whether, in the past 12 months, they have participated in any education or training courses, as part of their employment. I utilize this information as the dependent variable, which is a dummy indicating whether an individual has participated in training in the past 12 months. Overall, roughly 40% of the sample participate in training.

Individuals are also asked to name the reasons for training.[9] The possible answers are: "To maintain professional status and/or meet occupational standards", "To improve your skills in your current job", "To develop your skills generally", "To prepare you for a job you might do in the future or facilitate promotion", "To help you get started in your job", "Because of health/safety reasons" or "Other". Individuals are asked to indicate all applicable responses. Hence, all purposes of training are captured, even if an individual participated in multiple trainings for different reasons or a single course for multiple reasons. However, it is not possible to infer, which courses were undertaken for which purpose.

From 2007 onwards, this part of the survey was extended with various questions, e.g. regarding the number of courses, the overall duration as well as the transferability of the newly acquired skills. The main issue with the additional information is that they refer to the aggregated training courses, i.e. it is not possible to indicate for one training course the reason, costs and duration unless an individual has only participated in one training course.

Table 4.5 in the appendix provides the descriptive information of the aggregated training

the National Educational Panel Study (NEPS) in Germany, do not provide the (consistent) panel structure which is quite important in the analysis as I impute information from previous years.

[8]That is, I first utilize the panel structure to impute relevant data of previous or following years, e.g. the job satisfaction (see Section 4.3.3). Afterwards, I disregard the panel structure, utilize the data as a pooled cross-section and include year dummies.

[9]I take a closer look at the aims of training in Section 4.5.1.

courses. Panel A refers to the information on training participation and the aims of training, which are available for the years 2004-2019. The aim of improving skills, maintaining the professional status and developing general skills are indicated most often as the purpose of training. Additional information on the training courses are available from 2007 onwards and summarized in panel B. In total, only 22% report contributing to the costs of training, while more than 80% of the training participants believe their skills to be valuable for other employers at least to a moderate extent.

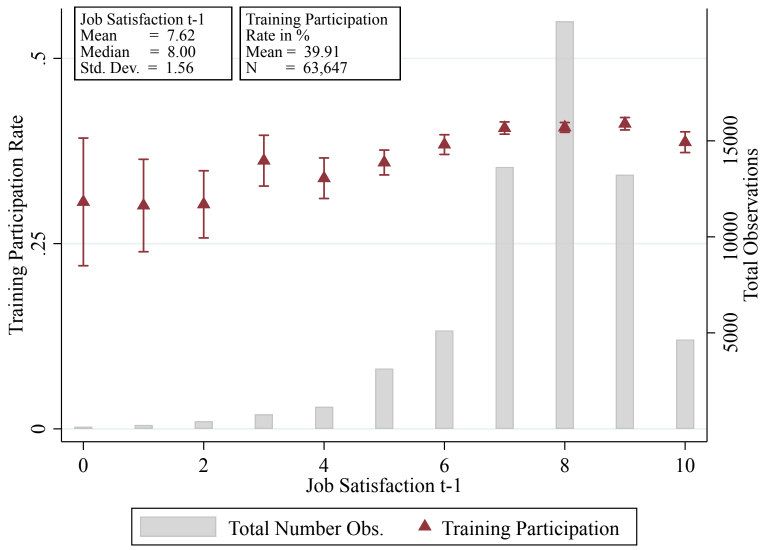
4.3.3 Job Satisfaction

In the HILDA, there are multiple questions regarding the satisfaction with the current employment. In all years, individuals are asked to rate their satisfaction about different aspects of their (main) job on a scale from 0 (Totally dissatisfied) to 10 (Totally satisfied). In particular, individuals rate their satisfaction regarding “the work itself (what you do)”, “your total pay”, “your job security”, “the flexibility available to balance work and non-work commitments” and “the hours you work”. Finally, individuals are asked “All things considered, how satisfied are you with your job?”. I use this last question to create a continuous measure of overall job satisfaction, which is my main variable of interest.

As I aim at estimating the effect on how the current job satisfaction influences the worker’s choice to invest into training, the timing of the measurements are pivotal. Ideally, one could measure the job satisfaction of the worker at the point in time at which the training decision is made. However, the HILDA only provides information once a year. Additionally, I do not observe the timing of the decision, but rather the timeframe in which training takes place (i.e. within the 12 months prior to the interview in t). Therefore, it is important to take a measure of job satisfaction from a point in time *before* training. This additionally contributes to minimizing issues with reverse causality stemming from the positive effect of training on job satisfaction (Burgard and Görlitz, 2014). Since I cannot assume that job satisfaction remains stable, taking the *most recent* measure prior to training is important. Consequently, I impute the information on job satisfaction from $t-1$. When interpreting the results, this measurement limitation must be kept in mind.

The main summary statistics regarding the job satisfaction in $t-1$ are summarized in the left text box in Figure 4.2. On average, the working population in Australia is quite

Figure 4.2: Training Participation Rates by Job Satisfaction



Source: The Household, Income and Labour Dynamics in Australia (HILDA): data for years 2004-2019, general release 19, HILDA, 2020, doi:10.26193/3QRFMZ, own calculations.
Notes: The figure shows the training participation rates by job satisfaction (in $t-1$) and the 95% confidence intervals (left y-axis). The question asked in the survey is "All things considered, how satisfied are you with your job?". Respondents can answer on an 11-point Likert scale ranging from "completely dissatisfied (0)" to "completely satisfied (10)". The grey bars (right y-axis) depict the distribution of the job satisfaction measure.

satisfied with their job with a median job satisfaction of 8 and an average of 7.62. The average satisfaction levels with the various job facets are presented by training status in Table 4.6. With the exception of flexibility and hours satisfaction, the satisfaction levels are significantly higher for training participants than for those workers who do not invest into training. Figure 4.2 displays the descriptive relationship between job satisfaction and training participation. The distribution of job satisfaction (x-axis) is plotted with gray bars (right y-axis). As can be seen, job satisfaction follows a normal distribution which is heavily skewed to the left. Overall, only 9% of the overall sample indicate that they have higher levels of dissatisfaction (i.e. 5 or lower). As a consequence, the information on the left half of the job satisfaction scale is rather noisy. On the left y-axis, the unconditional training participation rates are plotted by the level of job satisfaction. There is a clear upward trend in participation rates with job satisfaction. This holds especially for those who report medium levels of satisfaction (5-7 on the scale). For high levels of satisfaction, a minor dip in the participation rates is visible (9-10 on the scale). The left half of the scale provides some indication that high levels of dissatisfaction (0-2 on the scale) is associated with lower levels of training participation. However, due to the limited number of observations, this conclusion must be made with great caution.

4.3.4 Control Variables

For the choice of control variables in my estimation, I turn to the literature on the determinants of training participation. Various studies have found that job as well as firm characteristics influence the likelihood of investing into training. For instance, higher levels of experience are associated with a higher training probability (Lynch, 1992). Both workers with a permanent or with a full-time contract are more likely to participate (Oosterbeek, 1996; O'Connell and Byrne, 2012). The training incidence is higher in larger firms and depend on the sector (Lynch and Black, 1998; Oosterbeek, 1998; Maximiano, 2012).

Additionally, socio-demographic characteristics are related to training investments. Age is a determinant of training participation, where a reoccurring finding is that older workers receive significantly less training (Maximiano, 2012; Weaver and Habibov, 2017). On the other hand, training participation is increasing with education (Arulampalam and Booth, 1997; Leuven and Oosterbeek, 1999; Bassanini *et al.*, 2007). The picture is not quite as clear regarding gender differences. Some studies report higher training rates among men (Lynch, 1992; Fitzenberger and Muehler, 2015), while others find the opposite (Simpson and Stroh, 2002). In contrast, Oosterbeek (1996) argues that the gap is driven by occupational choice and, thus, disappears once controlling for such factors. Finally, recent studies find a significant relationship between personality traits, such as locus of control and risk attitudes, and training investment decisions (Caliendo *et al.*, 2020, 2022).

Consequently, I control for a wide range of variables: (i) socio-economic information (age, gender, marital status, number of children, disabilities, migration background, home ownership, highest educational degree, employment and unemployment experience, and gross monthly household income from 2 years ago)[10]; (ii) regional information (regional dummies, local unemployment rate) and year dummies; (iii) occupation characteristics (employment

[10] The number of children is not available in the years 2005, 2008, 2011, 2015, and 2019. The information is imputed from the previous years.

status, contract type, tenure, trade union membership, and ISCO88 occupation)[11]; (iv) firm characteristics (firm size and NACE industry)[12]; and (v) personality traits (Big Five traits, locus of control and risk attitudes).[13] Descriptive statistics for these control variables can be found by training status in Table 4.6 in the appendix.

4.4 Results

4.4.1 Estimation Strategy

The aim of this analysis is to estimate the relationship between a worker's job satisfaction and her training participation. The theoretical framework identifies two potential relationships: If the exit and voice reaction dominate, a U-shaped relationship is expected. In contrast, the neglect reaction would induce an overall positive relationship. As I lack exogenous variation in the job satisfaction, causal interpretations remain limited. However, by taking the timing of measurements into account and ensuring that the level of satisfaction is measured prior to training participation, I attempt to provide a more causal point of view.

In the following, I first exploit the panel structure of the HILDA data by imputing relevant information from the previous years. Afterwards, I treat the data like a pooled cross section across all years 2004–2019[14] and conduct a logit regression as the dependent variable is binary. Further, I cluster the standard errors on the individual level to account for individuals appearing multiple times in the dataset. In this regression, I consider a dummy variable indicating overall training participation (T) in the past 12 months as the dependent variable and job satisfaction (JS) in $t-1$ as the main independent variable of interest:

$$P(T=1)_{it} = \frac{\exp(\alpha_0 + \alpha_1 JS_{it-1} + \alpha_2 JS_{it-2} + \alpha_3 TH_{it-1;t-2} + \boldsymbol{X'_{it}\alpha_4})}{1 + \exp(\alpha_0 + \alpha_1 JS_{it-1} + \alpha_2 JS_{it-2} + \alpha_3 TH_{it-1;t-2} + \boldsymbol{X'_{it}\alpha_4})} \tag{4.5}$$

where i indicates individuals and t time. The self-reported job satisfaction (JS) is measured

[11] Trade union information is missing for the years 2004-2008 and is imputed backwards from 2009.

[12] For the occupational classification, I rely on the International Standard Classification of Occupations 88 (ISCO88) which categorizes occupations into 10 groups. There are no soldiers in my sample, such that only 9 occupational groups remain. The industries are collapsed into 12 categories based on the classification system NACE ("Nomenclature statistique des Activités Economiques dans la Communauté Européenne") used by the European Union (see Table 4.6).

[13] The personality traits (which are not the focus of this study) are measured for a few select years (Big Five in 2009, 2013 and 2017, locus of control in 2007, 2011, 2015, risk attitudes in 2014 and 2018). To maximize the sample, I average for each individual the information over all available years.

[14] I consider year effects by including a dummy for each year. The reference year is 2004.

in $t-1$, i.e. *before* training, and is standardized for comparability of the results. Thus, α_1 is the main effect of interest. In the main analysis, I vary the functional form of this variable to identify the dominant channel. I additionally control for the job satisfaction in $t-2$ to capture any changes in satisfaction that may occur in the year prior to the analyzed training decision timeframe (Chen *et al.*, 2011). I attempt to further reduce potential reverse causality issues by controlling for the recent training history (TH) to capture effects of previous courses on the job satisfaction (Burgard and Görlitz, 2014). For this, I include a dummy that takes on the value 1 if the individual has indicated participating in training in the past 12 months of the year $t-1$ and/or $t-2$.[15] A graphical overview of the timing of these variables can be found in Figure 4.3. Finally, in the vector $\boldsymbol{X_{it}}$, I control for the variables outlined in Section 4.3.4: (i) socio-economic information, (ii) regional and year information, (iii) occupation characteristics, (iv) firm characteristics, and (v) personality traits.

4.4.2 Participation in Training

Table 4.1 presents the results of the main regression estimation on the relationship between job satisfaction and training participation. Average marginal effects (ME) of the logit estimations are presented, with the exception of column (4) in which merely the coefficients (Coeff.) are reported as the marginal effect of the squared term cannot be calculated. The coefficients cannot be interpreted apart from their sign and significance. Column (1) displays the results from a linear specification and (2)-(4) examine the functional form of job satisfaction in $t-1$.

Linear Specification: Column (1) of Table 4.1 presents the results of a simple linear specification with all control variables. I find a positive and significant relationship, which indicates that more satisfied workers are more likely to invest into training: Increasing the job satisfaction in $t-1$ by one standard deviation (SD, equivalent to 1.56 points on the 11-point Likert scale) is associated with an increased probability of participating in training of 0.6 percentage points (p.p.). Comparing this to the unconditional training participation rate, this translates to an increase of 1.5 percent.

[15]Note that, for 2004, the dummy only refers to $t-1$ as there is no information on training participation in wave 2002. Excluding the year 2004 does not change the results. Results are available upon request.

On its own, this finding suggests that the neglect reaction is dominant, resulting in an overall positive relationship. Nevertheless, a more thorough investigation of the functional form is in order.

Table 4.1: Logit Estimation Results: Training Participation on Job Satisfaction (Average Marginal Effects)

	(1) ME	(2) ME	(3) ME	(4) Coeff.
	Linear Specification	Non-linear Specification		
Job Satisfaction $t-1$ (std.)	0.006***			0.019
	(0.002)			(0.013)
Job Satisfaction $t-1$ (std.) $\times$ Job Satisfaction $t-1$ (std.)				-0.010*
				(0.006)
Job Satisfaction $t-1$ (Dummy)		0.019***		
		(0.007)		
Medium Job Satisfaction $t-1$			0.019	
			(0.013)	
High Job Satisfaction $t-1$			0.032**	
			(0.013)	
Participation Rate	39.91	33.55	40.06	39.91
Effect in %	1.50	5.66		
p-value of Joint F-Test			0.00	0.00
Controls	✓	✓	✓	✓
Pseudo-R^2	0.15	0.15	0.15	0.15
Observations	63,647	63,647	63,647	63,647

Source: The Household, Income and Labour Dynamics in Australia (HILDA): data for years 2004-2019, general release 19, HILDA, 2020, doi:10.26193/3QRFMZ, own calculations.
Notes: The table displays the average marginal effects estimated based on logit estimations (columns 1-3) or coefficients from logit estimations (column 4). The dependent variable is a dummy indicating participation in training. The main explanatory variable of interest is the worker's job satisfaction (from $t-1$). All regressions include the full set of control variables. For the regressions, the (unconditional) average of the dependent variable ("Participation Rate"), the average effect in % (in relation to the unconditional participation rate) of the main explanatory variable ("Effect in %", columns 1 and 2), and the Pseudo-R^2 are displayed. Standard errors are in parentheses and clustered on person-level. * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$.
(1) Full specification. Detailed estimation results available in Table 4.10 in the Appendix. Job satisfaction is continuous and standarized.
(2) The job satisfaction dummy is equal to 1 if the (non-standardized) job satisfaction is greater than 5 and zero otherwise (reference category). Here, the participation rate refers to the unconditional average of the dependent variable for the reference group.
(3) Individuals with a (non-standardized) job satisfaction of 4-6 (7-10) have a medium (high) job satisfaction. The reference category is low satisfaction (with values 0-3). Here, the participation rate refers to the unconditional average of the dependent variable for the reference group. p-value of joint F-test presented.
(4) The size of the coefficients cannot be interpreted. The linear and squared terms of the standardized job satisfaction are included. For the predicted participation probabilities based on the non-standardized job satisfaction see Figure 4.4, Panel A. p-value of joint F-test presented.

Non-linear Specifications: Columns (2)-(4) present the results of non-linear specifications. In case the exit/voice channel dominates the neglect channel, I expect a U-shaped relationship between job satisfaction and training participation. Should, however, the neglect channel be more prevalent then I expect to find an overall positive relationship across the entire satisfaction scale.

For this investigation, I first generate a dummy which takes on the value one if the (non-standardized) job satisfaction is greater than the value of 5 (the mid-point of the scale) and zero otherwise (column 2). Hence, I compare those who report higher levels of satisfaction ("satisfied workers", right half of the scale) with those who report low levels of satisfaction ("unsatisfied workers", left half of the scale). The results suggest that satisfied workers are on average 1.9 p.p. or 5.7% more likely to invest into training than unsatisfied workers. This implies that the positive effect on the right hand side of the scale is more pronounced than the combined effect of the potential channels on the left hand scale. Thus, either the neglect channel dominates resulting in a positive relationship on the left hand as well, or the negative relationship induced by the exit/voice channel is weaker than the positive relationship on the right hand, resulting in an overall lower likelihood of investing for unsatisfied than satisfied workers.

Next, I collapse the sample into three groups: Individuals with low job satisfaction (0-3), medium job satisfaction (4-6), and high job satisfaction (7-10). In case the exit/voice channel dominates the neglect channel, I expect to see the medium satisfaction group to have a lower participation probability than the low satisfaction workers. In column (3), I exclude the low job satisfaction group as the reference category. There is no significant difference between the low and medium satisfaction groups, whereas the high job satisfaction workers are 3.2 p.p. more likely to invest into training than the reference group. The insignificant coefficient of the medium group may imply that the two channels of exit/voice and neglect cancel each other out. However, this result must be viewed with great caution because there are only very few observations on the left half of the scale. The insignificant coefficient may also simply be the result of too few observations. If that is truly the case, the positive sign of the (insignificant) coefficient points towards the neglect channel as the dominant reaction to dissatisfaction in the training context.

In column (4), I include the squared term of the job satisfaction. Note that here only the coefficients are presented rather than the marginal effect in order to present the functional form. Should low levels of job satisfaction result in workers intending to improve or leave the situation, I expect to see a U-shaped relationship between job satisfaction and training. Importantly, due to the standardization of the job satisfaction measure, the domain of the function also includes low negative values (in magnitude). As a consequence, a U-shaped relationship is achieved with a positive sign for both the linear and squared term. However, I find a positive and negative coefficient for the linear and squared terms, respectively, resulting in a presumably inverted U-shape. This would imply two points: First, there is a positive relationship for rather unsatisfied workers, supporting the dominance of the neglect channel. Second, for highly satisfied workers the training probability even decreases, portending to the possibility that training has decreasing returns with high levels of satisfaction. Figure 4.4, panel A, plots the predicted training participation probability based on this estimation. Here, the control variables are held at their means. As expected, the confidence intervals on the left are sizeable in comparison to those on the right, cautioning conclusions about the unsatisfied workers.

Finally, in Figure 4.4, panel B, I include the job satisfaction variable as a categorical variable. Here, the average marginal effects of the categories are depicted. As the number of (highly) unsatisfied workers is limited, I pool those individuals who report higher levels of dissatisfaction i.e. workers who indicate a value between 0 and 5 on the satisfaction scale. This is the reference category. As can be seen, a higher level of job satisfaction is associated with a higher probability of participating in training in comparison to the unsatisfied workers. If the voice/exit channel were to dominate, I would expect to see a lower training probability amongst the moderately satisfied workers. As this is not the case, these results substantiate the preceding findings.

Taken together, the results indicate that there is overall a positive association between job satisfaction and training participation. Tentatively, the conclusion can be made that, on average, unsatisfied workers are more likely to display the neglect reaction resulting in a lower training participation probability.

4.4.3 Robustness

In this section, I check for the robustness of my findings. The results are reported in Table 4.7. For comparison, the linear and squared specifications from the main results are presented in columns (1) and (2).

Potential Endogeneity: It is conceivable that the job satisfaction of a worker influences multiple choices regarding her employment situation. Hence, my regression includes some potentially endogenous control variables. These could moderate the effect of job satisfaction in the training context. Hence, in columns (3) and (4), I exclude the choice variables regarding the employment situation, namely the employment status, contract type, ISCO-occupation, and NACE-sector classification. The effect size increases in the linear specification, but otherwise the conclusions remain unchanged.

Training Type: Becker (1962) argues that the distribution of the return to training depends on the transferability of skills acquired during training where the worker (firm) reaps the benefits of general (specific) training. Previous studies have highlighted the importance of this distinction, as it depicts heterogeneous incentives for the worker (e.g. Caliendo *et al.*, 2020, 2022). In the context of job satisfaction, it could be argued that general training is especially of interest for unsatisfied individuals who intend to leave the current firm (i.e. exit reaction). Indeed, when looking at participation in general training as a dependent variable,[16] the two positive signs in the squared specification indicate a U-shaped relationship (column 6). In contrast, the two negative signs for specific training are less intuitive (column 8). Presumably, individuals with high levels of job satisfaction (perceive to) require less specific training. However, it must be kept in mind that the transferability of training skills is measured aggregately for all courses in the HILDA. Reducing the sample to those who participated in one or none courses, significantly reduces the variation in the training participation. The results are less precise but yield similar results. Results are available upon request.

Initiation: In columns (9) and (10), I turn to the initiation of training: If training participation is mandatory, the worker is not part of the decision process. In this case, it is conceivable that the job satisfaction is irrelevant for the participation decision. Hence, the relationship may be underestimated if some of the training courses in the sample are obligatory. As there is no information available regarding the initiation of training in the HILDA, I follow Smith *et al.* (2019) and exclude courses which had the purpose of a job introduction or for health and safety reasons.[17] Smith *et al.* (2019) argue that a large portion of firms

[16]I utilize information regarding the usefulness of the newly acquired skills in other firms. Individuals who indicate that they could use the skills to a great or very great extent are defined as general training participants, while those who indicate they could use the skills to a moderate or limited extent, or not at all are considered as specific training participants.

[17]Most individuals who participate in either of such courses additionally indicate further aims of training as well. In total, only 5 individuals report job introduction and/or health and safety reasons as the only aims of training. Since it is not possible to distinguish whether one course followed multiple aims or the person participated in multiple courses with different aims each, I exclude all individuals who indicate participation

provide such courses mandatorily. Indeed, column (9) indicates that the effect is underestimated in the baseline specification. However, column (10) reinforces the slightly inverted U-shape relationship. Hence, the main conclusions remain unchanged.

Fixed Effects: Finally, specifications (11) and (12) attempt to provide a more causal estimation by exploiting the panel structure and applying a fixed effects logit estimation.[18] By comparing the individuals with themselves across time, I can hold time-constant unobserved variables fixed, reducing potential biases. As this estimation requires the independent variables to vary over time, the control variables gender, migration background, and the personality traits[19] are omitted. Further, the number of observations decreases here, because the fixed effects logit estimation excludes those individuals for whom the dependent variable does not change for all observed years.[20] Finally, I follow Cruz-Gonzalez *et al.* (2017) and correct for the incidental parameter bias which arises in binary response models (Neyman and Scott, 1948; Fernández-Val and Weidner, 2016; Cruz-Gonzalez *et al.*, 2017).[21] Both the linear and squared specifications point towards a positive and linear relationship between job satisfaction and training participation, which reinforces the previous findings of a dominant neglect channel. Further, the presented average marginal effects in the linear specification reveal a larger effect than in the simple logit regression: increasing the job satisfaction in $t-1$ by one SD is associated with an increase in the participation probability by 1.1 p.p., which translates to an effect size of 2.49%. It can be concluded that the effect size in the logit model is biased downwards due to unobserved time constant variables.[22] However, the fixed effects estimation does not provide causal results in case there

for either an introduction or health and safety reasons.

[18]There is a noteworthy within-person variation in the job satisfaction: For roughly 62% of the observations there is a change in job satisfaction between $t-2$ and $t-1$. Overall, 57.3% change their satisfaction between 1 and 3 points on the 11 point Likert scale (in either direction), while 2.3% exhibit a change of at least 5 points. Only 38.1% of the estimation sample do not change their job satisfaction between two consecutive years.

[19]Because there are very few years which include information on the personality traits, these were averaged across all available years to maximize the estimation sample. Consequently, they are stable by design in this sample.

[20]Roughly 17.4% of the main estimation sample is excluded because these individuals never participate in training. Additional 6.3% are excluded because they always participate in training. Thus, for 76.3% of the main estimation sample there is some variation in the training status over the years.

[21]I employ the analytical correction method with one lag, both individuals and time effects, and bias correction for both individuals and time effects (Cruz-Gonzalez *et al.*, 2017). I also test the robustness of these findings with further specifications, e.g. the jackknife method (Cruz-Gonzalez *et al.*, 2017). Results are stable and available upon request.

[22]When replicating the main results of the logit regression with the reduced fixed effects sample, the effect in the linear specification increases to 1.8% and the squared specification points towards a linear relationship.

are time-varying unobservables. This is the case for example for the current performance on the job. Consequently, it cannot be ruled out that these results are biased as well, cautioning causal interpretations. Nevertheless, overall, the logit and fixed effects logit estimations both provide evidence that the neglect channel is the dominant one.

4.5 Potential Mechanisms

In this section, I attempt to disentangle the potential mechanisms that drive the relationship between job satisfaction and training investments. For this, I aim at isolating the voice from the exit reaction to check whether the neglect channel dominates the voice and exit reactions to the same degree. I employ different strategies for this. First, I consider the aim of training, which can shed light on the motivation and, thus, the channel underlying the training decision (Section 4.5.1). Second, I conduct a heterogeneity analysis with respect to the intention to quit. Hereby, I identify groups for which the exit (voice) channel is prevalent enabling a direct comparison between the exit (voice) and neglect channels (Section 4.5.2). Finally, not every dissatisfactory situation can be solved equally with training. Hence, I check whether there are varying effects for the available job satisfaction facets (Section 4.5.3).

4.5.1 Aim of Training

The HILDA provides information on the aims of training. Specifically, individuals can indicate participation with the aim of maintaining their status and/or meeting occupational standards, improving their skill, learning general skills, and preparing for a potential future job or promotion.[23] These aims can shed some light on the motivation behind the training investment decision. Consequently, Table 4.2 replicates equation (4.5) with dummy variables indicating the training participation for a specific aim as alternative dependent variables, respectively. For ease of comparison, the baseline results of the linear and squared specification are presented in columns (1) and (2). The predicted participation probabilities by job satisfaction of the squared specifications are presented in Figure 4.5 for each dependent

Results are available upon request.

[23]I do not consider the aim “To help you get started in your job” as I am not interested in this type of training. Also, the aims “Because of health/safety reasons” and “Other” are not further considered as they do not reflect the exit, voice or neglect channel. Finally, following Smith *et al.* (2019) the aims “To help get started in your job” and “Because of health/safety reasons” could likely depict mandatory training.

variable.

I argue that the aim of maintaining status and/or meeting standards (columns 3 and 4), as well as improving skills (columns 5 and 6) reflect the voice channel; a worker who would be unsatisfied with a lower status might actively seek out ways to meet certain standards. Similarly, a worker who wishes to improve her skills as she is unsatisfied with her current performance could look for training to improve. Consequently, I expect only the voice and neglect channel to be of relevance in the regressions of columns (3) to (6). The results are very similar to the baseline results, pointing towards an overall positive relationship. This implies that the neglect channel dominates the voice channel.

In contrast, the aim of preparing for a future job or promotion (columns 9 and 10) reflects the exit channel: These individuals are preparing to leave their current position.[24] Consequently, in these columns, the exit and neglect reactions are relevant. Column (10) is the first specification that points towards a U-shaped relationship: individuals with low levels of satisfaction have an increasing likelihood of participating in training with the aim of preparing for a new job or promotion (compare Figure 4.5, panel E).

Finally, it is not as straightforward to ascribe a single channel to the aim of learning general skills as it can reflect both the voice and exit channel. Both individuals who want to improve and leave the current situation may benefit from improving their general skills. Consequently, these results provide little new information.

In sum, these results cautiously indicate that on average the exit channel is dominated *less* by the neglect channel than the voice channel is.

[24] Note that a transfer within the same firm with the aim of leaving the dissatisfactory job (or position) is also considered to reflect the exit reaction (Farrell, 1983).

Table 4.2: Logit Estimation Results: Training Aim on Job Satisfaction (Average Marginal Effects)

	(1) ME	(2) Coeff.	(3) ME	(4) Coeff.	(5) ME	(6) Coeff.	(7) ME	(8) Coeff.	(9) ME	(10) Coeff.
	Training		Training Aim							
	Participation		Maintain Status		Improve Skills		General Skills		Future Job/Promotion	
Job Satisfaction $t-1$ (std.)	0.006***	0.019	0.005***	0.026*	0.007***	0.019	0.009***	0.043***	0.005***	0.063***
	(0.002)	(0.013)	(0.002)	(0.015)	(0.002)	(0.014)	(0.002)	(0.015)	(0.002)	(0.020)
Job Satisfaction $t-1$ (std.)		-0.010*		-0.007		-0.017***		-0.011		0.011
$\times$ Job Satisfaction $t-1$ (std.)		(0.006)		(0.007)		(0.006)		(0.007)		(0.008)
Participation Rate	39.91	39.91	25.77	25.77	30.75	30.75	23.99	23.99	11.60	11.60
Effect in %	1.50		1.94		2.28		3.75		4.31	
p-value of Joint F-Test		0.00		0.01		0.00		0.00		0.00
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Pseudo-R^2	0.15	0.15	0.15	0.15	0.14	0.14	0.12	0.12	0.08	0.08
Observations	63,647	63,647	63,647	63,647	63,647	63,647	63,647	63,647	63,647	63,647

Source: The Household, Income and Labour Dynamics in Australia (HILDA): data for years 2004-2019, general release 19, HILDA, 2020, doi:10.26193/3QRFMZ, own calculations.

Notes: The table displays the average marginal effects estimated based on logit estimations (uneven columns) or coefficients from logit estimations (even columns). The dependent variables are dummies indicating participation in training with certain aims (see column headers and below). The main explanatory variable of interest is the worker's standardized job satisfaction (from $t-1$). In the even columns, the squared term of the job satisfaction is included. All regressions include the full set of control variables. For each regression, the (unconditional) average of the dependent variable ("Participation Rate"), the average effect in % (in relation to the unconditional participation rate) of the main explanatory variable ("Effect in %", uneven columns), p-value of joint F-test (even columns), and the Pseudo-R^2 are displayed. Standard errors are in parentheses and clustered on person-level. * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$.

In the even numbered columns, the size of the coefficients cannot be interpreted. For the predicted participation probabilities based on the non-standardized job satisfaction, see Figure 4.5.

(1)/(2) Main results from Table 4.1, columns (1) and (4).

(3)/(4) Dependent variable: Training participation to maintain professional status and/or meet occupational standards.

(5)/(6) Dependent variable: Training participation to improve your skills in your current job.

(7)/(8) Dependent variable: Training participation to develop your skills generally.

(9)/(10) Dependent variable: Training participation to prepare you for a job you might do in the future or facilitate promotion.

4.5.2 Quit Intention

In this section, I exploit information on the quit intention and subsequent quit behavior. In the HILDA, employed individuals are asked "What do you think is the per cent chance that you will leave your job voluntarily (that is, quit or retire) during the next 12 months?" (on a scale from 0% to 100%). I utilize this question as a measure of quit intention and perform a heterogeneity analysis with respect to quit intentions.

For the exit channel to be an actual reaction to dissatisfaction, it would be required to observe a negative relationship between job satisfaction and the intention to quit. To check this, I estimate the effect of job satisfaction on the intention to quit, which are both measured in $t-1$ (i.e. before training takes place). In Table 4.8, I indeed find that increasing levels of satisfaction are associated with decreased intentions to quit, which confirms findings from previous studies (e.g. Lance, 1988).

In the next step, in Table 4.3, I consider heterogeneous effects of job satisfaction on training participation by the workers' quit intentions.[25] Columns (1) and (2) replicate the main findings with the linear and squared specification for the full sample. Panel A considers overall training participation as the dependent variable. Panel B replicates the analysis with training participation with the aim of qualifying for a new job or promotion as the dependent variable because this aim reflects the exit channel the best. The corresponding predicted training probabilities across satisfaction are depicted in Figure 4.6.

Those who do not intend to quit their job (i.e. a zero chance of quitting, see column 3 and 4) do not exhibit the exit reaction to dissatisfaction. In other words, these individuals either react with the voice or the neglect channel. The results barely change, providing further evidence that the voice channel is dominated by the neglect channel.

[25]There is sufficient variation in the job satisfaction measure across all subgroups. Notably, with increasing quit intention the average level of job satisfaction decreases and the corresponding standard deviation increases, but the full range of the scale is represented in all subgroups.

Table 4.3: Logit Estimation Results: Training Participation on Job Satisfaction by Quit Intention (Average Marginal Effects)

	(1) ME	(2) Coeff.	(3) ME	(4) Coeff.	(5) ME	(6) Coeff.	(7) ME	(8) Coeff.	(9) ME	(10) Coeff.
	Full Sample		Likelihood to Quit in the Next 12 Months in % ($t-1$)							
			0		1-49		50-99		100	
A. Training										
Job Satisfaction $t-1$ (std.)	0.006***	0.019	0.005	0.012	0.007	0.033	0.004	-0.026	0.003	-0.017
	(0.002)	(0.013)	(0.003)	(0.018)	(0.006)	(0.033)	(0.004)	(0.037)	(0.007)	(0.069)
Job Satisfaction $t-1$ (std.)		-0.010*		-0.026***		-0.006		-0.022*		-0.011
× Job Satisfaction $t-1$ (std.)		(0.006)		(0.009)		(0.018)		(0.013)		(0.020)
Participation Rate	39.91	39.91	41.74	41.74	39.88	39.88	36.15	36.15	37.67	37.67
Effect in %	1.50		1.20		1.76		1.11		0.80	
p-value of Joint F-Test		0.00		0.01		0.38		0.14		0.79
Pseudo-R^2	0.15	0.15	0.18	0.18	0.14	0.14	0.12	0.12	0.13	0.13
B. Training for Future Job/Promotion										
Job Satisfaction $t-1$ (std.)	0.005***	0.063***	0.005**	0.052*	0.008*	0.107**	0.001	0.022	0.011**	0.166*
	(0.002)	(0.020)	(0.003)	(0.027)	(0.004)	(0.045)	(0.003)	(0.054)	(0.006)	(0.091)
Job Satisfaction $t-1$ (std.)		0.011		-0.002		0.040*		0.006		0.019
× Job Satisfaction $t-1$ (std.)		(0.008)		(0.014)		(0.024)		(0.019)		(0.027)
Participation Rate	11.60	11.60	11.70	11.70	11.85	11.85	11.19	11.19	12.93	12.93
Effect in %	4.31		4.27		6.75		0.89		8.51	
p-value of Joint F-Test		0.00		0.13		0.05		0.92		0.09
Pseudo-R^2	0.08	0.08	0.09	0.09	0.08	0.08	0.08	0.08	0.12	0.12
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	63,647	63,647	34,709	34,709	15,170	15,170	10,222	10,222	2,166	2,166

Source: The Household, Income and Labour Dynamics in Australia (HILDA): data for years 2004-2019, general release 19, HILDA, 2020, doi:10.26193/3QRFMZ, own calculations.

Notes: The table displays the average marginal effects estimated based on logit estimations (uneven columns) or coefficients from logit estimations (even columns). In panel A the dependent variable indicates participation in any training, in panel B it indicates participation in training for a future job or promotion. The main explanatory variable of interest is the worker's standardized job satisfaction (from $t-1$). In the even columns, the squared term of the job satisfaction is included. All regressions include the full set of control variables. For each regression, the (unconditional) average of the dependent variable ("Participation Rate"), the average effect in % (in relation to the unconditional participation rate) of the main explanatory variable ("Effect in %", uneven columns), p-value of joint F-test (even columns), and the Pseudo-R^2 are displayed. Standard errors are in parentheses and clustered on person-level. * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$. In the even numbered columns, the size of the coefficients cannot be interpreted. For the predicted participation probabilities based on the non-standardized job satisfaction, see Figure 4.6.

(1)/(2) Main results from Table 4.1, columns (1) and (4).
(3)/(4) only include individuals who indicate a zero chance of quitting their job in the next 12 months ($t-1$).
(5)/(6) only include individuals who indicate a chance of 1-49% of quitting their job in the next 12 months ($t-1$).
(7)/(8) only include individuals who indicate a chance of 50-99% of quitting their job in the next 12 months ($t-1$).
(9)/(10) only include individuals who indicate a chance of 100% of quitting their job in the next 12 months ($t-1$).

Looking at the linear specifications in panel A only, the effect sizes (albeit all insignificant) decrease with increasing levels of quit intentions. Considering the squared specifications, all coefficients are insignificant and the curves for the predicted participation probabilities flatten out (compare Figure 4.6, panel 1B to 1D). This suggests that the exit channel gains dominance and counteracts the neglect channel. Nevertheless, a clear U-shaped relationship cannot be found and the overall effects remain fairly small.

However, when considering the effect on training for a new job or a promotion (panel B of Table 4.3), the results are more pronounced. The results of the full sample are highly driven by those who do not intend to quit (which is also the largest part of the sample). However, for those with quit intentions, a U-shaped relationship becomes evident.[26] This provides some tentative evidence that individuals who intend to leave their job due to job dissatisfaction may turn to training to qualify for a different job. Once again, it must be cautioned that the left half of the scale is quite noisy which can be seen by the large confidence intervals in Figure 4.6. This may also in part contribute to insignificant coefficients.

As a final step, in Table 4.9, I check whether job satisfaction is indeed related to job changes. Here, the dependent variable indicates a job change between t and $t+1$ (any change in column (1), a voluntary change in column (2),[27] and a change due to job dissatisfaction in column (3)[28]), which is regressed on job satisfaction in t, $t-1$, and $t-2$. I additionally control for training participation between $t-1$ and t, the interaction between job satisfaction (in t) and training participation (between $t-1$ and t), as well as the training history. As it is not possible to calculate the marginal effect of an interaction term for a logit regression, coefficients are presented in Table 4.9 and predicted job change probabilities by job satisfaction in t are graphically depicted in Figure 4.7.

Panel A controls for participation in any type of training. Here, we see a very clear pattern across all three dependent variables (in line with previous studies, e.g. Clark *et al.*,

[26] Remember that the positive signs for both the linear and squared term indeed yield a U-shaped relationship because the standardization of the job satisfaction variable shifts the domain of definition to the left such that the variable can also take on negative values.

[27] The reasons for a voluntary job change include: not satisfied with job; to obtain a better job/just wanted a change/to start a new business; retired/did not want to work any longer; own sickness, disability or injury; pregnancy/to have children; to stay at home to look after children, house or someone else; travel/have a holiday; returned to study/started study/needed more time to study; spouse/partner transferred; too much travel time/too far from public transport; change of lifestyle.

[28] There is comparably little variation in this dependent variable: only 3.6% of the estimation sample changes their job due to job dissatisfaction, while 8.1% quit voluntarily and 11.6% change their job for any reason.

1998): dissatisfied workers are more likely to change their job. Similarly, individuals who participated in training are less likely to change their job. The interaction between job satisfaction and training is negative and significant in all three specifications. Focusing on the voluntary job change, Figure 4.7 panel 1B, it can be seen that unsatisfied workers who participated in training are more likely to quit than unsatisfied workers who did not participate, suggesting that training is viewed as a tool to qualify for a different position. For satisfied workers, this difference disappears. In panel B of Table 4.9, I replicate the analysis in which I control for training for a future job or promotion. Here, we see the same pattern, however, the interaction term is no longer significant.

In sum, this analysis provides some tentative evidence that job dissatisfaction increases the quit intentions of workers. For workers with higher quit intentions the exit channel gains dominance over the neglect channel, resulting in higher training rates. Finally, dissatisfied workers who participated in training are more likely to quit their job than dissatisfied non-participants.

4.5.3 Job Satisfaction Facets

As pointed out in the theoretical model in Section 4.2, workers can reap different non-pecuniary returns to training depending on the source of dissatisfaction (e.g. learn new skills vs. learn to work more efficiently). It is possible, however, that training courses do not provide the necessary tools to solve the initial issue (e.g. commuting distances), or that workers are not aware of courses which could help to improve the situation (e.g. communication courses to improve issues with colleagues). Thus, the voice channel may not gain dominance if overall job satisfaction cannot sufficiently capture the source of dissatisfaction. Hence, I turn to the five facets of job satisfaction regarding the work itself (what you do), their total pay, the security of the job, the flexibility available to balance work and non-work commitments, as well as the hours worked. In Table 4.4, I replace in equation (4.5) the overall job satisfaction with all five available job satisfaction facets. As before, I present the linear and squared specifications.

Table 4.4: Logit Estimation Results: Training Aim on Job Satisfaction Facets (Average Marginal Effects)

	(1) ME	(2) Coeff.	(3) ME	(4) Coeff.	(5) ME	(6) Coeff.	(7) ME	(8) Coeff.	(9) ME	(10) Coeff.
	Training		Training Aim							
	Participation		Maintain Status		Improve Skills		General Skills		Future Job/Promotion	
Work Itself Satisfaction $t-1$ (std.)	0.005**	0.031**	0.008***	0.058***	0.004*	0.019	0.008***	0.052***	0.003	0.047**
	(0.002)	(0.014)	(0.002)	(0.016)	(0.002)	(0.015)	(0.002)	(0.016)	(0.002)	(0.020)
Work Itself Satisfaction $t-1$ (std.)		0.001		0.006		-0.006		-0.002		0.018*
× Work Itself Satisfaction $t-1$ (std.)		(0.007)		(0.008)		(0.007)		(0.008)		(0.010)
Pay Satisfaction $t-1$ (std.)	-0.001	-0.006	-0.005**	-0.037**	-0.002	-0.019	-0.003	-0.025	-0.000	-0.003
	(0.002)	(0.015)	(0.002)	(0.016)	(0.002)	(0.015)	(0.002)	(0.016)	(0.002)	(0.020)
Pay Satisfaction $t-1$ (std.)		-0.001		-0.008		-0.007		-0.005		0.000
× Pay Satisfaction $t-1$ (std.)		(0.007)		(0.008)		(0.007)		(0.008)		(0.010)
Security Satisfaction $t-1$ (std.)	0.008***	0.021	0.012***	0.060***	0.009***	0.031*	0.008***	0.036*	0.002	0.055**
	(0.002)	(0.017)	(0.002)	(0.019)	(0.002)	(0.017)	(0.002)	(0.018)	(0.002)	(0.023)
Security Satisfaction $t-1$ (std.)		-0.014*		-0.010		-0.012		-0.011		0.024**
× Security Satisfaction $t-1$ (std.)		(0.007)		(0.009)		(0.008)		(0.008)		(0.011)
Flexibility Satisfaction $t-1$ (std.)	-0.012***	-0.087***	-0.014***	-0.121***	-0.008***	-0.083***	-0.006***	-0.065***	-0.001	-0.019
	(0.002)	(0.016)	(0.002)	(0.018)	(0.002)	(0.017)	(0.002)	(0.018)	(0.002)	(0.022)
Flexibility Satisfaction $t-1$ (std.)		-0.023***		-0.029***		-0.032***		-0.023**		-0.010
× Flexibility Satisfaction $t-1$ (std.)		(0.008)		(0.009)		(0.009)		(0.009)		(0.012)
Hours Worked Satisfaction $t-1$ (std.)	0.006**	0.035**	0.005**	0.041**	0.005**	0.039**	0.003	0.017	0.001	-0.007
	(0.002)	(0.015)	(0.002)	(0.017)	(0.002)	(0.015)	(0.002)	(0.017)	(0.002)	(0.021)
Hours Worked Satisfaction $t-1$ (std.)		0.003		0.007		0.006		-0.005		-0.014
× Hours Worked Satisfaction $t-1$ (std.)		(0.008)		(0.009)		(0.008)		(0.009)		(0.011)
Participation Rate	39.91	39.91	25.77	25.77	30.75	30.75	23.99	23.99	11.60	11.60
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Pseudo-R^2	0.16	0.16	0.15	0.15	0.14	0.14	0.12	0.12	0.08	0.08
Observations	63,647	63,647	63,647	63,647	63,647	63,647	63,647	63,647	63,647	63,647

Source: The Household, Income and Labour Dynamics in Australia (HILDA): data for years 2004-2019, general release 19, HILDA, 2020, doi:10.26193/3QRFMZ, own calculations.

Notes: The table displays the average marginal effects estimated based on logit estimations (uneven columns) or coefficients from logit estimations (even columns). The dependent variables are dummies indicating participation in training with certain aims (see column headers and below). The main explanatory variable of interest is the worker's standardized job satisfaction (from $t-1$). In the even columns, the squared term of the job satisfaction is included. All regressions include the full set of control variables. For each regression, the (unconditional) average of the dependent variable ("Participation Rate"), the average effect in % (in relation to the unconditional participation rate) of the main explanatory variable ("Effect in %", uneven columns), p-value of joint F-test (even columns), and the Pseudo-R^2 are displayed. Standard errors are in parentheses and clustered on person-level. * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$.
In the even numbered columns, the size of the coefficients cannot be interpreted.
(1)/(2) Dependent variable: Overall training participation.
(3)/(4) Dependent variable: Training participation to maintain professional status and/or meet occupational standards.
(5)/(6) Dependent variable: Training participation to improve your skills in your current job.
(7)/(8) Dependent variable: Training participation to develop your skills generally.
(9)/(10) Dependent variable: Training participation to prepare you for a job you might do in the future or facilitate promotion.

For the work itself and security satisfaction, the results indicate positive relationships with the training participation probability. This provides further evidence that the neglect channel is prevalent; workers who enjoy their tasks and are satisfied with the security of their job are willing to invest into their skills via training, while unsatisfied workers are not. For both facets, this positive relationship flattens out and a slight U-shaped relationship becomes evident for dissatisfied workers in the context of training with the aim of a job change or promotion. In other words, in this context the exit channel gains importance.

For the satisfaction with the total pay, all specifications result in negative effects which would insinuate the dominance of the voice channel. However, these effects are overall very small and in most cases insignificant. This could indicate that the voice channel gains significance in this context, however, on average, does not dominate the neglect channel to such an extent that there is a clear significant negative relationship.

Similarly, there is a stronger negative association between flexibility satisfaction and training participation. Individuals who are unhappy with the flexibility to balance work and non-work commitments are more likely to invest into training than those who are satisfied. This finding is in line with the voice channel as workers may aim to improve their skills and performance in order to increase the flexibility of their job.

Finally, if a worker is unsatisfied with the hours worked, the most efficient voice reaction may be to talk to the employer in an attempt to increase or decrease the (contractual) working hours. If in turn, this dissatisfaction arises due to overtime, a worker may be interested in increasing her productivity to reduce the necessary overtime. However, the estimation results point towards a positive relationship between this satisfaction facet and the training probability. This suggests that training is either not viewed as the correct voice channel or the neglect channel dominates.

Overall, these findings highlight the fact that workers exhibit different reactions to dissatisfaction depending on the source of dissatisfaction: Dissatisfaction with some job facets may result in a voice or exit reaction, while others cause workers to exhibit signs of neglect. This lends weight to the complexity of the measure of job satisfaction and stresses the importance of considering the different facets of job satisfaction.[29] Importantly, the facets analyzed here are likely not all facets that can induce job dissatisfaction, for instance

[29] This notion has been receiving some attention, compare for example Boles *et al.* (2007).

the satisfaction with the colleagues and boss, with commuting, or with the autonomy are expected to play an important role as well.

4.6 Conclusions

As Boswell *et al.* (2005) point out "a firm's intellectual capital is increasingly critical for sustained competitiveness" (p.882). Thus, keeping the skills of workers up-to-date in the face of the continuously evolving labor market is a key goal for firms and their workers. Consequently, it is of interest to understand which factors influence the training investment decision in order to increase the willingness to participate (OECD, 1996).

In this paper, I analyze the worker's decision to invest into training and account for the effect of her job satisfaction. My theoretical model predicts a U-shaped relationship if individuals attempt to change dissatisfactory situations (voice reaction) or plan to leave the job (exit reaction). In contrast, dissatisfaction may be met with neglect (neglect reaction), which would result in an overall positive relationship. From a theoretical point of view, it is unclear which channel dominates the relationship between job satisfaction and training participation on average.

There are four main take-aways of the empirical analysis (cautioned due to a small number of very unsatisfied workers). First, the Australian data provides indicators that there is an overall positive relationship, suggesting that the neglect channel is on average the more dominant reaction. This means that unsatisfied workers on average participate less in training even though training could help solve (some) problems that can cause dissatisfaction (i.e. workers neglect their job rather than improve the situation). In this case, employers should keep in mind that offering optional training may not lead workers to actually participate even if it were beneficial for the worker.

Second, closer inspections of both the aim of training and the heterogeneities across quit intentions reveal that the exit reaction is dominated *less* by the neglect channel than the voice channel is. This lends weight to the concern that dissatisfaction on the job leads workers to neglect their duty or invest into human capital that is designated to be taken to a different employer. Both cases are not beneficial for the current employer.

Third, heterogeneities can be identified across the source of dissatisfaction. For instance, the voice channel gains dominance if the dissatisfaction arises in the pay domain, whereas the neglect channel remains dominant for satisfaction with the work itself. This highlights the importance of understanding which problems cause dissatisfaction. Additionally, different sources of dissatisfaction may be solved with different types of training. This may appear obvious, as not all problems are equally easily solved by participating in training. However, it is not ex ante clear which factors lead workers to react with which reaction.

Finally, the initial findings of this paper in combination with the work of Burgard and Görlitz (2014), shed light on a valuable cycle: Workers with a higher level of job satisfaction are more willing to participate in training. Such training courses in turn have been argued to increase the job satisfaction of the participating workers (Burgard and Görlitz, 2014). Thus, higher levels of satisfaction after training are likely to increase the willingness to participate in further training courses in the future. Consequently, employers are advised to encourage their workers to voice the sources of dissatisfaction. Identifying and resolving such sources may result in higher levels of satisfaction and, thus, a higher willingness to participate in training. Alternatively, the firm might encourage the worker to participate in training aimed at improving the issue at hand, and, thus, potentially kick-start the training-job satisfaction cycle. Finally, employers may be advised to inform their workers of all potential (monetary and non-monetary) returns to training to ensure that their workers understand whether training could be a good investment for them.

Nevertheless, this analysis is not without its shortcomings. First, with very few observations who report a low level of job satisfaction, conclusions regarding (highly) dissatisfied workers must be made with great caution. Second, measurement timing is quite important in the context of job satisfaction, as this measure cannot be assumed to be stable. Hence, the most recent measurement of job satisfaction may not be an adequate proxy for the job satisfaction from the time of the training decision. Third, it is not possible to control for performance, which is likely to impact job satisfaction as well as training participation. However, poor performers may be interested in increasing their productivity with training, while high performers may wish to stay high performers. Hence, it is ex ante not clear in which direction the omission of performance biases the presented results. Lastly, the HILDA does not provide the opportunity to certainly distinguish between mandatory and optional training. Hence, the results are likely underestimated. It would be of further interest to analyze whether there is a heterogeneous effect of job satisfaction on optional training that was initiated by the firm vs. by the worker herself. In order to improve the understanding of the relationship between job satisfaction and training participation and to provide adequate policy recommendations, more research is required. Especially, understanding which job satisfaction facets induce which kind of reaction (voice, exit, loyalty or neglect) would be of great value to elicit targeted actions to increase training participation.

4.7 Appendix

Table 4.5: Descriptives Course Characteristics for Training Participants

	(1)
A: Years 2004 - 2019	
Observations[a]	25,401
Share of Estimation Sample	0.40
What were the aims of any of this training?[b]	
To maintain professional status and/or meet occupational standards	0.65
To improve your skills in your current job	0.77
To develop your skills generally	0.60
To prepare you for a job you might do in the future or facilitate promotion	0.29
To help you get started in your job	0.06
Because of health/safety concerns	0.29
Other	0.01
B: Years 2007 - 2019	
Observations[a]	21,570
Were any of these conducted...[b]	
at your place of employment during paid work time?	0.72
at your place of employment, but in your own time?	0.16
at some other place during paid work time?	0.54
at some other place, but in your own time?	0.22
Total number of training days[c]	7.61
Average number of hours of instruction per day[c]	5.91
Dummy for own costs	0.22
To what extent do you think you could use the new skills you have acquired from any of this training if you got a new job with a different employer?	
Not at all	0.04
Only to a limited extent	0.12
To a moderate extent	0.31
To a great extent	0.32
To a very great extent	0.21
Did not learn any new skills	0.00

Source: The Household, Income and Labour Dynamics in Australia (HILDA): data for years 2004-2019, general release 19, HILDA, 2020, doi:10.26193/3QRFMZ, own calculations.

Notes: The table shows mean values of course characteristics. For non-continuous variables, the average can be interpreted as the share of individuals for whom the dummy variable is equal to one. Questions refer to the aggregated training courses.

[a] The numbers of observations of the presented survey questions vary slightly due to item non-response.

[b] Multiple responses possible.

[c] Denotes continuous variable.

Table 4.6: Summary Statistics of Explanatory Variables

	(1) No Training	(2) Training	(3) Difference
Observations	38,246	25,401	
Share of the estimation sample	0.40	0.60	
Job Satisfaction			
Job Satisfaction in $t-1$	7.59	7.68	-0.09***
Work Satisfaction in $t-1$	7.55	7.70	-0.15***
Pay Satisfaction in $t-1$	7.10	7.17	-0.06***
Security Satisfaction in $t-1$	7.89	8.07	-0.18***
Flexibility Satisfaction in $t-1$	7.44	7.25	0.19***
Hours Satisfaction in $t-1$	7.27	7.26	0.01
Training History			
Training Participation in $t-1$ and/or $t-2$	0.39	0.78	-0.39***
Socio-Economic Variables			
Age^a	42.19	42.41	-0.22***
Female	0.47	0.53	-0.06***
Married	0.57	0.61	-0.03***
Number of Children^a	1.52	1.55	-0.04***
Disabled	0.15	0.16	-0.01***
Migration Background	0.20	0.19	0.00
Owner of House or Dwelling	0.72	0.74	-0.03***
Highest Educational Degree			
Primary Education	0.19	0.10	0.10***
Lower Secondary Education	0.14	0.10	0.04***
Upper Secondary Education	0.25	0.23	0.02***
(Advanced) Diploma	0.10	0.13	-0.02***
University	0.30	0.45	-0.14***
Work Experience (in Years)^a	21.54	21.41	0.13
Unemployment Experience (in Years)^a	0.61	0.46	0.16***
Gross Monthly HH Income of 2 Years Ago (in 1000 €)^a	10.31	10.63	-0.33***
Regional Information			
Region			
West Australia	0.09	0.09	-0.00
North Australia	0.01	0.01	-0.00*
South Australia	0.10	0.12	-0.02***
Queensland	0.21	0.21	0.00
Southwales	0.29	0.29	0.00
Victoria	0.30	0.28	0.01***
Unemployment Rate in Region^a	5.15	5.11	0.04***
Job-Specific Characteristics			
Employment Status			
Full-Time	0.76	0.79	-0.03***
Part-Time	0.24	0.21	0.03***
Contract Type			
Permanent	0.09	0.10	-0.01***
Temporary	0.91	0.90	0.01***
Tenure (in Years)^a	10.25	10.66	-0.42***
Member Trade Union	0.22	0.36	-0.15***
ISCO88			
Managers	0.14	0.13	0.01***
Professionals	0.20	0.35	-0.15***
Technicians and Associate Professionals	0.17	0.19	-0.03***
Clerical Support Workers	0.15	0.09	0.06***
Service and Sales Workers	0.10	0.10	0.01**
Skilled Agricultural, Forestry and Fishery Workers	0.01	0.01	0.00***
Craft and Related Trades Workers	0.09	0.05	0.03***
Plant and Machine Operators, and Assemblers	0.08	0.05	0.03***
Menial Jobs	0.06	0.03	0.03***
Firm-Specific Characteristics			
Firm Size			
Small	0.75	0.69	0.06***
Medium	0.10	0.12	-0.02***
Large	0.15	0.19	-0.04***
NACE Industry			
Manufacturing	0.05	0.03	0.02***
Agriculture	0.02	0.01	0.01***

(Table continues on the next page)

Table 4.6: Summary Statistics of Explanatory Variables (Continued)

	(1)	(2)	(3)
Mining, Quarrying, Energy, Water	0.03	0.03	-0.00
Chemicals, Pulp, Paper	0.03	0.02	0.01***
Construction	0.07	0.05	0.02***
Iron, Steel	0.02	0.01	0.01***
Textile, Apparel	0.00	0.00	0.00***
Wholesale, Retail	0.15	0.07	0.09***
Transportation, Communication	0.07	0.05	0.02***
Public Service	0.33	0.57	-0.24***
Financials, Private Services	0.18	0.14	0.04***
Other	0.04	0.03	0.01***
Personality Characterstics			
Big Five Factor Openness[a]	4.18	4.32	-0.14***
Big Five Factor Conscientiousness[a]	5.13	5.18	-0.05***
Big Five Factor Extraversion[a]	4.38	4.49	-0.11***
Big Five Factor Agreeableness[a]	5.36	5.47	-0.10***
Big Five Factor Neuroticism[a]	5.12	5.18	-0.06***
Locus of Control[a]	5.52	5.56	-0.05***
Risk Affinity[a]	4.56	4.72	-0.16***

Source: The Household, Income and Labour Dynamics in Australia (HILDA): data for years 2004-2019, general release 19, HILDA, 2020, doi:10.26193/3QRFMZ, own calculations.
Notes: Table shows mean values of explanatory variables by training status and their differences (column 3). Significant differences are indicated by asterisks. * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$
[a] Denotes continuous variable.

Table 4.7: Robustness: Logit Estimation Results: Training Participation on Job Satisfaction (Average Marginal Effects)

	(1) ME	(2) Coeff.	(3) ME	(4) Coeff.	(5) ME	(6) Coeff.	(7) ME	(8) Coeff.	(9) ME	(10) Coeff.	(11) ME	(12) Coeff.
	Baseline		Exogonous Controls		Training Type				Potentially Optional		Fixed Effects	
					General Training		Specific Training					
Job Satisfaction $t-1$ (std.)	0.006***	0.019	0.009***	0.029**	0.006***	0.129***	0.006***	-0.117***	0.011***	0.040***	0.013***	0.056***
	(0.002)	(0.013)	(0.002)	(0.013)	(0.002)	(0.017)	(0.002)	(0.018)	(0.002)	(0.015)	(0.003)	(0.018)
Job Satisfaction $t-1$ (std.)		-0.010*		-0.011*		0.016**		-0.038***		-0.019***		-0.001
× Job Satisfaction $t-1$ (std.)		(0.006)		(0.006)		(0.008)		(0.008)		(0.007)		(0.007)
Participation Rate	39.91	39.91	39.91	39.91	20.66	20.66	18.01	18.01	30.87	30.87	44.09	44.09
Effect in %	1.50		2.26		2.90		3.33		3.56		2.05	
p-value of Joint F-Test		0.00		0.00		0.00		0.00		0.00		0.00
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Pseudo-R^2	0.15	0.15	0.14	0.14	0.15	0.11	0.15	0.08	0.16	0.16	0.20	0.20
Observations	63,647	63,647	63,647	63,647	55,458	55,458	55,458	55,458	55,321	55,321	48,564	48,564

Source: The Household, Income and Labour Dynamics in Australia (HILDA): data for years 2004-2019, general release 19, HILDA, 2020, doi:10.26193/3QRFMZ, own calculations.

Notes: The table displays the average marginal effects estimated based on logit estimations (uneven columns) or coefficients from logit estimations (even columns). The dependent variable is a dummy indicating participation in training (except columns 5-8). The main explanatory variable of interest is the worker's standardized job satisfaction (from $t-1$). In the even columns, the squared term of the job satisfaction is included. All regressions include the full set of control variables (except columns 3 and 4). For each regression, the (unconditional) average of the dependent variable ("Participation Rate"), the average effect in % (in relation to the unconditional participation rate) of the main explanatory variable ("Effect in %", uneven columns), p-value of joint F-test (even columns), and the Pseudo-R^2 are displayed. Standard errors are in parentheses and clustered on person-level. * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$.

In the even numbered columns, the size of the coefficients cannot be interpreted.

(1)/(2) Main results from Table 4.1, columns (1) and (4).

(3)/(4) Excluding potentially endogenous variables (employment status, contract type, ISCO88, NACE). The remaining job and firm control variables are: tenure, member trade union/association, firm size.

(5)/(6) The dependent variable is equal to one if the individual participated in general training.

(7)/(8) The dependent variable is equal to one if the individual participated in specific training.

(9)/(10) Individuals who indicated that they participated in training with the aim "To help you get started in your job" or "Because of health/safety reasons" are excluded, as these are potentially mandatory training courses (compare Smith *et al.*, 2019). Remaining courses are potentially optional, but can still be mandatory.

(11)/(12) Fixed effects logit regression. Sample size is reduced because the regression excludes individuals for whom the dependent variable does not change across all observed years. The control variables that do not change over time are omitted (gender, migration background, personality traits). To correct for the incidental parameter bias, I employ the analytical correction method with one lag, both individuals and time effects, and bias correction for both individuals and time effects (Cruz-Gonzalez *et al.*, 2017).

Table 4.8: OLS Estimation Results: Quit Intention (in Percent) on Job Satisfaction

	(1)	(2)
Job Satisfaction $t-1$ (std.)	-4.337***	-4.757***
	(0.151)	(0.170)
Job Satisfaction $t-1$ (std.) × Job Satisfaction $t-1$ (std.)		-0.311***
		(0.081)
Average Quit Likelihood	17.81	17.81
Effect in %	-24.14	
p-value of Joint F-Test		0.00
Controls	✓	✓
$\overline{R^2}$	0.10	0.10
Observations	63,547	63,547

Source: The Household, Income and Labour Dynamics in Australia (HILDA): data for years 2004-2019, general release 19, HILDA, 2020, doi:10.26193/3QRFMZ, own calculations.

Notes: The table displays the coefficients from OLS estimations. The dependent variable is the self-reported likelihood of quitting the job within the next 12 months (in %). The main explanatory variable of interest is the worker's standardized job satisfaction (from $t-1$). In column 2, the squared term of the job satisfaction is included. All regressions include the full set of control variables. For each regression, the (unconditional) average of the dependent variable ("Average Quit Likelihood"), the average effect in % (in relation to the unconditional participation rate) of the main explanatory variable ("Effect in %", uneven columns), p-value of joint F-test (even columns), and the $\overline{R^2}$ are displayed. Standard errors are in parentheses and clustered on person-level. * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$.

Table 4.9: Logit Estimation Results: Job Change between t and $t+1$ on Job Satisfaction

	(1) Coeff.	(2) Coeff.	(3) Coeff.
	Any Job Change	Voluntary Job Change	Job Change due to Job Dissatisfaction
A. Training			
Job Satisfaction t (std.)	-0.451***	-0.471***	-0.509***
	(0.018)	(0.020)	(0.026)
Training	-0.211***	-0.155***	-0.195***
	(0.033)	(0.039)	(0.060)
Job Satisfaction t (std.) × Training	-0.074***	-0.093***	-0.137***
	(0.027)	(0.030)	(0.040)
Job Satisfaction $t-1$ (std.)	-0.022	-0.026	-0.035
	(0.017)	(0.019)	(0.026)
Pseudo-R^2	0.11	0.11	0.11
B. Training for Future Job/Promotion			
Job Satisfaction t (std.)	-0.470***	-0.496***	-0.544***
	(0.016)	(0.018)	(0.024)
Training for Promotion/New Job	-0.188***	-0.126**	-0.222**
	(0.049)	(0.056)	(0.092)
Job Satisfaction t (std.) × Training for Promotion/New Job	-0.060	-0.061	-0.095
	(0.043)	(0.047)	(0.065)
Job Satisfaction $t-1$ (std.)	-0.022	-0.026	-0.035
	(0.017)	(0.019)	(0.027)
Pseudo-R^2	0.11	0.11	0.11
Controls	✓	✓	✓
Observations	55,244	55,244	55,244

Source: The Household, Income and Labour Dynamics in Australia (HILDA): data for years 2004-2019, general release 19, HILDA, 2020, doi:10.26193/3QRFMZ, own calculations.
Notes: The table displays the average coefficients from logit estimations. The dependent variable is a dummy indicating a job change between t and $t+1$ (see below for more details). The main explanatory variables of interest are the worker's standardized job satisfaction (from t), training participation and the interaction thereof. All regressions include the full set of control variables. For each regression, the Pseudo-R^2 is displayed. Standard errors are in parentheses and clustered on person-level. * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$.
The size of the coefficients cannot be interpreted.
The sample size is reduced because the job change information is imputed from $t+1$ and missing for roughly 3,000 individuals. As 2020 is not available, the year 2019 is additionally excluded.
Panel A considers participation in any training, panel B in training for a future job/promotion.
(1) Dependent variable: Any Job Change
(2) Dependent variable: Voluntary Job Change
(3) Dependent variable: Job Change due to Job Dissatisfaction

Table 4.10: Logit Estimation Results: Participation in Training (Average Marginal Effects)

	(1) Training
Job Satisfaction $t-1$ (std.)	0.006***
	(0.002)
Job Satisfaction $t-2$ (std.)	-0.002
	(0.002)
Training History of the Last 2 Years	0.289***
	(0.004)
Age	0.000
	(0.001)
Female	0.014**
	(0.006)
Married	0.010**
	(0.005)
Number of Children	0.005**
	(0.002)
Disabled	0.010*
	(0.005)
Migration Background	-0.007
	(0.006)
Owner of House or Dwelling	-0.007
	(0.005)
Highest Educational Degree (Ref.: Primary Education)	
Lower Secondary Edu	0.038***
	(0.009)
Upper Secondary Education	0.062***
	(0.008)
(Advanced) Diploma	0.072***
	(0.009)
University	0.078***
	(0.009)
Work Experience (in Years)	-0.000
	(0.001)
Unemployment Experience (in Years)	-0.002
	(0.002)
Gross Monthly HH Income of 2 Years Ago (in 1000 €)	-0.001***
	(0.000)
Region (Ref.: West Australia)	
North Australia	-0.007
	(0.023)
South Australia	-0.008
	(0.010)
Queensland	-0.011
	(0.009)
Southwales	-0.018**
	(0.009)
Victoria	-0.024***
	(0.009)
Unemployment Rate in Region	0.003
	(0.003)
Year Dummies (Ref.: Year 2004)	
Year 2005	-0.042***
	(0.011)
Year 2006	-0.057***
	(0.012)
Year 2007	-0.129***
	(0.012)
Year 2008	-0.074***
	(0.011)
Year 2009	-0.092***
	(0.011)
Year 2010	-0.116***
	(0.011)
Year 2011	-0.094***
	(0.011)
Year 2012	-0.099***

(Table continues on the next page)

Table 4.10: Logit Estimation Results: Participation in Training (Continued)

	(1)
	(0.011)
Year 2013	-0.095***
	(0.011)
Year 2014	-0.110***
	(0.011)
Year 2015	-0.118***
	(0.011)
Year 2016	-0.125***
	(0.011)
Year 2017	-0.122***
	(0.011)
Year 2018	-0.117***
	(0.011)
Year 2019	-0.117***
	(0.011)
Full-Time Employment	0.044***
	(0.006)
Temporary Contract Type	0.011*
	(0.007)
Tenure (in Years)	-0.000
	(0.000)
Member Trade Union	0.068***
	(0.005)
ISCO88 (Ref.: Menial Jobs)	
Managers	0.036***
	(0.012)
Professionals	0.070***
	(0.011)
Technicians and Associate Professionals	0.057***
	(0.011)
Clerical Support Workers	-0.005
	(0.011)
Service and Sales Workers	0.064***
	(0.012)
Skilled Agricultural, Forestry and Fishery Workers	0.035
	(0.022)
Craft and Related Trades Workers	0.021
	(0.013)
Plant and Machine Operators, and Assemblers	0.020
	(0.013)
Firm Size (Ref.: Small)	
Medium	0.028***
	(0.006)
Large	0.001
	(0.006)
NACE Industry (Ref.: Other)	
Manufacturing	-0.031**
	(0.016)
Agriculture	-0.026
	(0.022)
Mining, Quarring, Energy, Water	0.031*
	(0.017)
Chemicals, Pulp, Paper	-0.034*
	(0.018)
Construction	-0.009
	(0.015)
Iron, Steel	-0.068***
	(0.024)
Textile, Apparel	-0.110**
	(0.043)
Wholesale, Retail	-0.061***
	(0.014)
Transportation, Communication	-0.011
	(0.015)
Public Service	0.080***
	(0.012)

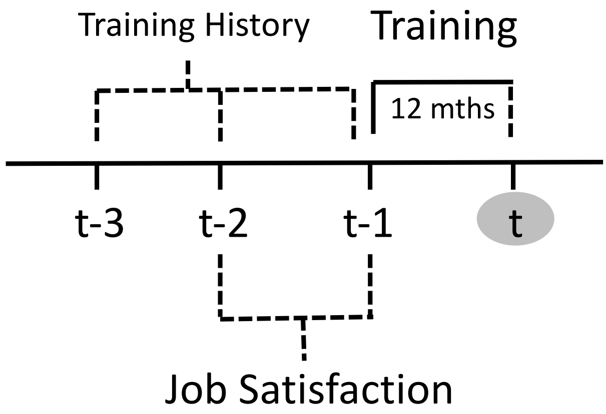
(Table continues on the next page)

Table 4.10: Logit Estimation Results: Participation in Training (Continued)

	(1)
Financials, Private Services	0.000
	(0.013)
Big Five Factor Openness (std.)	0.007**
	(0.003)
Big Five Factor Conscientiousness (std.)	-0.001
	(0.003)
Big Five Factor Extraversion (std.)	0.011***
	(0.002)
Big Five Factor Agreeableness (std.)	0.004
	(0.003)
Big Five Factor Neuroticism (std.)	0.003
	(0.003)
Locus of Control (std.)	-0.003
	(0.003)
Risk Affinity (std.)	0.007***
	(0.003)
Pseudo-R^2	0.15
Observations	63,647

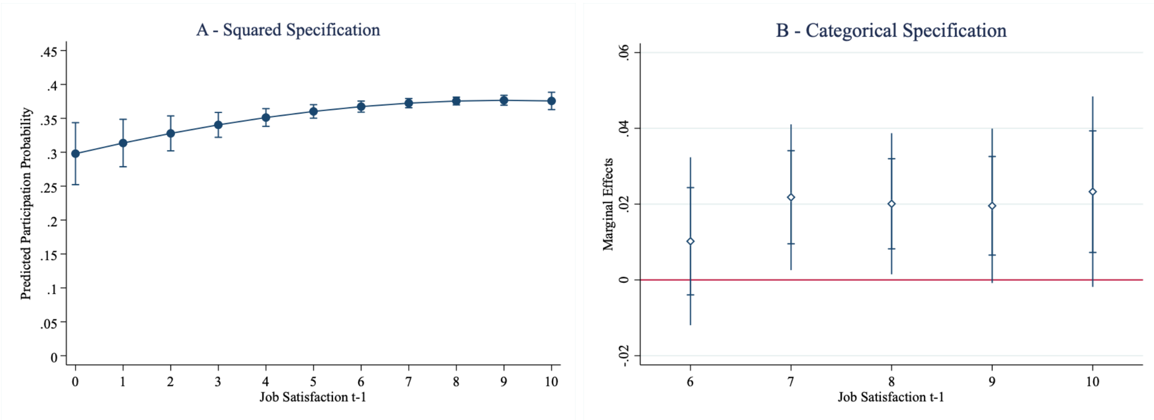
Source: The Household, Income and Labour Dynamics in Australia (HILDA): data for years 2004-2019, general release 19, HILDA, 2020, doi:10.26193/3QRFMZ, own calculations.
Notes: The table displays the average marginal effects estimated based on logit estimations corresponding to column (1) of Table 4.1.The dependent variable is a dummy indicating participation in training. The main explanatory variable of interest is the worker's standardized job satisfaction (from $t-1$). The regression includes the full set of control variables. The Pseudo-R^2 is displayed. Standard errors are in parentheses and clustered on person-level.
* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$.

Figure 4.3: Description of the Data Structure



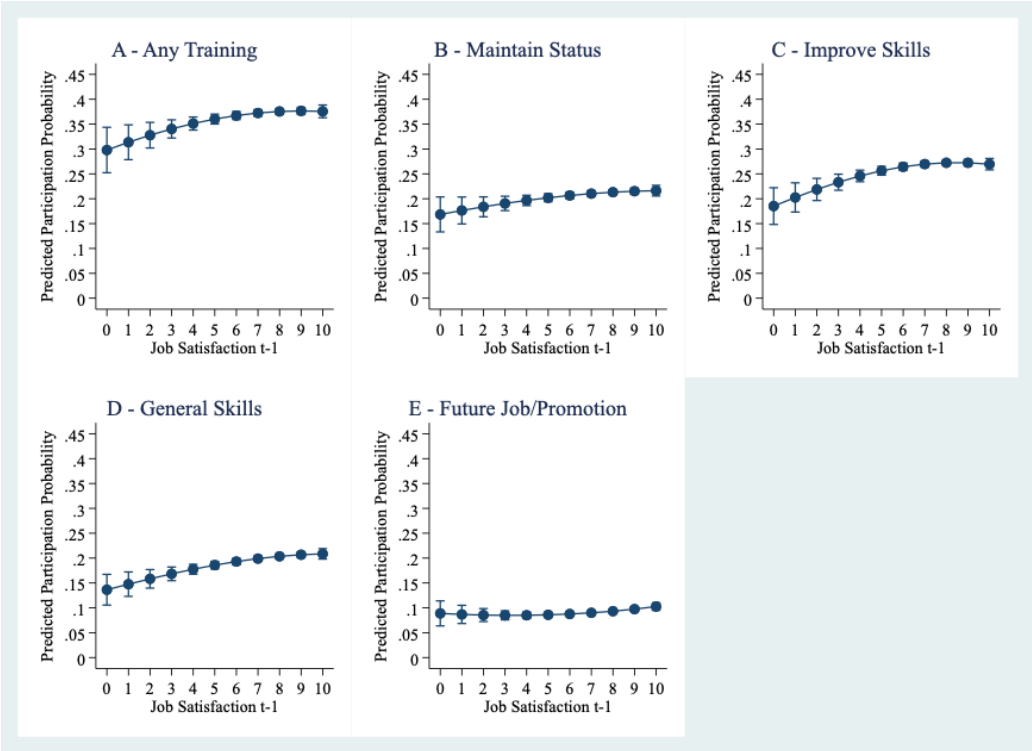
Source: Own illustration.
Notes: The figure gives an overview of the timing of the main variable measurements. The variable measuring the training participation in year t refers to participation in the 12 months prior to the interview. Job satisfaction is measured in the year $t-1$. Further, job satisfaction in $t-2$ is added to the specification to control for changes in the satisfaction prior to training. To minimize any reverse causality, the recent training history is controlled for by including a dummy indicating participation in training in the year $t-1$ and/or $t-2$ (which also refer to participation in the 12 months prior to the interview). Overall, training participation is available in the years 2003-2019. Due to the control of the training history, I use the data from the years 2004-2019 in my sample (where the training history only refers to $t-1$ for the year 2004).

Figure 4.4: Logit Estimation Results: Training Participation on Job Satisfaction, Squared and Categorical Specifications



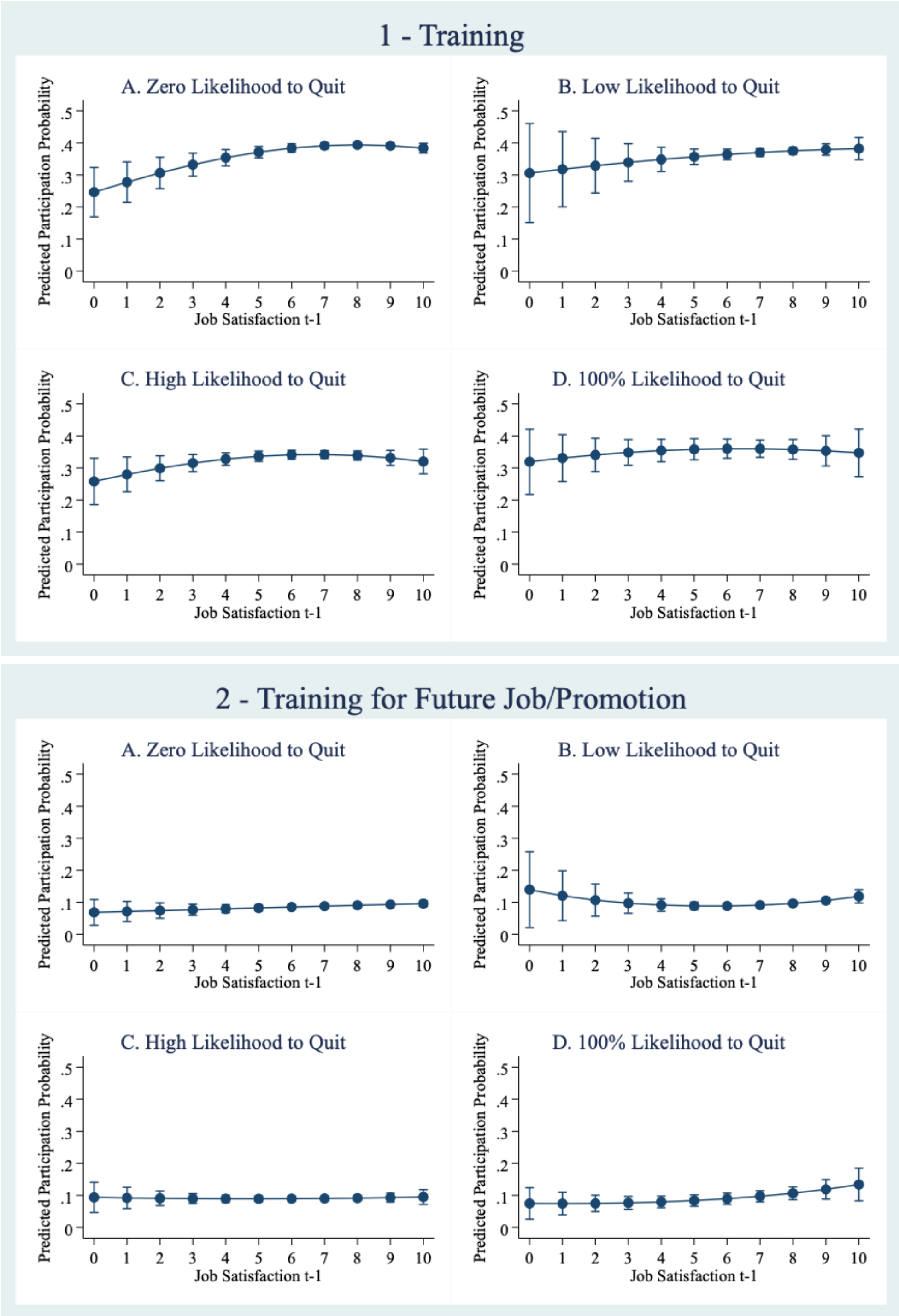
Source: The Household, Income and Labour Dynamics in Australia (HILDA): data for years 2004-2019, general release 19, HILDA, 2020, doi:10.26193/3QRFMZ, own calculations.
Notes: Panel A: The figure shows the predicted participation probabilities by job satisfaction ($t-1$) and their 95% confidence intervals based on the logit estimation with the squared specifications from Table 4.1, column (4). The dependent variable indicates training participation. Standard errors are clustered on person-level and all control variables are included in the specification which are held at the mean (N=63,647).
Panel B: The figure shows marginal effects resulting from a logit estimation of the training participation on the categorical job satisfaction ($t-1$) measure. The reference group is rather unsatisfied workers (i.e. 0-5 on the satisfaction scale). The dependent variable indicates training participation. Standard errors are clustered on person-level and all control variables are included in the specification (N=63,647). The 99% and 90% confidence intervals are depicted; the horizontal caps denote the upper and lower end of the 90% confidence interval.

Figure 4.5: Predicted Training Aim by Job Satisfaction



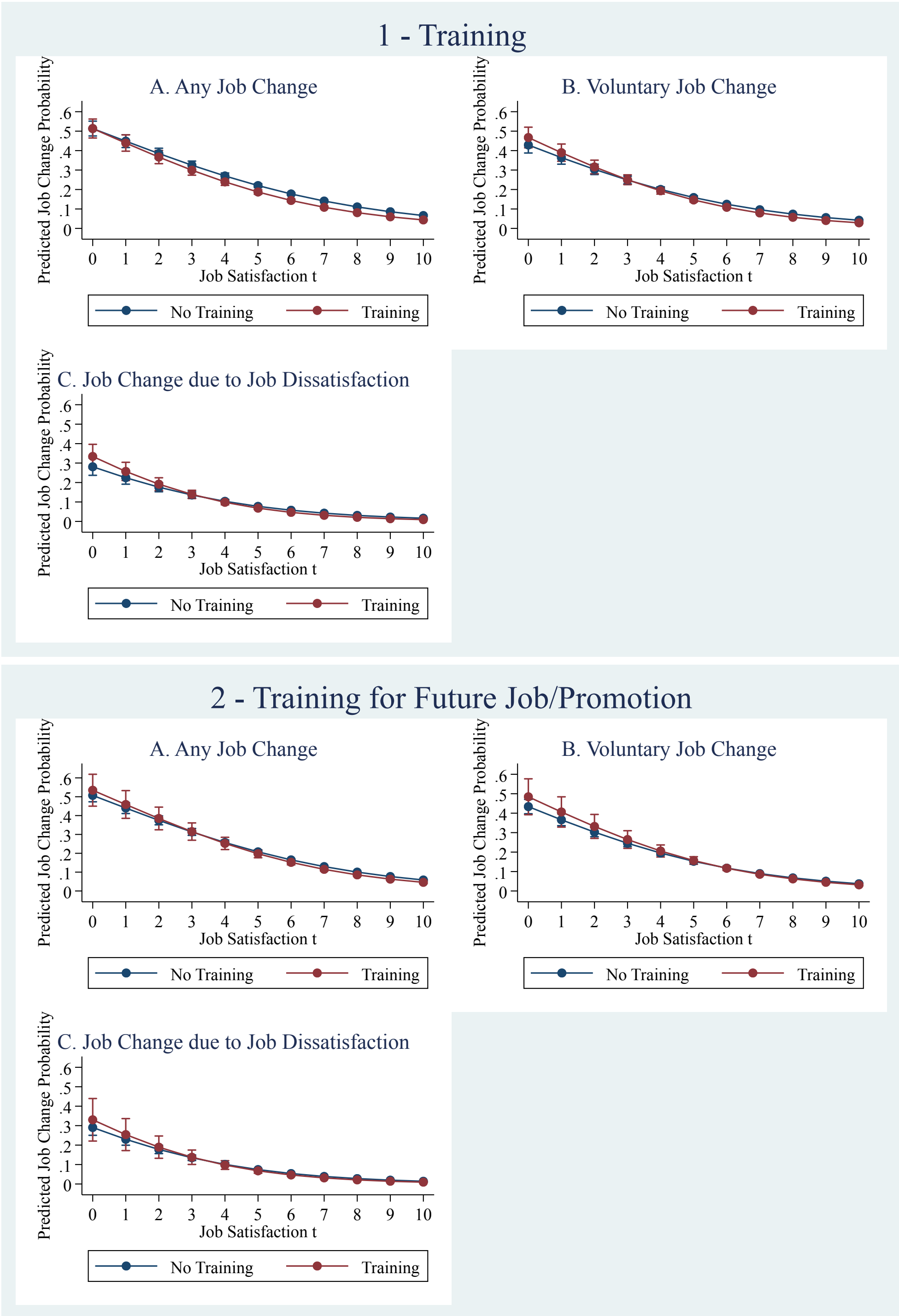
Source: The Household, Income and Labour Dynamics in Australia (HILDA): data for years 2004-2019, general release 19, HILDA, 2020, doi:10.26193/3QRFMZ, own calculations.
Notes: The figures show the predicted participation probabilities by job satisfaction ($t-1$) and their 95% confidence intervals based on the logit estimations with the squared specifications from Tables 4.1 and 4.2. The dependent variables indicate training participation for the reasons highlighted in the panel titles and below. Standard errors are clustered on person-level and all control variables are included in the specification which are held at the mean (N=63,647). Dependent variables:
Panel A: Any training participation
Panel B: Training participation to maintain professional status and/or meet occupational standards
Panel C: Training participation to improve your skills in your current job
Panel D: Training participation to develop your skills generally
Panel E: Training participation to prepare you for a job you might do in the future or facilitate promotion

Figure 4.6: Predicted Training Probability by Job Satisfaction and Quit Likelihood



Source: The Household, Income and Labour Dynamics in Australia (HILDA): data for years 2004-2019, general release 19, HILDA, 2020, doi:10.26193/3QRFMZ, own calculations.
Notes: The figures show the predicted participation probabilities by job satisfaction $(t-1)$ and quit likelihood, and their 95% confidence intervals based on the logit estimations with the squared specifications from Table 4.3. Standard errors are clustered on person-level and all control variables are included in the specification which are held at the mean (N=55,244). Panel 1 considers participation in any training, panel 2 in training for a future job or promotion. The subpanels only include individuals who indicate the chance of quitting their job $(t-1)$ highlighted in the panel titles.
Subpanels A: a zero chance of quitting in the next 12 months $(t-1)$, $N = 34,709$.
Subpanels B: a chance of 1-49% of quitting in the next 12 months $(t-1)$, $N = 15,170$.
Subpanels C: a chance of 50-99% of quitting in the next 12 months $(t-1)$, $N = 10,222$.
Subpanels D: a chance of 100% of quitting in the next 12 months $(t-1)$, $N = 2,166$.

Figure 4.7: Predicted Job Change by Job Satisfaction and Training



Source: The Household, Income and Labour Dynamics in Australia (HILDA): data for years 2004-2019, general release 19, HILDA, 2020, doi:10.26193/3QRFMZ, own calculations.
Notes: The figures show the predicted probabilities of a job change between t and $t+1$ by job satisfaction $(t-1)$ and their 95% confidence intervals based on the logit estimations with the squared specifications from Table 4.9. Standard errors are clustered on person-level and all control variables are included in the specification which are held at the mean (N=55,244). The probabilities are depicted in red for those workers who participated in training, in blue for non-participants. Panel 1 refers to any training, panel 2 to training for a future job or promotion.
The dependent variables are highlighted in the panel titles.
Subpanel A: Any Job Change
Subpanel B: Voluntary Job Change
Subpanel C: Job Change due to Job Dissatisfaction

Chapter 5

The Impact of the German Minimum Wage on Individual Wages and Monthly Earnings*

Abstract

This paper evaluates the short-run impact of the introduction of a statutory minimum wage in Germany on the hourly wages and monthly earnings of workers targeted by the reform. We first provide detailed descriptive evidence of changes to the wage structure in particular at the bottom of the distribution and distinguish between trends for regularly employed and marginally employed workers. In the causal analysis, we then employ a differential trend adjusted difference-in-differences (DTADD) strategy to identify the extent to which these changes in wages and earnings can be attributed to the minimum wage introduction. We find that the minimum wage introduction can account for hourly wage growth in the order of roughly 6.5% or €0.45/hour and an increase in monthly earnings of 6.6% or €53/month. Despite finding wage growth at the bottom of the distribution, the paper documents widespread non-compliance with the mandated wage floor of €8.50/hour.

5.1 Introduction

On January 1st, 2015, a coalition government in Germany introduced the country's first national statutory minimum wage in history. In contrast to most evaluation studies that

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exploit marginal changes in the existing minimum wage laws in the United States or other countries, the German case study proves particularly interesting because it represents a high-impact, binding minimum-wage introduction with a large share of the population affected. With incremental changes, identification of effects has found mixed results, thus, yielding substantial uncertainty for the derivation of out-of-sample predictions with regard to this highly topical policy tool. This challenge is particularly problematic in light of the fact that substantial increases or new introductions of minimum wages have found their way into current debates in several countries (e.g., the US). Against this background, the German reform offers a unique opportunity to more clearly establish causality and contribute to the broader debate in Germany and around the world. The primary goal of the reform, which set a wage floor of €8.50 in all regions and economic sectors with few exceptions, was to increase gross hourly wages for low-wage workers. Against this background, this paper investigates the following two questions. Firstly, *how did the introduction of the German minimum wage impact the distribution of hourly wages in the economy?* Secondly, *how do these effects differ across pay groups and worker types?* Our causal analysis focuses on the short-run effects of the reform: the available data allow for the identification of changes to the wage distribution through mid-2016.

Due to the recency of its introduction, very few studies have investigated the impact of the statutory minimum wage reform in Germany on the wage and earnings distribution in a causal fashion using data from the post-reform period. Such studies include Bellmann *et al.* (2017), Caliendo *et al.* (2017b) and Pusch and Seifert (2017). Using data from the IAB Establishment Panel for the state of Saxony, Bellmann *et al.* (2017) find a strong, positive effect of the reform on gross monthly earnings, not only for workers earning below €8.50 prior to the reform, but also for workers previously earning slightly above this threshold, an indication of "spillover effects". Caliendo *et al.* (2017a) identify the impact of the reform on different segments of the wage and earnings distribution by exploiting the variation in the intensity, or 'bite' across German regions (*Raumordnungsregionen*). On the basis of data from the Socio-Economic Panel (SOEP) through 2015, they document above-average growth rates for wages in the bottom tail of the distribution as well as higher growth rates in the bottom segments in regions with a larger minimum wage bite. Moreover, these results as well as recent work by Burauel *et al.* (2017), Mindestlohnkommission (2016) and Pusch and Seifert (2017) demonstrate that a meaningful share of workers still receive pay below the mandated wage floor also after the reform, constituting evidence of non-compliance.[1]

The present paper belongs to the first wave of evaluations using post-reform data and builds on these studies mentioned above by providing descriptive as well as causal evidence of wage changes around the time of, or on account of, the minimum wage. Our results also offer evidence regarding the distributional effects of the minimum wage which, with the exception of ex-ante evaluation studies, has been scarce.

Beyond the German context, a large literature has grappled with the distributional effects of minimum wages. In one of the earliest papers to address this question, DiNardo *et al.* (1996) study the importance of several institutional factors such as the decline in union coverage and the real minimum wage for explaining hourly wage inequalities in the United States. Using CPS data, they attribute 25% of inequality growth among men and 30% of inequality growth among women to the decreasing real value of the minimum wage over time. Lee (1999) likewise investigates the relationship between the real minimum wage and wage inequality using CPS data and corroborates this result. More recent papers by Autor *et al.* (2008) and Autor *et al.* (2016), however, attribute a much larger role to market factors such as skill-biased technological change rather than minimum wages in explaining wage inequality. Nevertheless, Autor *et al.* (2008) find that, in particular for women in the lower tail of the distribution, the intertemporal decline in the real minimum wage contributed meaningfully to wage inequality. Going beyond effects on the hourly price of labor (wages) and using the same data as these above mentioned studies, Neumark *et al.* (2004) explore several channels of minimum wage effects, including monthly earnings, employment probability and hours worked in addition to hourly wages. The authors find the largest increases to hourly wages in the bottom tail of the distribution, but they show that subsequent reductions in the hours worked and employment opportunities counteract the positive wage effect. Allowing for lagged responses to the minimum wage, they moreover find that the overall effect on monthly earnings becomes negative for low-wage workers. With the exception of some of the very recent substantial state hikes in minimum wages, minimum

[1]See Caliendo *et al.* (2019b) for a general overview of the causal effects of the minimum wage introduction on a large set of outcome variables.

wage adjustments in the long history of the US minimum wage have predominantly been small and incremental in comparison to the bite of the German statutory minimum wage.

In Great Britain, where a national statutory minimum wage was introduced in 1998, several studies assess its impact on the wage and earnings distribution. Manning (2013), Low Pay Commission (2016) and Low Pay Commission (2015) provide overviews of this work. Using several different data sources,[2] these studies predominantly conclude that the British minimum wage decreased wage inequality at the lower tail of the distribution (see for example Dickens and Manning (2004), Dolton *et al.* (2012) and Butcher *et al.* (2012)).

The institutional setting, design and bite of minimum wage reforms as well as the pre-reform wage distribution differ greatly from country to country and are likely to influence the effect of reforms in the United States, Great Britain and Germany. Moreover, the spectrum of measured compliance – the degree to which a wage floor is actually enforced – varies substantially across countries and groups of workers as well as over time. Furthermore, measured compliance rates differ depending on whether the data employed in the analysis is based on statements from employees or employers. Ashenfelter and Smith (1979) calculate differences as large as 13 percentage points. Metcalf (2008) arrives at similar results. Previous literature has established different non-compliance rates across groups of workers, with larger rates among workers in low-wage sectors and those with immigrant backgrounds (Cortes, 2004; Weil, 2005). Using rich survey data from the Socio-Economic Panel Survey (SOEP), we are able to quantify the degree of non-compliance with the German minimum wage on average as well as across different types of workers.

The remainder of the paper is structured as follows. Section 5.2 provides a brief background to the timeline and eligibility rules of the reform. Section 5.3 describes the data used in the analysis and introduces the econometric method applied to identify causal effects of the reform. Section 5.4 offers a detailed analysis of trends in wages and salary earnings at the mean as well as separately for the bottom wage segments. Section 5.5.1 presents the results for the entire sample while Section 5.5.2 examines heterogeneous treatment effects for individuals in socially insured regular employment and the marginally employed separately. Section 5.5.3 tests the robustness of our results and Section 5.6 concludes.

[2]These include the Labor Force Survey, the New Earnings Survey, General Household Survey, British Household Panel Survey and the Annual Survey of Hours and Earnings.

5.2 Institutional Background

Following years of debating the introduction of a minimum wage in Germany, the debate became more concrete during the Federal elections in September 2013 and even more so by the end of November of that same year when an emerging Grand Coalition government announced the intention to implement a national, statutory minimum wage of €8.50 per hour effective January 1, 2015. The German parliament passed the proposal into law by July 2014. Prior to this implementation, minimum wages existed only at the sectoral level and differed fundamentally from the statutory wage floor in that previous minimum wages were negotiated by employers' associations and unions.[3] The new €8.50 minimum wage applied almost universally across all regions and sectors, with few exclusions. Exempted groups include: trainees, most interns, the long-term unemployed during the first 6 months of employment, and minors prior to completing vocational training. Moreover, sectors with their own bargained minimum wages received a temporary exemption until the end of 2017, at which time all sectors were to be integrated into the national minimum wage regime. Nevertheless, very few sectoral minimum wages fell below the national minimum.

5.3 Methodology

5.3.1 Data and Sample Restrictions

Nationally representative data from the 2010-2016 waves of the Socio-Economic Panel (SOEP) form the basis for our analysis. The SOEP is a panel survey conducted annually in Germany since 1984 and contains about 15,000 households (Goebel *et al.*, 2019). It surveys households regarding their composition, income and relevant employment information, including gross monthly earnings and working hours. Individual hourly wages and gross monthly earnings form the central outcome variables of interest in the present analysis. Although the SOEP does not ask respondents their hourly wage directly, it can be calculated as the quotient of two variables ascertained in the survey, namely monthly earnings and usual weekly hours worked, with the denominator multiplied by 4.33 weeks/month.[4]

[3] Fitzenberger and Doerr (2016) provide an overview of these sectoral minimum wages. Due to their nature as negotiated wage floors, the sectoral minimum wages are not comparable to the mandated, statutory minimum.

[4] Respondents are asked to disregard additional payments and fringe benefits such as vacation or Christmas money or a 13th/14th salary in the calculation of their monthly earnings. While legal precedence has

Because the field interviews predominantly end in the first half of the year, this time frame enables us to study pre-reform trends, anticipation effects and two years of post-reform effects. Furthermore, the survey asks respondents about their contractual as well as actual hours worked by asking them to report paid and unpaid hours usually worked in their *main* job.[5] This information allows us to investigate the possible adjustment channel of increased unpaid overtime work. In the following, we refer to the sum of paid and unpaid hours as 'actual hours worked' and the number of paid hours as 'contractual hours worked', the latter of which presents the primary measure for analysis, as it is less prone to measurement error.[6]

The SOEP consists of several subsamples that together (weighted) represent the entire population. In this paper, we utilize both the cross-sectional and longitudinal samples, as they possess different, complementary advantages. Central parameters representative of the entire population are constructed using the cross-sectional sample and weights. The measurement of individual changes in hourly wages and monthly earnings, however, requires that individuals were present and employed in at least two consecutive SOEP waves. Thus, for this latter analysis, we employ the panel sample and weights. Together, these two samples enable us to paint a full picture of the minimum wage effects. The following table summarizes the sample restrictions applied throughout the paper.

On average, the SOEP contains about 16,000 annual observations of employed individuals above the age of 18. This number includes both full-time and part-time workers as well as the marginally employed and self-employed. We exclude roughly 16 percent of these observations from the sample due to their exemption status from the minimum wage, discussed in detail above. Making these exclusions ensures that treatment and control groups defined in the causal analysis remain comparable. The following analysis applies exclusively to this sample of the population.[7] The remaining 49,719 individuals form the sample population

determined that employers may include these payments in the basis for the minimum wage, these payments play only a minor role in the low wage sector, which is of primary concern in this paper.

[5]Hours worked in secondary jobs are not included.

[6]The ability to work fewer hours at a later time in the year in order to compensate for accumulated overtime renders a clear determination of the number of unpaid overtime hours difficult for some respondents. Moreover, previous research has found that, when asked about their hours worked, employees tend to overestimate them (see for example Bound *et al.* (2001)). Any measurement error would persist both before and after the reform and should therefore not drive our results. Nevertheless, unpaid hours are likely more susceptible to any measurement error than contractual hours because contractual hours are made explicit in all employment contracts.

[7]Individuals with sector-specific minimum wages are excluded from the analysis.

Table 5.1: Sample Size by Survey Year

	(1) 2012	(2) 2013	(3) 2014	(4) 2015	(5) 2016	(6) Total
Employed	16,155	18,199	16,066	15,822	14,895	81,137
Hourly Wage Undefined	-3,734	-4,236	-3,392	-3,553	-3,445	-18,360
Exempt from Minimum Wage or has Sector-Specific minimum Wage	-2,522	-2,904	-2,458	-2,727	-2,447	-13,058
Cross-Sectional Sample	9,899	11,059	10,216	9,542	9,003	49,719
Not Observed in $t+2$	-3,341	-4,026	-3,336	-/-	-/-	-29,248
Job Loss	-62	-51	-75	-/-	-/-	-188
Missing Information	-363	-279	-330	-/-	-/-	-972
2-Year Panel Sample	6,133	6,703	6,475	-/-	-/-	19,311

Source: SOEP v33 2012-2016, own calculations.

for the cross-sectional analysis (see Table 5.1).

Building upon the cross-sectional sample, we construct the sample for the longitudinal analysis, referred to subsequently as the panel sample. With a reference year in time t, the panel sample draws upon individual information from the wave two periods later, in time $t+2$. Therefore, the panel setting imposes additional restrictions on the sample. Individuals must participate in at least two SOEP waves that lie two years apart and make all necessary information available for the determination of hourly wages. Due to item non response and panel attrition, only part of the cross-sectional sample fulfills these requirements.[8] The panel focus permits the evaluation of *individual* changes in hourly wages or monthly earnings. In the following, we designate this sample the 'two-year panel'. Analogously, we create a 'one-year panel' consisting of individuals who make available the necessary information in periods t and $t+1$. For the analysis of wage changes due to the minimum wage reform, the two year panel is preferred because it can better capture the effects of lagged implementation. Nevertheless, for completeness we also provide estimates for the one-year panel.

5.3.2 Econometric Specification

In order to distinguish a causal effect of the minimum wage introduction from secular wage trends that would have developed even absent the reform, we employ a Differential Trend Adjusted Difference-in-Differences (DTADD) (Blundell and Dias, 2009). A difference-in-differences (DiD) strategy would not suffice because hourly wages of low-wage workers do

[8] At the time of writing this study, the period of observation ends in 2016. Therefore, there are no observations in $t+2$ for the years 2015 and 2016.

not exhibit a parallel trend[9] with any control group and, thus, such estimates would prove biased. For the DTADD strategy, average individual wage growth of the treatment and control group forms the foundation for the analysis. We define the treatment group as individuals earning below €8.50/hour and the control group as individuals with an hourly wage just above the wage floor, between €8.50 and less than €10.00 per hour. As we focus on low-wage earners, we truncate the control group at €10.00 to ensure comparability between the treatment and control group. $\overline{w^i_{t+2} - w^i_t}$ represents the average individual wage growth of group i between two years, $t \in \{2012, 2014\}$, where i refers to either the treatment group ($i = T$) or the control group ($i = C$). Then the DTADD estimator of the minimum wage effects can be expressed as follows:

$$\underbrace{[\overline{(w^T_{2016} - w^T_{2014})} - \overline{(w^T_{2014} - w^T_{2012})}]}_{Observed} - \underbrace{[\overline{(w^C_{2016} - w^C_{2014})} - \overline{(w^C_{2014} - w^C_{2012})}]}_{Counterfactual} \tag{5.1}$$

The first difference of the DTADD estimator is defined through the four terms of the group-specific average individual wage growth between time t and $t + 2$ in the parentheses: $\overline{(w^T_{2016} - w^T_{2014})}$, $\overline{(w^T_{2014} - w^T_{2012})}$, $\overline{(w^C_{2016} - w^C_{2014})}$, and $\overline{(w^C_{2014} - w^C_{2012})}$. The second difference is then calculated within each group, such that it depicts the difference between the time period of the minimum wage implementation and the previous period for the observed scenario and the counterfactual scenario: $\overline{(w^T_{2016} - w^T_{2014})} - \overline{(w^T_{2014} - w^T_{2012})}$ and $\overline{(w^C_{2016} - w^C_{2014})} - \overline{(w^C_{2014} - w^C_{2012})}$. The third difference is the difference between the "observed" scenario and the "counterfactual" scenario. The observed (counterfactual) scenario summarizes the change in average two-year wage growth in the treatment group (control group) between 2012-2014 and 2014-2016.

If, for instance, hourly wages in the treatment group increased on average by €0.2 between 2012 and 2014, but by €0.5 between 2014-2016, wage growth in the treatment group would then lie €0.3 higher in the period between 2014 and 2016 than in the period before. However, one could not exclude the possibility that business cycle effects stemming from Germany's economic growth during that time positively influenced wage growth between 2014-2016. For this reason, it is essential to employ a counterfactual situation that captures how wage growth would have evolved absent the reform. For this purpose, we include the

[9]The dynamic of individual wages generally decreases with the hourly wage percentile.

change in wage growth of the control group. Our method relies on the assumption that any changes observed for wage growth in the control group also would have occurred in the treatment group had the reform not taken place. If, for example, average wage growth in this group between 2014 and 2016 surpassed that in the previous period (2012 to 2014) by €0.1, only €0.2 and not €0.3 could be ascribed to the introduction of the minimum wage. The difference between changes in growth in the treatment group and the changes observed in the control group present the treatment effect of interest.

In contrast to the DiD analysis, this identification strategy does not require the common trend assumption to hold. Rather, it modifies this assumption to stating that existing differences between the treatment and control group would have remained unchanged on average over time. The assumption requires that business cycle effects equally impact the treatment and control group between 2012-2014 and 2014-2016. Given the consistently strong business cycle during these years, this assumption likely holds.[10] A further threat to identification could arise if the control group is affected by the minimum wage. Previous studies have established the existence of such "spillover" effects in the United States and Germany for earlier reforms, at least in the long run (Lee, 1999; Neumark *et al.*, 2004; Dickens and Manning, 2004; Aretz *et al.*, 2013; Autor *et al.*, 2016). Data from the IAB Establishment Panel suggest that also for the statutory minimum wage reform, effects on wages may have also spilled over to higher segments of the wage distribution already in the short run (Mindestlohnkommission, 2016). For this reason, Section 5.5.3 tests the validity of this assumption and does not find evidence of any significant spillover effects.

To illustrate the identification strategy applied in this paper, Table 5.2 provides descriptive statistics of wage growth for the treatment and control groups. The sample includes only observations present and employed in both t and $t+2$. Panel A summarizes the available number of observations used in the later analysis. Panel B displays the average absolute change in hourly wages. Panel C supplements this information with the relative change in wage dynamics, defined as $ln(\frac{w_{it+2}}{w_{it}}) * 100$. This last panel allows for an evaluation of wage effects relative to the initial value (w_{it}) at the individual level. Columns (1) - (3) present these values for the period used for the identification of treatment effects of the minimum

[10] According to the German Statistical Office, GDP per capita increased by 5.8% between 2012-2014 and by 5.7% between 2014-2016.

Table 5.2: Average Growth in Contractual Hourly Wages

	(1)	(2)	(3)	(4)	(5)	(6)
	DTADD			Placebo		
	2014/16	2012/14	Difference (1)-(2)	2012/14	2010/12	Difference (4)-(5)
Panel A: Observations						
Wage<8.50	545	549		549	533	
$8.50 \leq$ Wage < 10	438	412		412	397	
Panel B: Absolute Change (in Euro)						
Wage<8.50	2.7	2.1	0.6	2.1	2.0	0.1
	(3.8)	(3.9)		(3.9)	(3.3)	
$8.50 \leq$ Wage < 10	1.4	1.5	-0.1	1.5	1.1	0.4
	(3.5)	(3.2)		(3.2)	(2.4)	
DTADD			0.7*			-0.3
Panel C: Log Change ($\times$100)						
Wage<8.50	28.8	22.5	6.3	22.5	22.0	0.5
	(33.8)	(35.8)		(35.8)	(32.8)	
$8.50 \leq$ Wage < 10	10.5	11.6	-1.1	11.6	8.6	3.0
	(26.0)	(23.7)		(23.7)	(22.5)	
DTADD			7.4***			-2.5

Source: SOEP v33 2010-2016, own calculations. Results are based on contractual hourly wages and are Unweighted. Standard errors in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

wage introduction. Columns (4) - (6) demonstrate the critical identification assumption of time-constant differences between the treatment and control group by providing the same values for earlier periods.

Table 5.2 shows an average increase in hourly wages of €2.70 among individuals who earned below €8.50 in 2014 and remained employed in 2016 (see column (1) of panel B). In the same period, average hourly wages of the control group rose by approximately €1.40. Such differences, however, also existed in the previous period from 2012 to 2014: the treatment group experienced wage growth in the order of €0.60 higher than that of the control group (€2.10 - €1.50). Due to this systematic difference in wage growth trends, a simple DiD estimator would yield biased results. The DTADD approach accounts for the above-described differences in wage dynamics of individuals earning above and below €8.50 prior to the reform. Controlling for the counterfactual scenario, the true difference becomes:

$$\underbrace{(2.70 - 2.10)}_{Observed} - \underbrace{(1.40 - 1.50)}_{Counterfactual} \approx 0.70 \tag{5.2}$$

To place this effect in relation to the individual, pre-reform wage level, we consider the logged change in panel C, which indicates a relative change of 7.4 percentage points additional wage growth between 2014 and 2016 due to the minimum wage introduction. With a mean hourly wage of €6.90 in the treatment group during the initial period, this difference equates to €0.50 extra per hour (6.90 × 0.074) in comparison to the control group.

To complete the analysis of the causal effect of the minimum wage reform on hourly wages, we use regression analysis to additionally control for differential characteristics of the treatment and control group that likewise influence hourly wages, independently of the minimum wage reform. The regression equation can be stated as follows:

$$\Delta w_{it} = \beta_0 + \beta_1 T_{it} + \beta_2' Y_{it} + \beta_3' T_{it} \times Y_{it} + \beta_4' X_{it} + \beta_5' Change_{it} + \varepsilon_{i,t} \tag{5.3}$$

Δw_{it} captures the individual hourly wage change from time t to $t+2$. T_{it} represents the treatment indicator that takes the value of one if the individual earned less than €8.50 per hour in period t and zero otherwise. β_1, therefore, represents the average wage growth of individuals who earned less than €8.50 in time t. Interacting this term with the time vector Y_{it} demonstrates whether significant deviations from the average growth, β_1, occurred in any specific year. As such, the coefficient of interest, β_3, identifies for $Y_{it} = 2014$ wage changes attributable to the minimum wage. Individual characteristics captured by X_{it} include: age, sex, marital status, citizenship status, highest educational attainment level, place of residence and the number of children under the age of 16 living in the household. Additionally, the following employment characteristics enter into the regression in the form of dummy variables: part-time employment, time-limited contract, firm size and economic sector. $Change_{it}$ further contains information regarding whether the individual changed employment characteristics between periods t and $t+2$, including: eligibility for the minimum wage, job change, receiving a permanent contract, firm size and sector. ε_{it} is an idiosyncratic error term. We estimate the regression equation with OLS. Results are presented in Section 5.5.

Table 5.3: Earnings, Working Hours and Hourly Wage - by Year

	(1) 2012	(2) 2013	(3) 2014	(4) 2015	(5) 2016
Monthly Gross Earnings	2,622.77	2,649.42	2,703.05	2,818.06	2,846.49
in Euros	(1,534.92)	(1,577.11)	(1,639.14)	(1,684.00)	(1,685.27)
Weekly Hours Worked	34.18	34,10	33,75	34,03	33.98
Contractual	(9.81)	(9,64)	(9,96)	(9,78)	(9.77)
Actual	37.76	37.58	36.98	37.17	37.11
	(11.72)	(11.65)	(11.81)	(11.59)	(11.51)
Hourly Wage in Euros	17.22	17.41	17.88	18.54	18.74
Contractual	(8.51)	(8.72)	(9.06)	(9.25)	(9.24)
Actual	15.58	15.8	16.28	17.00	17.16
	(7.22)	(7.52)	(7.80)	(8.05)	(8.06)
Observations	9,899	11,059	10,216	9,542	9,003

Source: SOEP v33 2012-2016, own calculations. The table shows weighted averages based on the cross-sectional sample; standard deviations in parentheses.

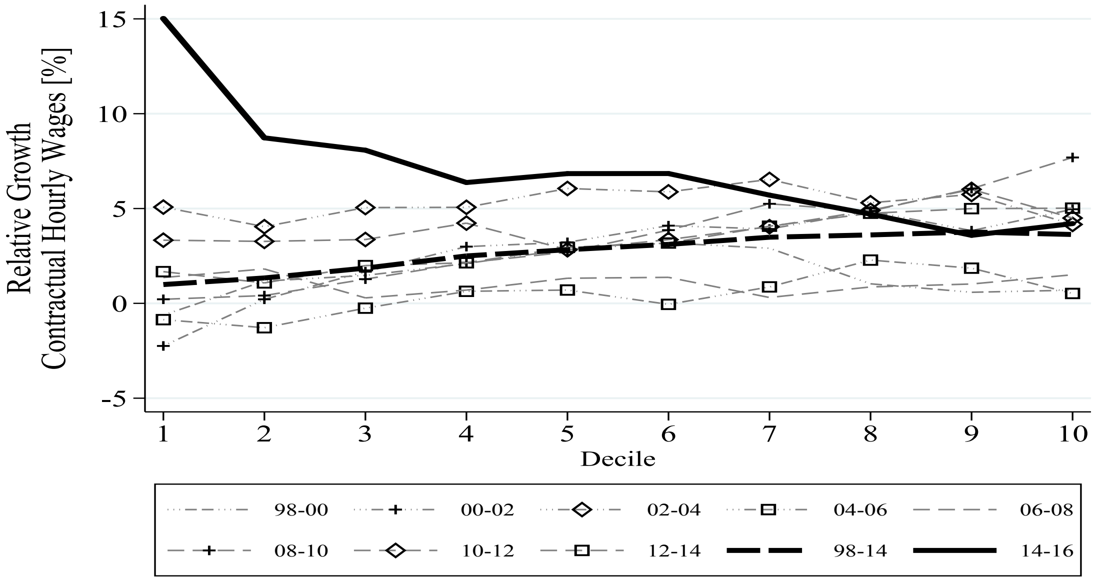
5.4 Trends in Wages and Salary Earnings

5.4.1 Wage Growth throughout the Distribution

Before turning our attention to the causal analysis, this section describes trends in gross hourly wages before and after the minimum wage reform. Table 5.3 presents descriptive statistics for the central variables of the cross-sectional analysis in each year between 2012–2016. Among the population of employees eligible for the minimum wage, mean gross monthly earnings amount to €2,620 in 2012 and €2,850 in 2016 in unadjusted nominal terms. Dividing the monthly income by usual (contractual) monthly hours worked, we arrive at our working concept of hourly wages, which increase between 2012 and 2016 from approximately €17.2 to €18.7. Because actual hours worked surpass contractual hours, the use of contractual hours yields a significantly higher hourly wage. However, this observation is valid also for the pre-reform period.

A look at the evolution of contractual wages in Germany during the past decades helps to understand the role of the minimum wage introduction for the evolution of wages immediately following the reform. Figure 5.1 exhibits growth rates in decile-specific average contractual hourly wages throughout the wage distribution for two-year changes between 1998 and 2016. We denote these growth rates ‘anonymized growth rates’ because this procedure measures growth not at the individual level, but rather based on decile-specific averages, which may be comprised of a different pool of people from one year to the next.

Figure 5.1: Relative Changes in Contractual Hourly Wage by Wage Decile - Various Two-Year Time Periods



Source: SOEP v33, panel sample, own calculations.

The light-grey, dashed lines show the growth rates based on the two years' difference during the pre-reform period. The black dashed line represents the average over these years before the minimum wage introduction. The black, solid line shows the two year difference between 2014-2016. As such, Figure 5.1 shows that the correlation between wage decile and wage growth systematically differs from the trend in the pre-reform period. The average pre-reform growth rate lies at around 2.5%, with the upper wage deciles experiencing faster growth at about 3.5% compared to the lower ones at below 2%. Between 2014 and 2016 in contrast, wage growth in the lower deciles lay well above the decile-specific average of the past years, accelerating from a meager 1% average growth to 15%. At the same time, wage growth in the higher deciles continued at about the same rate after the reform compared to the average of the previous years.

5.4.2 Changes in Wage Inequality

Concerns regarding growing wage inequality in Germany motivated support for the minimum wage reform of 2015. For this reason, this section briefly discusses the evolution of wage inequality both prior to and after the minimum wage introduction. The mean log deviation (MLD) in wages serves as a standard measure of inequality, which we also utilize here. Two advantages of MLD make it particularly appropriate for our analysis: it is especially sensitive to changes at the bottom of the wage distribution where the minimum wage binds and it can be decomposed into wage difference between and within groups (see for example Cowell, 2011). Table 5.4 displays the MLD for the entire cross-section. The first row shows the lower and the third row the upper limit of the 95% confidence interval. The second row contains the point estimate.

Table 5.4: Inequality in Contractual Gross Hourly Wages (MLD Coefficient)

	(1) 2012	(2) 2013	(3) 2014	(4) 2015	(5) 2016
Lower Limit	0.111	0.112	0.116	0.113	0.106
Point Estimate	0.115	0.117	0.121	0.118	0.111
Upper Limit	0.120	0.121	0.125	0.122	0.116

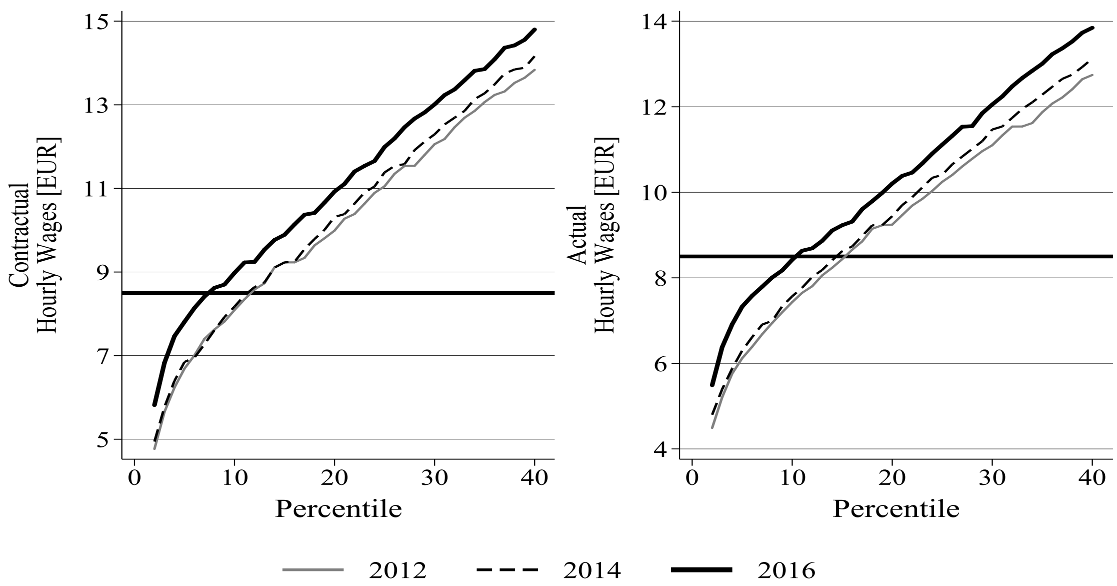
Source: SOEP v33 2012-2016, cross-sectional sample, own calculations. Results are weighted and lower and upper limits refer to a 95% confidence interval using a bootstrapping procedure with 200 iterations.

While inequality in the entire cross-sectional sample increased during the period from 2012-2014, this trend reversed by 2015, in the year immediately following the introduction of the minimum wage. Table 5.4 shows a statistically significant reduction in inequality of average hourly wages in 2016 compared to 2014 before the introduction of the minimum wage. This result should not be interpreted as a causal effect of the minimum wage, as any number of factors could have contributed to this evolution. Instead, results place the minimum wage reform in the context of increasing wage inequality that began to decrease during the same period as the minimum wage introduction. Section 5.5 builds on this descriptive evidence by exploring a causal link between wage growth and the reform.

5.4.3 Developments in the Bottom Wage Segments

The previous section showed trends in average wages throughout Germany. This section focuses on developments in the bottom 40 percentiles of the gross hourly wage distribution between 2012 and 2016. Figure 5.2 highlights these developments using Pen's Parade. This graphical concept first sorts all workers in the given year according to their hourly wage, from lowest to highest. The next step entails plotting the average wage in each percentile against each consecutive percentile of workers. Plotting Pen's Parade for between 2012-2016 together allows for a comparison of wage growth over several years. Figure 5.2 shows Pen's

Figure 5.2: Pen's Parade of Contractual and Actual Gross Hourly Wages in the Bottom 40% of the Wage Distribution



Source: SOEP v33, cross-sectional sample, own calculations.

Parade for workers earning in the bottom 40% of the hourly wage distribution.

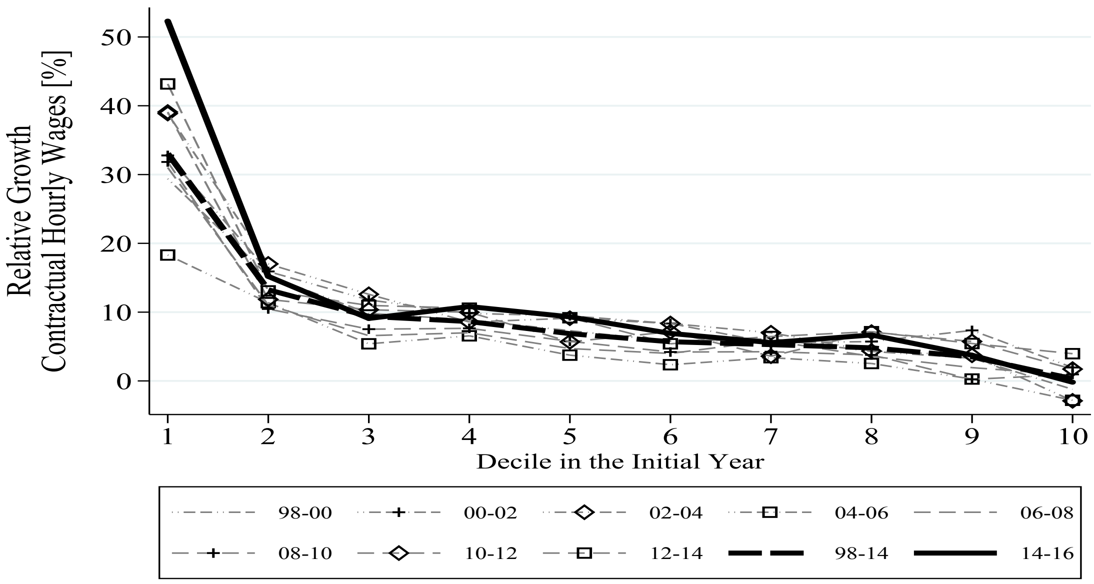
The left-hand panel of Figure 5.2 depicts Pen's Parade of average hourly wages calculated on the basis of contractual hours worked and the right-hand panel the corresponding rates on the basis of actual hours worked. The figure confirms and shows in more detail the wage growth in the low-wage segments targeted by the reform. In addition, the image quantifies the share of workers earning below the minimum wage level of €8.50/hour in gross terms before and after the reform. The horizontal line demarcates the wage floor. Whereas the share lying below the horizontal line amounts to 12% in both 2012 and 2014, it is reduced to 7% by 2016. The nationally representative survey weights enable a conversion of this percentage into the number of employees – roughly 1.8 million – still earning below the minimum wage after the first quarter of 2016. In 2015 this number amounted to roughly 2.1 million, down from about 2.8 million prior to the reform. Measured in actual rather than contractual hours worked, as displayed in the right-hand panel, the share of non-compliance is higher, but the magnitude of the reduction from approximately 14.5% in 2012 and 2014 to 10% in 2016 shows a similar pattern. Note that the sample only includes individuals eligible for the minimum wage such that wages under €8.50 cannot be explained by exempted groups of employees.

5.4.4 Individual Wage Growth

Following the cross-sectional analysis of changes in (anonymized) wages throughout the distribution, this section utilizes the panel sample in order to focus on changes to the wages of individuals who earned below the minimum wage prior to the reform and remained employed after its introduction. Figure 5.3 illustrates these changes with a personalized wage growth curve. The personalized wage growth curve describes the relationship between average individual wage growth and the *individual's* position in the wage distribution in the initial, pre-reform period. Whereas a Pen's Parade depicts how the wage, for example, in the 30^{th} percentile of the wage distribution in 2016 changed in comparison to the wage at this percentile in 2014, the personalized curve describes the development over time of the average wage of individuals who earned at the 30^{th} percentile of the wage distribution in 2014 (and in any percentile in 2016).

Like the anonymized (cross-sectional) wage growth curve in Figure 5.1, Figure 5.3 exhibits the change in wages from 2014-2016 as a solid, thick black line and juxtaposes this growth to historical two-year changes in wages between 1998 and 2014. Light grey, dashed lines capture individual two-year changes and the thick black dashed line the average of these between 1998-2014.

Figure 5.3: Personalized Growth Curves for Gross Hourly Wages



Source: SOEP v33, panel sample, own calculations.

In the bottom decile of the wage distribution for each initial period, wages grow by 30-40% and then sink to a rate under 20% by the second decile, indicating historically high growth rates of the average individual with the lowest wages in the initial period. High growth rates at the bottom demonstrate that, for many individuals, low wages represent a transitory phenomenon. Workers with wages in the lowest decile tend to be young with short work biographies who then gain human capital and work experience that subsequently promote them into higher wage categories. From 2014-2016, growth at the bottom increased even further, to about 50%.

5.4.5 Mobility between Wage Segments

This section examines the transitions of individuals across wage segments of the distribution, as workers may occupy different positions throughout their working biography. For this exercise, we use transition matrices to illustrate mobility. The matrices describe the probability to transition from a wage segment in time t to another segment in time $t+2$, for instance from below the minimum wage to the segment between the €8.50 wage floor and €10.50. In contrast to the wage curves in Figures 5.1 and 5.3, the transition matrix also accounts for individuals switching from employment to not working. Table 5.5 presents a transition matrix for contractual hourly wages in 2012/2014 and 2014/2016. We distinguish between four wage segments as well as the transition out of employment and vice versa. We define the following groups as non-employed: trainees and apprentices, those participating in older worker part-time schemes (*Altersteilzeit*), but who report zero hours, those in military or the civil social service, working in an establishment for disabled people and those reporting non-employment.

Each row describes a certain wage group status in the initial period, 2012 for the upper panel and 2014 for the lower panel. The columns represent the share of each group that transitions from the given wage group to the wage group denoted in the column title (each row adds up to one). The shares in the main diagonal correspond to the share of each wage segment that remained in that wage group two years later. The table shows that the share of individuals that remained in employment remunerated below the minimum wage level of €8.50 substantially decreased after the introduction of the minimum wage: in the period from 2012 to 2014, 38% remained in this wage category, while from 2014 to 2016 the share

Table 5.5: Transitions for Contractual Gross Hourly Wages (2012-2016)

	(1) Not Employed	(2) Below EUR 8.50	(3) EUR 8.50 -10.50	(4) EUR 10.50 -12.00	(5) Above EUR 12.00
	Wage Group in 2014				
Wage Group in 2012					
Not Employed	0.922	0.021	0.015	0.007	0.035
	(0.004)	(0.002)	(0.002)	(0.001)	(0.003)
Below EUR 8.50	0.274	0.379	0.198	0.078	0.07
	(0.027)	(0.029)	(0.024)	(0.024)	(0.014)
EUR 8.50-10.50	0.137	0.073	0.369	0.185	0.236
	(0.020)	(0.015)	(0.028)	(0.025)	(0.027)
EUR 10.50-12.00	0.132	0.011	0.069	0.314	0.474
	(0.025)	(0.004)	(0.019)	(0.042)	(0.039)
Above EUR 12.00	0.093	0.006	0.01	0.013	0.879
	(0.007)	(0.001)	(0.003)	(0.002)	(0.008)
	Wage Group in 2016				
Wage Group in 2014					
Not Employed	0.930	0.011	0.015	0.005	0.039
	(0.004)	(0.002)	(0.002)	(0.001)	(0.003)
Below EUR 8.50	0.217	0.235	0.302	0.097	0.149
	(0.026)	(0.024)	(0.030)	(0.023)	(0.027)
EUR 8.50-10.50	0.162	0.073	0.377	0.21	0.177
	(0.025)	(0.013)	(0.029)	(0.023)	(0.023)
EUR 10.50-12.00	0.166	0.029	0.116	0.237	0.452
	(0.032)	(0.016)	(0.021)	(0.031)	(0.037)
Above EUR 12.00	0.094	0.004	0.008	0.016	0.878
	(0.006)	(0.002)	(0.002)	(0.003)	(0.007)

Source: SOEP v33 2012-2016, panel sample. N = 14,538 in the sample 2012-2014 and N = 14,398 in the sample 2014-2016, own calculations. All probabilities stated in decimal value (0.285 = 28.5%). Standard deviations in parentheses.

dropped to 24%. At the same time, a slightly smaller share of workers previously earning below the minimum wage transitioned out of employment from 2014 to 2016 compared to 2012 to 2014 and a much larger share (30% compared to 20%) experienced upward wage mobility into a higher wage segment between €8.50 and €10.50. It is also noteworthy that the share of workers paid below the minimum wage in the previous period and who transitioned into an even higher segment with an hourly wage above €12.00 doubled in 2014/2016 compared to 2012/2014. Finally, the share of non-workers who remained out of work slightly increased in 2014/2016 compared to 2012/2014. Moreover, transitions out of employment from the wage segment just above the minimum wage between €8.50-€10.50 as well as €10.50-€12.00 increased from 14% to 16% and from 13% to 17%, respectively.

The descriptive evidence provided in this section paints a clear picture: following many years of low wage growth at the bottom of the wage distribution, the introduction of the statutory minimum wage is associated with significant growth in wage dynamics in the bottom decile of the distribution,[11] and, consequently, a compression of the wage distribution. Nevertheless, compliance with the minimum wage remains imperfect and many eligible workers still earn an hourly wage below €8.50/hour. The following section addresses the question to what extent the observed changes in wage growth can be causally attributed to the minimum wage introduction.

5.5 Results of the Causal Effects Analysis

5.5.1 Main Results

Table 5.6 summarizes the results from the regression analysis for changes in contractual hourly wages of all workers eligible for the minimum wage. In order to control for non-linear relationships, the dependent variable is defined in logarithmic rather than absolute terms. Therefore, coefficients should be interpreted as percentage changes. In addition to showing results for the two-year changes, (columns 4 - 6), Table 5.6 also provides results for one-year changes (columns 1 - 3) in order to describe potential differences in the effects across the time period following the reform. Columns (1) and (4) present results for the baseline specification using only treatment indicators and year fixed effects as control variables. Columns (2) and (5) additionally include sociodemographic and employment characteristic controls. Columns (3) and (6) also include controls for changes in employment.

The first row of Table 5.6 quantifies the differential wage dynamics within the one-year panel sample between treatment and control groups. According to the one-year analysis, hourly wages of workers earning below €8.50 grew on average by 10.83% faster than the control group (workers earning €8.50-€10.00) between 2012-2015. The introduction of the minimum wage further increased this growth by about 4 percentage points, which is captured by the DTADD interaction term for 2014-2015 in column (1). This treatment effect can be considered causal, is significant at the 90% confidence level and proves robust to

[11] For the first wage decile, a t-test reveals a statistically significant difference ($p < 0.001$) in the relative growth rate of contractual hourly wages in 2014-2016 in comparison to all other periods (1998-2014). For the second decile, this difference is insignificant ($p \approx 0.12$).

Table 5.6: Minimum Wage Effect on Relative Wage Growth

	(1)	(2)	(3)	(4)	(5)	(6)
One-Year Analysis						
Hourly Wage < EUR 8.50	10.83***	12.57***	12.49***			
	(1.57)	(1.59)	(1.59)			
× DTADD 2014-2015	4.01*	4.13*	3.96*			
	(2.14)	(2.12)	(2.11)			
× Placebo 2012-2013	-2.21	-1.5	-1.42			
	(2.19)	(2.17)	(2.17)			
Two-Year Analysis						
Hourly Wage < EUR 8.50				10.89***	12.59***	12.93***
				(1.92)	(1.95)	(1.94)
× DTADD 2014-2016				7.44***	6.75**	6.47**
				(2.71)	(2.68)	(2.68)
× Placebo 2010-2012				2.49	2.29	2.07
				(2.63)	(2.61)	(2.59)
Constant	6.62***	13.44***	7.31**	11.58***	20.04***	10.59***
	(0.92)	(2.77)	(3.45)	(1.17)	(3.55)	(4.09)
Control Variables						
Year Fixed Effects	✓	✓	✓	✓	✓	✓
Socio-Demographic Info.		✓	✓		✓	✓
Employment Characteristics		✓	✓		✓	✓
Changes in Employment			✓			✓
Observations	3,523	3,523	3,523	2,874	2,874	2,874
$\overline{R^2}$	0.043	0.081	0.085	0.056	0.087	0.098

Source: SOEP v33 2010-2016, own calculations. Robust standard errors in parentheses, clustered at the individual level. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

the inclusion of controls for sociodemographic and employment characteristics as well as for changes in employment status. With a mean wage of €6.90/hour for the treatment group in 2014, the economic magnitude of the treatment effect amounts to an additional €0.30/hour (€6.90 × 0.04) above and beyond the wage growth that would have been expected absent the minimum wage introduction. An alternative way to consider the effect offers insight into the issue of non-compliance with the minimum wage: without the reform, hourly wages in the treatment group would have been expected to grow by €0.90/hour (€6.9 × 0.125), reaching €7.80/hour (€6.90 + €0.90). Instead, the minimum wage caused average wages in the treatment group to rise to €8.10, which still falls, on average, below the legal wage floor, indicating substantial non-compliance.

The two-year analysis shows that hourly wages of employees earning below €8.50 continue to increase through the second quarter of 2016 and grow dynamically in comparison to the control group. According to the two-year perspective, the marginal treatment effect of the minimum wage introduction on hourly wage growth is 6.47 percentage points in the preferred specification with full controls, an even higher and statistically more significant impact than that found in the one-year analysis. From the mean of €6.90/hour, this effect amounts to €0.45/hour more than would have been the case absent the reform (€6.90 × 0.065 = €0.45). Even with this larger effect, however, the average hourly wage of the treatment group fell shy of the €8.50 legal wage threshold at €8.24/hour (€6.90 + €0.89 + €0.45).

Finally, the third row of results for the one-year and two-year analyses lend credence to the validity of the crucial identifying assumption for the DTADD approach, namely time-persistent differences between treatment and control groups. Specifically, the placebo test examines whether wages of the treatment and control groups grew at different speeds during the period of 2012-2013 than in 2013-2014. The observed differences prove statistically insignificant in all specifications.

To answer the question of whether the minimum wage not only increased hourly wages, but also the overall labor income position of the target group, it becomes necessary to consider the effect on monthly earnings. After all, the goal of the reform was not just to increase wages per hour, but rather to improve the economic situation of low-income individuals. Monthly earnings combine two possible dimensions of adjustment: hours worked and hourly wages. In a related contribution Burauel *et al.* (2020) demonstrate that the minimum wage introduction not only increased wages, but also had a negative impact on average hours worked. Therefore, in the following, we investigate the net effect of these two opposing forces. Table 5.7 depicts the results of the DTADD estimation from equation 5.1 where the change in gross monthly earnings replaces the change in wages as the dependent variable.

The one-year analysis of Table 5.7 reveals that the effect of the minimum wage on the gross monthly earnings of the treatment group could not be statistically distinguished from zero. Similar to the results for changes in (log) wages, gross monthly (log) earnings experienced a higher growth rate in the treatment group than in the control group during the period under investigation (2012-2015): the first row of the first two columns indicates that earnings grew by roughly 10.5% more in the treatment than in the control group. The minimum wage, however, did not affect this relationship. Although the minimum wage

Table 5.7: Minimum Wage Effect on Relative Gross Monthly Earnings

	(1)	(2)	(3)	(4)
	One-Year Analysis		Two-Year Analysis	
Hourly Wage < EUR 8,50	10.98***	10.54***	8.91***	8.24***
	(1.91)	(1.90)	(2.42)	(2.42)
× DTADD 2014-2015	1.39	1.09		
	(2.69)	(2.63)		
× DTADD 2014-2016			8.70**	6.58*
			(3.54)	(3.40)
× Placebo 2012-2013	-4.45	-3.63		
	(2.71)	(2.64)		
× Placebo 2010-2012			4.15	3.08
			(3.53)	(3.46)
Constant	7.79***	17.68***	12.69***	11.63**
	(1.25)	(4.24)	(1.57)	(5.23)
Control Variables				
Year Fixed Effects	✓	✓	✓	✓
Sociodemographic Information		✓		✓
Employment Characteristics		✓		✓
Changes in Employment		✓		✓
Observations	3,523	3,523	2,874	2,874
$\overline{R}^2$	0.022	0.071	0.027	0.122

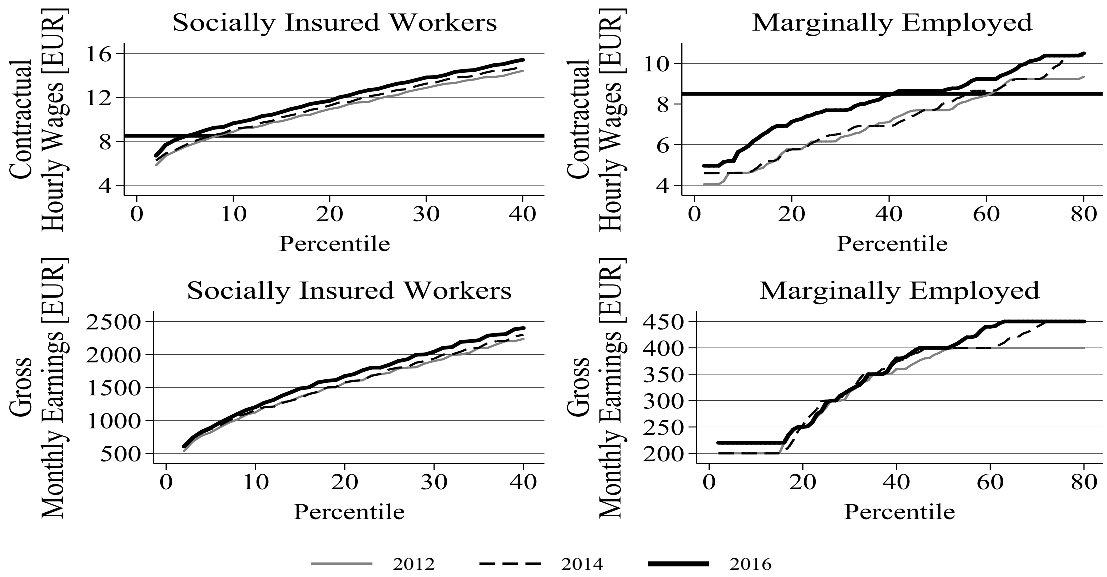
Source: SOEP v33 2010-2016, own calculations. Robust standard errors in parentheses, clustered at the individual level. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

led to a rise in hourly wages, it also lowered hours worked for this same group. In sum, the net impact of the minimum wage on monthly earnings of the target group can not be distinguished from zero in the one-year horizon. Nevertheless, the two-year analysis demonstrates a positive impact of the minimum wage introduction on the monthly earnings of 6.6 percentage points (roughly €54/month).

5.5.2 Heterogeneity of Effects by Employment Type

As argued in Burauel *et al.* (2018), one would expect the introduction of the minimum wage to differentially impact employees with socially insured positions and the marginally employed. Marginally employed individuals have an incentive to reduce their hours worked in order to remain below the threshold of €450 monthly, beyond which workers become subject to social security contributions. Moreover, the wages of marginally employed workers lie well below those of the regularly employed and, due to a lower skill level on average, generally have a weaker position when negotiating wages with employers (see also Stegmaier *et al.*, 2015). At the same time, the minimum wage is more likely to price these workers

Figure 5.4: Evolution of Hourly Wages and Monthly Earnings by Employment Type



Source: SOEP v33, cross-sectional sample, own calculations.

out of the market than the regularly employed when their marginal productivity of labor falls below the wage floor. Garloff (2016), Schmitz (2017) and Caliendo *et al.* (2018) show that, in fact, the minimum wage decreased the number of marginally employed workers. Therefore, for this group, we also examine the wage and earnings effects of the minimum wage for these two types of employment separately.

Figure 5.4 juxtaposes Pen's Parade for the regularly employed (including both part- and full-time) to that of the marginally employed. The upper panel considers hourly wages and the lower panel describes gross monthly earnings. The red horizontal line in the upper panel denotes the minimum wage level. The figure documents that remuneration below the minimum wage in 2016 is predominantly a phenomenon of the marginally employed. While one observes an increase in wages up to the 60^{th} percentile of this group, roughly 40 percent of this population receives an hourly wage below the legal wage floor. The distribution of hourly wages for the socially insured workers remains noticeably above that for the marginally employed. As a consequence, the relative growth patterns from 2014-2016 compared to 2012-2014 shown in the upper panel of Figure 5.4 are more pronounced for the marginally employed.

The lower panel of Figure 5.4 shows the evolution of monthly gross earnings for the socially insured compared to the marginally employed workers between 2012 and 2016. The left panel reveals only a slight improvement for the socially insured in terms of gross monthly earnings. For the marginally employed, in contrast, the share of the group earning below the tax threshold of €450/month decreases by 10 percentage points: whereas in 2014, 70 percent of the marginally employed earned within the limits of the tax preference, in 2016 only 60 percent did so.

Turning to the causal effects for regularly employed and marginally employed workers separately, Table 5.8 shows results based on the two-year panel sample. The subgroup analysis further splits the sample of regularly employed individuals into full- and part-time categories to examine potential heterogeneous treatment effects.[12] This further partition reduces the sample size and, thus, the power of the separate regressions compared to using the full sample. Analogously to the results of the full sample, the column titled "Hourly Wage < 8.50" (column 3) reflects the different wage dynamics between treatment and control groups. "DTADD 2014-2016" (column 5) identifies the change in hourly wage attributable to the minimum wage introduction. "Placebo 2010-2012" (column 7) tests the critical identification assumption for the DTADD, namely whether wage differences between treatment and control groups can be considered time-constant. All regressions consider the full set of controls.

The differential analysis according to regular employment status reveals substantial heterogeneity in the treatment effect. During the period under investigation, wage growth was the most dynamic for the marginally employed, followed by the part-time regularly employed, increasing 17.4% and 14.5%, respectively, more in the treatment compared to the control group. In contrast, wage growth for full-time employees in the treatment group surpassed that of the control group by 10.7%. Despite the high growth rates of the part-time regularly employed, this growth cannot be attributed to the minimum wage. For this group, the effect of the reform is negative, but statistically insignificant. The reform did, however, positively impact hourly wages of full-time employees by 7.8 percentage points. According to the subgroup analysis, the minimum wage introduction had the largest, positive effect on the hourly wages of the marginally employed, who experienced a growth rate 15.5 percentage points higher in the treatment than in the control group. Finally, Panel B of Table 5.8

[12]Full-time is defined as working more than 30 hours per week.

Table 5.8: Minimum Wage Effect on Gross Hourly Wage Growth by Employment Type

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Observations 2014							
	Treat-ment	Control Group	Hourly Wage <8.50		DTADD 2014-2016		Placebo 2010-2012	
Panel A: Hourly Wages								
Entire Sample	545	438	12.93***	(1.94)	6.47**	(2.68)	2.07	(2.59)
Socially Insured Workers	382	383	11.79***	(2.15)	4.57	(2.99)	2.36	(2.85)
Full-Time Regularly Employed	270	303	10.73***	(2.46)	7.79**	(3.44)	3.64	(3.19)
Part-Time Regularly Employed	112	80	14.53***	(4.52)	-5.01	(6.07)	-0.28	(6.65)
Marginally Employed	163	55	17.40***	(4.80)	15.51**	(6.90)	2.43	(6.66)
Panel B: Monthly Earnings								
Socially Insured Workers	382	383	9.60***	(2.56)	3.54	(3.51)	5.29	(3.56)
Marginally Employed	163	55	3.85	(6.37)	13.14	(9.21)	-11.96	(12.01)

Source: SOEP v33 2012-2016, own calculations. Robust standard errors in parentheses, clustered at the individual level. All regressions include the full set of controls, including demographic and employment characteristics as well as information regarding changes in employment. Individuals will only appear in the sample in those years for which the row-specific condition is fulfilled. To deal with changes in employment, e.g. from marginal employment to part-time employment, we control for changes in eligibility, job, contract term, company size and sector. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

considers the net effect on gross earnings, which results from changes in hourly wages and in hours worked, for the socially insured and marginally employed separately. Despite positive treatment effects on hourly wages of the marginally employed, the reduction in hours worked counteracts the wage effect (compare Burauel *et al.*, 2020). Neither for socially insured nor for the marginally employed can any positive impact of the minimum wage reform on gross monthly earnings be detected. At the same time, partitioning workers into these categories renders the sample sizes smaller than in the entire sample and the sample size may simply become too small to detect an effect.

5.5.3 Robustness Analysis - Spillover Effects

As discussed in Section 5.3.2, the causal identification of the DTADD treatment effect relies on the assumption that the introduction of the minimum wage did not affect the selected control group. A priori, the direction of potential spillover effects is unclear. On the one hand, rising wage costs in the lower segment of the distribution could cause employers to decrease wages of higher earners in order to pass along the additional costs of the reform. However, in reality, wages tend to be sticky and long-term contracts as well as social norms may prevent employers from doing so. Negative spillover effects in the form of wage compression tend to be associated with new hires rather than the current stock of employees, rendering this type of spillover a predominantly long-term phenomenon. On the other hand, wages may also rise for workers previously earning just above the minimum wage if employers wish to retain the wage structure within their establishment. Data from the IAB Establishment Panel Survey suggest this latter direction is more likely: 14 percent of all responding establishments report increasing wages not only for those previously earning below the minimum, but also for those earning above the mandated threshold (Mindestlohnkommission, 2016). The presence of positive spillover effects would bias the estimates of wage growth downward if the control group does not correctly reflect the counterfactual situation.

The existing literature finds that spillover effects appear mostly in groups earning close to the minimum wage cutoff. For this reason, we test the existence of possible spillover effects by comparing the results of our main specification from Table 5.6 with a robustness estimation in which we employ an alternative control group consisting of workers earning between €10.00 and €11.50 (while the definition of the original treatment group remains unchanged). If wages of our preferred control group of employees earning between €8.50 and €10.00 were not affected by the reform, we should not observe changes in wage growth between the original control group and alternative control group. The validity of this approach rests on the assumption that any potential spillover effects shrink as one moves further away from the minimum wage cut-off toward higher segments of the wage distribution. This assumption likely holds, as other studies have found that the spillover effects in Germany were in fact small and decreasing in higher segments of the wage distribution (Mindestlohnkommission, 2018; Caliendo *et al.*, 2019b).

Table 5.9 summarizes results for the one-year and two-year comparison and demonstrates that results remain robust to this alternative control group. It shows a positive and statistically significant treatment effect for the original treatment group between 2014-2015 (columns 1 and 2). For the two-year analysis, the treatment effect has a similar magnitude, although it loses its significance (columns 3 and 4). Only a marginal difference exists in the general wage dynamics between workers earning between €8.50-€10.00 and those earning between €10.00-€11.50. These differences, however, did not change during the time period under investigation, neither for the one-year nor for the two-year analysis (see "Spillover

Table 5.9: Robustness: Spillover Effects on Contractual Gross Hourly Wages

	(1)	(2)	(3)	(4)
	Change in Contractual Hourly Wages			
One-Year Analysis				
Hourly Wage < EUR 8,50	10.83***	12.56***		
	(1.57)	(1.58)		
× DTADD 2014-2015	4.01*	4.00*		
	(2.14)	(2.11)		
× Placebo 2012-2013	-2.21	-1.45		
	(2.19)	(2.17)		
EUR 10 ≤ Wage < EUR 11.50	-1.76	-2.93**		
	(1.43)	(1.42)		
× Spillover DTADD 2014-2015	-0.04	-0.02		
	(1.92)	(1.88)		
× Spillover Placebo 2012-2013	1.28	1.96		
	(1.95)	(1.94)		
Two-Year Analysis				
Hourly Wage < EUR 8,50			18.67***	21.41***
			(3.11)	(3.10)
× DTADD 2014-2016			8.28*	6.48
			(4.53)	(4.44)
× Placebo 2010-2012			1.94	1.25
			(4.10)	(4.02)
EUR 10 ≤ Wage < EUR 11.50			-3.04	-2.9
			(2.17)	(2.22)
× Spillover DTADD 2014-2016			0.56	-0.91
			(3.15)	(3.16)
× Spillover Placebo 2010-2012			3.71	3.05
			(2.88)	(2.88)
Constant	7.16***	6.94**	15.79***	21.59***
	(1.02)	(2.88)	(1.69)	(4.71)
Control Variables				
Year Fixed Effects	✓	✓	✓	✓
Sociodemographic Information		✓		✓
Employment Characteristics		✓		✓
Changes in Employment		✓		✓
Observations	4,927	4,927	4,036	4,036
$\overline{R^2}$	0.052	0.089	0.061	0.103

Source: SOEP v33 2010-2016, own calculations. DTADD regressions, robust standard errors in parentheses, clustered at the individual level with * p<0.1, ** p<0.05, *** p<0.01. Results are unweighted and based on the panel sample.

DTADD" and "Spillover Placebo"). These results are furthermore robust to alternative definitions of the additional control group, including individuals earning up to €13.00/hour. In conclusion, the robustness test does not find any evidence of spillover effects in the short run for the German minimum wage reform (2015-2016).

5.6 Conclusion and Discussion

In this paper, we descriptively examine the evolution of the wage and earnings structure of German workers around the time of the introduction of the minimum wage reform and causally identify the impact of the reform on the wage and income distribution. The descriptive analyses illustrate an acceleration of wage growth for workers earning below €8.50/hour after the introduction of the wage floor in January 2015. In the bottom 10th percentile of the wage distribution, wages increased by 15% between 2014 and 2015 despite a consistently lower growth rate of below 2% in previous periods (1998-2014). Between 2014 and 2016, contractual and actual hourly wages of low wage workers experienced above-average growth, not only with respect to previous periods, but also in comparison to high-wage earners. In line with this trend, the analysis further finds reduction in mean log deviations of wages throughout the distribution from 2014 to 2016, indicating a compression in the overall wage distribution. Notwithstanding above-average wage growth at the bottom of the distribution, however, hourly wages of approximately 1.8 million workers still remained below the legal wage floor at the end of the first quarter of 2016 compared to 2.8 million before the reform. As such, the cross-sectional analysis paints an ambivalent picture, with substantial wage gains for many in the low-income segments of the distribution, but also with a large number of workers for whom compliance remains an issue.

As a complement to the cross-sectional analysis, the panel allowed for an investigation of individual wage growth and mobility. Particularly high growth rates in the bottom decile of the distribution indicate that very low wages represent a transitory phenomenon for many workers. This group tends to consist of young workers with short employment biographies, who gain experience and quickly transition into higher wage segments. The panel analysis further finds that workers earning below the minimum wage before the introduction had a higher probability of transitioning into higher wage segments than had been the case in previous years: the probability of transitioning into the segment between €8.50 and €10.50 increased by 10 percentage points and the probability of transitioning into a job paying over €12.00 increased by 7.5 percentage points. Meanwhile, the probability of this group to leave employment decreased by 6 percentage points and the probability of the non-employed to take up a job decreased by 1 percentage point from 2014-2016 compared to 2012-2014.

Moving beyond the description of trends to the causal analysis, we employ a DTADD strategy to establish the extent to which increases in wages and earnings can be ascribed to the reform of 2015. In the mid-run, we find that the minimum wage introduction can account for hourly wage growth in the order of 6.47 percentage points, or €0.50/hour more than would have otherwise been the case for the treatment group of individuals earning below €8.50/hour before the reform. Further, we examine whether the positive impact on hourly wages translated into an improvement of the earnings position of low-wage workers in terms of gross monthly earnings. The one-year analysis yields no effects, while the two-year analysis shows a positive and marginally significant treatment effect on monthly earnings of 6.6 percentage points, or €54/month.

Subgroup analysis according to type of employment (socially insured vs. marginally employed) revealed that the minimum wage had the highest positive impact on the wages of marginal workers, who experienced a 15.5 percentage points higher growth rate on account of the reform, followed by the full-time regularly employed with an additional increase in hourly wages of 7.8 percentage points. Despite positive treatment effects for hourly wages in both of these groups, however, no impact of the minimum wage reform on monthly earnings could be detected when estimating the effect for these groups separately. The absence of an effect may be attributed to a reduction in power (small sample size) after partitioning the sample into the socially insured and marginally employed.

The introduction of the statutory minimum wage in Germany presents a substantial intervention into the labor market. This paper investigated its short-term impacts on the wage and earnings distribution, accounting for detectable effects through the second quarter of 2016. Evaluations of minimum wages in other countries have established that the full implementation of national, statutory minimum wages tend to experience a delay due to lags in wage and salary policy responses or adjustments to production processes of employers and/or time needed to clarify legal details. Therefore, continued evaluation of the medium to long-run effects will prove indispensable for understanding the full impact of the reform. Going forward, it remains to be seen whether the positive treatment effect will persist or even grow over time and whether the compliance gap will close, for instance due to stronger sanctions for non-compliance or to social pressure. More compliance, on the other hand, could induce stronger negative employment effects, which would carry further repercussions for the wage distribution. Moreover, it is likely that the relatively favorable business cycle that accompanied the introduction prevented a larger negative employment reaction. This situation may change if faced with a future recession. Finally, substitution effects in the medium run cannot be ruled out. It is possible that firms begin to favor workers exempted from the minimum wage or that they alter their production processes to outsource work packages abroad or to the self-employed in order to cut costs. All of these adjustments could influence the long-run income distribution in Germany.

Future research could furthermore consider whether the increase in the initial minimum wage level to €8.84/hour on January 1, 2017 or the end of the transition period for exempted economic sectors on December 31, 2017 affected wages, earnings and employment. Both of these changes influence the number of people on the labor market with the legal right to a higher wage. Lastly, more research is needed to understand the adjustment mechanisms used by employers to cope with the additional costs of higher wages. Possible channels include, but are not limited to: higher production expectations toward workers, passing on the costs to consumers through higher prices, or decreasing extra payments and non-monetary fringe benefits of workers.

Chapter 6

The Impact of the German Minimum Wage on Working Hours*

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Patrick Burauel, Marco Caliendo*, Markus M. Grabka, Cosima Obst, Malte Preuss and Carsten Schröder

The Impact of the Minimum Wage on Working Hours

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Abstract: The present paper analyzes how the statutory minimum wage introduced on January 1, 2015, has affected working hours in Germany up to 2016. The data used come from the Socio-Economic Panel (SOEP), which provides not only contractual working hours but also actual hours worked. Using a difference-in-differences estimation approach, we find a significant and robust reduction in *contractual* working hours among employees who are subject to social security contributions and earned less than the minimum wage before the introduction. The effect in 2015 is about −5 % and corresponds to a 1.7 hours reduction in average weekly working hours. The effect on actual hours is smaller and estimated less precisely. Extending the analysis until 2016 does not yield significant effects on contractual or actual working hours, while some specifications reject the common trend assumption.

Keywords: minimum wage, working hours, DiD estimation
JEL Classification: J23, J38, J81

1 Introduction

Germany's new national minimum wage of €8.50 per hour, stipulated in Coalition Agreement between CDU/CSU and SPD, was introduced in the August 2014 Act Regulating a General Minimum Wage. The minimum wage

***Corresponding author: Marco Caliendo,** University of Potsdam, August-Bebel-Str. 89, 14482 Potsdam, Germany; and IZA, Bonn, Germany; and DIW, Berlin, Germany; and IAB, Nuremberg, Germany, E-mail: caliendo@uni-potsdam.de

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went into effect on January 1, 2015. The Minimum Wage Act represents one of the most significant institutional changes in the German labor market since the reform of laws governing modern services in the labor market (Hartz I-IV).

The introduction and design of minimum wage policies has been the subject of vigorous debate among economic policy makers for some time. Critics of the minimum wage have argued, for instance, that a statutory minimum wage would interfere with price-setting mechanisms on the labor market, reducing overall economic efficiency and leading to lower employment and higher unemployment (e. g. SVR 2013). Economic labor market models show that possible employment effects of the minimum wage depend on the amount of market power that employers possess over employees. The prediction of negative employment effects—and, thus, higher unemployment—is made particularly under the assumption that institutional settings such as the minimum wage affect price-setting (wage levels) on a perfect labor market. In contrast, a minimum wage is expected to lead to positive employment effects and lower unemployment if employers are in a dominant position on the labor market and keep the demand for labor artificially low to their own advantage (monopsony model of a labor market, see Manning 2003). In job search models, the introduction of a minimum wage may also reduce or even offset negative employment effects resulting from increased wage costs if the minimum wage creates incentives for non-employed people to seek and accept employment (see Cahuc et al. 2014). The question of how the minimum wage affects employment and unemployment in a real labor market is, therefore, one that can only be answered empirically.

In past studies on the effects of the minimum wage in Germany, the focus was generally on changes in the absolute number of employed people (the “extensive margin”, see, e. g. Caliendo et al. (2018) and Caliendo et al. (2019) for a general overview). Yet, the minimum wage may also result in changes in the number of hours worked per employed person (“intensive margin”). The goal of this paper is to empirically examine these effects on working hours up to the year 2016 in Germany. To this end, we use various specifications of a difference-in-differences (DiD) approach. This methodology studies changes in outcome variables for units of investigation whose wage structure had to be adapted after the introduction of the minimum wage (treatment group) relative to changes for units of investigation whose wage structure required no or little adaptation after the introduction of the minimum wage (control group). More precisely, employees who qualified to receive the minimum wage and earned less than €8.50 per hour before the reform serve as our treatment group, and those who earned slightly over €8.50 (up to €10 per hour) as our control group. We conducted our analyses separately for employees subject to social security contributions and for employees in marginal employment (minijobs), as the monthly earnings threshold of €450 for the latter group creates incentives to reduce the working hours after introduction of the minimum wage. We also distinguish between contractual working hours and actual hours worked. Contractual and actual working hours may deviate if overtime takes place regularly. However, overtime is subject to minimum wage regulation as well and needs to be compensated for. Hence, it is of interest to analyze both concepts as not only contractuals hours but also overtime and its compensation can be adjusted in response to the minimum wage. The data used here come from the Socio-Economic Panel (SOEP).

Our results show that in 2015, the minimum wage had a significant negative effect of −5.1 percent on contractual working hours of employees who were subject to social security contributions and who earned less than €8.50 per hour before the reform. The effect measured for actual hours worked was negative as well, but smaller at −2.5 percent and statistically insignificant. We find strong negative effects on working hours for workers in minijobs, but these are statistically insignificant, presumably due to the relatively low number of observations. This effect gets significant, when we control for sociodemographic and job characteristics. Extending the analysis to 2016 does not yield significant effects, neither for employers subject to social security contribution nor for minijobers.

The results provided must be interpreted with caution as the analysis comes with some caveats. Measurement errors could arise as the data provided is self-reported. Further, while we provide evidence that the common trend assumption holds in the main analysis, the assumption must be rejected for some of the analyzed subgroups. Consequently, the results for these groups cannot be interpreted as causal. The shortcomings are discussed in more detail for the respective analyses and are addressed in the conclusion as well.

This article is structured as follows. Section 2 discusses the current state of the research. Section 3 presents our methodological approach. Section 4 describes our database and sample definition, and presents a first descriptive analysis. The causal analysis and various robustness tests are documented in Section 5 and Section 6 summarizes the findings.

2 State of the research

Overall, the theoretical predictions on how minimum wages affect outcomes like employment, unemployment, and working hours are ambiguous. They depend not only on how high the minimum wage is relative to wage levels in the absence of regulation,[1] but also on the specific framework conditions on the supply and demand sides of the markets in question. Thus, conclusions about the effects of minimum wages can only be provided empirically and in relation to the concrete case at hand (Arni et al. 2014).

Since increasing wages mean rising labor costs, employers could reduce their employees' working hours as a way of adapting to the minimum wage. Yet, employees might also have incentives to reduce their working hours following an increase in hourly wages.

In Germany, a number of descriptive analyses have found evidence of reductions in working hours as an adaptation strategy (see Bellmann et al. 2016, 2017a; Bruttel et al. 2018; Holtemöller 2016; Mindestlohnkommission 2016, 2018; Sauer/Wojciechowski 2016; Vom Berge et al. 2018; Weber 2016). Also the first descriptive analyses conducted by the Minimum Wage Commission (2016) suggest that the statutory minimum wage may have led to a reduction in working hours in the more heavily affected portions of the labor market. Their findings show that full-time employees who were paid below the minimum wage in 2014 reduced their weekly working hours by as much as approximately 10 percent after the introduction of the minimum wage. Bruttel et al. (2018) report an even stronger decrease of about 21 percent in weekly working hours among full-time employees who earned less than €8.50 before the reform. In a study focused solely on changes in working hours among people in "minijobs", who are exempt from social security contributions as long as the monthly income threshold of €450 is not exceeded, Wanger and Weber (2016) report a 5 percent decline in hours between 2014 and 2015 in East Germany, particularly around the minijob threshold of €450.

In contrast to the former paper, which made use of data from the German Microcensus, Pusch and Rehm (2017) used German PASS data to conduct DiD estimations. Their results suggest a negative effect on actual working hours among workers with wages below €8.50 in 2014, with part of the effect resulting from a reduction in overtime work. Descriptive analyses based on SOEP data show that while hourly wages increased disproportionately at the bottom of the wage distribution after the introduction of the minimum wage, monthly earnings remained largely stable (Grabka/Schröder 2018). The authors argue that this is due to reduced working hours. Bossler and Gerner (2019) analyze firm level data and find that contracted working hours fall in affected firms after the introduction of the minimum wage. This effect, however, is temporarily restricted to 2015.

1 A commonly used indicator for describing the level of the minimum wage on a specific labor market is the Kaitz Index. It is represented by the ratio of the minimum wage to the average wage.

Yet, the results rely on firm data only. Heterogeneity within firms thus cannot be analyzed and the employee's perspective is missing.

The international literature on the effect of minimum wages on working hours is relatively sparse. One important exception is the study by Michl (2000), whose results suggest that the absence of employment effects in Card and Krueger's (1994) study on data from New Jersey was due to changes in working hours by workers who were still employed after an increase in the minimum wage. In a study on Great Britain, Stewart and Swaffield (2008) report that the general minimum wage did not reduce the number of employed people but did reduce the working hours of low-skilled workers. Findings by Connolly and Gregory (2002) based on a variety of DiD estimates, in contrast, show that working hours of women in full-time and part-time work did not change after introduction of the minimum wage in Great Britain. Similar findings are reported by Zavodny (2000) and Couch and Wittenburg (2001) for teens in the USA: An increase in the minimum wage was followed by a decline in employment rates but no change in working hours. Finally, McGuinness and Redmond (2018) find that the increase in the minimum wage in Ireland had a negative and statistically significant effect on the working hours of minimum wage workers. This was primarily driven by the large effect found for minimum wage workers with temporary contracts, whose working hours decreased by approximately 3.5 hours per week.

3 Methodology

In this study, we use various specifications of a difference-in-differences (DiD) approach. The aim of this microeconometric method is to compare changes in one outcome variable before and after the introduction of a (policy) measure in a group that was affected by the measure (the treatment group) with changes in the same outcome variable in a control group that was not affected. The possibilities to empirically analyze the effects of the statutory minimum wage are limited because the minimum wage was introduced across the board in a single step, with only a few transitional regulations and exemptions. This makes it more difficult to distinguish the control from the treatment group.

For this reason, we base our definition of control and treatment groups on the approach taken by Stewart and Swaffield (2008) using individual gross hourly wages. We compare individuals who should have received a raise in hourly wages directly after the introduction of the minimum wage (those with gross wages below €8.50 per hour in 2014) with those who were paid just above the minimum wage (between €8.50 and €10 euros per hour in 2014).

The standard DiD model takes the form:

$$\log(hours_{i,t}) = \gamma + \delta_1 D_i + \delta_2 T_{i,2015} + \delta_3 D_i \times T_{i,2015} + \upsilon_{i,t}, \tag{1}$$

where $hours_{i,t}$ is the outcome of interest, namely the working hours of subject i in period t. D_i indicates whether an employee belongs to the control ($D_i = 0$) or to the treatment group ($D_i = 1$) in period t. $T_{i,2015}$ is a dummy which is equal to one if the year is equal to 2015. The regression coefficient pertaining to the interaction of the treatment and period dummy, δ_3 identifies the treatment effect of interest. As the outcome variable is the logarithm of the working hours, the treatment effect must be interpreted as the percentage change in working hours due to the minimum wage introduction. This equation is basically equivalent to the following:

$$Y_{i,t} = \alpha + \beta_2 D_i + \varepsilon_{i,t}, \tag{2}$$

where $Y_{i,t}$ is defined as the change over time in the outcome variable, namely the growth rate of working hours between t and $t+1$: $Y_{i,t} = \log(hours_{t+1}) - \log(hours_t)$. β_2 captures the treatment effect and is equal to δ_3. There is a technical advantage of implementing eq. (2) rather than eq. (1): In eq. (2) it is possible to include the year 2013 and incorporate the placebo test into the main specification (which will be discussed in more detail below). This simplifies the process of conducting the placebo test and keeping an overview especially for the subgroups. In this case it is necessary, to include an interaction term of the treatment and year indicators. The equation extends then to:

$$Y_{i,t} = \alpha + \beta_1 D_{i,t} \times T_{i,2013} + \beta_2 D_{i,t} \times T_{i,2014} + \beta_3 T_{i,2014} + \beta'_4 \boldsymbol{X_{i,t}} + \beta_5\ Change_{i,t} + \varepsilon_{i,t} \tag{3}$$

$D_{i,t}$ indicates whether an employee belongs to the control ($D_{i,t} = 0$) or to the treatment group ($D_{i,t} = 1$) in period t. The time dummies, $T_{i,2013}$ and $T_{i,2014}$, equal one if the year is equal to 2013 or 2014, respectively. Accordingly, β_1 resembles the placebo test in the year 2013 (which will be discussed in more detail below), while β_2 identifies the treatment effect of interest. To increase the comparability between the treatment and control group, additional control variables are included. $\boldsymbol{X_{i,t}}$ is a vector of socio-demographics and job characteristics, e. g. gender, place of residence, part-time employment, or firm size. To control for potential changes in the employment of individual i, vector $Change_{i,t}$ is introduced to the estimation which includes dummy variables indicating whether an employee changed job between t and $t+1$ and whether this change came along with a loss in minimum wage eligibility, a shift in contract type, sector or company size.

With the DiD approach, causal effects are identified based on the assumption that units of investigation in the control and treatment groups would have experienced comparable changes in the outcome variable (common trend assumption) if the minimum wage had not been introduced. The validity of this identifying assumption is generally tested by comparing the development of the outcome variable in both groups before the introduction of the policy of interest. If common trends existed before the introduction of the minimum wage, one can assume that the outcomes in both groups would have continued to follow the same trajectory without the introduction of the minimum wage. In order to create such a common trend, one may have to include additional observable characteristics that vary over time and may affect the outcome variable (conditional DiD estimator). A multiple regression model makes it possible to relax the common trend assumption such that a common trend only has to apply conditional on a number of control variables. Although this assumption cannot be tested conclusively, a period of time prior to introduction of the minimum wage can be used to falsify the assumption. These "placebo" tests are also presented as part of the analysis below.

Furthermore, possible distortions in the estimator must be taken into consideration when implementing the DiD approach. First, the treatment group may have been able to foresee the introduction of the measure, meaning that they changed their behavior prior to the measure's introduction (anticipation effects), which would affect the before-after comparison between the treatment and control groups. Second, one has to ensure that the implementation of the measure did not affect the outcome variable for the control group in any way (spillover effects). The introduction of a minimum wage could, for instance, have changed the wages of workers who already earned (slightly) over €8.50 per hour before the introduction of the minimum wage if the minimum wage affected the entire wage structure of enterprises (Aretz et al. 2013) or even the economy as a whole (Autor et al. 2016). To ensure reliability of the causal analysis, such spillover effects need to be ruled out. In chapter 5.3.2 we analyze these issues in more detail. Here, we introduce a third wage group with gross hourly wages between €10 and €11.50.

At last, eq. (1) is applied to test the effect of the minimum wage on changes in working hours between t and $t+2$, i. e. from 2014 and 2016. $Y_{i,t}$, $Change_{i,t}$ and $T_{i,t}$ are redefined accordingly such that they correspond with the two periods $t=2012$ and $t=2014$. We choose to estimate the two years model separately from the one-year analysis as it implies the smallest data demands.

4 Data and descriptives

4.1 Database and sample definition

The data used here come from the Socio-Economic Panel (SOEP), Version v33. The SOEP is a panel study of around 15,000 households in Germany who are surveyed annually since 1984 (see Goebel et al. 2019). In the SOEP study, every year the same households and individual household members are asked questions about their labor market participation, hours worked, and monthly labor income. Due to the panel character of the SOEP data, changes in working hours can be analyzed across the entire period of observation. Here, we used data from the surveys conducted from 2012 to 2016.

SOEP respondents' information on contractual weekly working hours and actual hours worked in their main job serve as the key outcome variables in this study. Every year, all employed respondents in a main job are asked to state their contractual weekly working hours without overtime as well as the average number of hours worked, that is, contractual working hours plus any paid and unpaid overtime. Like contractual working hours, overtime work is subject to the minimum wage regulations and, thus, has to be either paid or compensated by time off. Both concepts of working hours are relevant to the analysis here, as changes may have occurred in both contractual working hours as well as overtime work and overtime wages following the introduction of a minimum wage. It should be noted, however, that overtime pay is not always reported precisely in the SOEP. In the following, we, therefore, do not distinguish between paid and unpaid overtime.[2]

In addition to identifying employees' working hours, it is also of central importance to our analysis to identify those individuals who were entitled to higher hourly wages under the statutory minimum wage. To determine hourly wages, we extrapolate stated contractual working hours and the average number of weeks in a month (4.33) to find monthly working hours. The quotient of gross monthly wages and monthly working hours represents contractual gross hourly wages. We do not make use of actual hours worked, because they are surveyed over indeterminate (varying) periods of time and the question of whether overtime is paid cannot be clearly answered in all cases. The use of contractual

2 A more differentiated analysis of the potential effects on overtime would make a major contribution to better understanding the effects of the minimum wage reform on the working conditions of employed people. Here, however, our database has limitations: the SOEP contains only qualitative information on whether a respondent is able to take time off for overtime over longer periods of time (for instance, by keeping track of overtime on timesheets).

working hours is, therefore, less sensitive to measurement error, although it represents the upper bound of individual wages.

Second or side jobs, or marginal employment by people who are registered as unemployed[3] are not taken into consideration here. We do have information on this available, but it is only comparable to a limited degree with our information on main jobs.[4] Bonus pay such as vacation pay, bonus month pay, or profit-sharing may be taken into consideration according to the minimum wage regulation,[5] but as the SOEP survey is conducted mainly in the first half of the year, many employees still do not have this information at hand at the time of the survey. Since employees who receive bonuses tend to be in the upper wage segment, this limitation is expected not to be central to the analysis below.[6]

When interpreting the results presented in the following, it should be kept in mind that the SOEP data are survey data. This means that respondents' answers may contain measurement inaccuracies. This is true both for actual hours worked and for wages. According to Bound et al. (2001), who summarized the results of several studies, survey respondents tend to overestimate their working hours. Respondents' answers about contractual working hours are presumably less error-prone, as this information is usually stated explicitly in their employment contract and on their monthly pay slips.

Respondents can also decline to answer certain questions (item nonresponse). In the SOEP study, gaps in key variables such as wages are filled in for all respondents using statistical imputation procedures. As the procedures used are subject to various assumptions, however, we do not use imputed values in the analyses presented here.

There are further aspects that should be kept in mind when interpreting the results. These are due to the differing temporal horizons of some questions and the respective answers. The SOEP questionnaire asks respondents to state their earnings in the previous month but asks for contractual working hours in the

3 According to the Federal Employment Agency, individuals who are registered unemployed are considered to be seeking employment if they do not work more than three hours per week.

4 With regard to side jobs, the SOEP questionnaire contains a question on how many hours per week respondents spend on that job, but this does not make it possible to distinguish between contractual working hours and actual hours worked. Furthermore, in the SOEP it is not possible to distinguish between dependent employment and self-employment in side jobs.

5 See, e. g. BAG decision of May 25, 2016, AZ. 5 AZR 135/16.

6 As an example, according to the SOEP, only 10 percent of all employed people in the lowest decile of the hourly wage distribution earned a thirteenth or fourteenth month, Christmas, vacation, or other bonus in 2014 or 2015. Only in the second decile of the hourly wage distribution do more employed people (45 percent) report receiving such bonuses.

current month. If a respondent started a new job with a different number of working hours and/or pay in the middle of the month in which they were surveyed, this could result in over- or underestimation of hourly wages.

Measurement error may lead to some individuals being assigned to the wrong wage segments—for instance, employees with hourly wages above or below the minimum wage.[7] To minimize the effect of outliers on the results, we recoded outliers in the hourly wage distribution to lie within the outermost percentiles of the entire wage distribution.[8] This means that hourly wages below (above) the first (last) percentile were recoded to the first (ninety-ninth) percentile.

It should also be noted that the classification of employed people into sectors and occupations is based on self-reported data. One, therefore, cannot rule out the possibility that respondents may have simplified their sector or occupation or provided information that was too vague to precisely identify sectors with a sector-specific minimum wage.

Aside from the definitions and measures chosen, measurement errors may be critical for the analysis when they are correlated with the outcome variables or the treatment indicator. If they are not correlated, they may influence the standard error but do not distort the identified treatment effects. In the regression analyses below, we control for these kinds of correlations across a broad spectrum of explanatory variables.

In our analyses, we use *cross-sectional* and *longitudinal samples*. Annual benchmark figures for the population as a whole can be extrapolated using the specific SOEP sample for each year (*cross-sectional sample*). The changes in individual working hours before and after the reform, which are of key interest here, require that individuals in at least two subsequent SOEP waves be observed in employment (*longitudinal sample*). We, therefore, need differently defined samples to produce a complete picture. Table 1 summarizes the size of the populations and the required sample definitions by year. The following section explains the steps and restrictions in detail.

Every year in the SOEP, there are an average of around 16,000 observations of employed people aged 18 and over in a main job. This includes both full-time and part-time workers as well as workers who are not subject to social security contributions, that is, workers in marginal employment and self-employed people. We exclude around 16 percent of these observations from the population

7 A further example of measurement error in survey responses on income is the phenomenon of "heaping," that is, rounding off to large round numbers such as €500 or €1000.

8 This approach is well established in the analysis of income and wage distribution; see Atkinson et al. (1995), Fabig (2000), and OECD (2011), as well as Haupt (2016).

Table 1: Sample size by survey year.

	2012	2013	2014	2015	2016	Total
Employed	**16,155**	**18,199**	**16,066**	**15,822**	**14,895**	**81,137**
Hourly wage not determinable	−3,734	−4,236	−3,392	−3,553	−3,445	−18,360
Ineligible for minimum wage/no minimum wage in the sector	−2,522	−2,904	−2,458	−2,727	−2,447	−13,058
Cross-sectional sample	**9,899**	**11,059**	**10,216**	**9,542**	**9,003**	**49,719**
Not observed in *t* + *1*	−2,315	−2,970	−2,601	−2,292	-/-	−19,181
Lost job in *t* + *1*	−47	−63	−55	−77	-/-	−242
Missing information in *t* or *t* + *1*	−408	−344	−354	−297	-/-	−1,403
Longitudinal sample One-year analysis	**7,129**	**7,682**	**7,206**	**6,876**	-/-	**28,893**
Not observed in *t* + *2*	−1,547	−1,620	−1,352	−6,876	-/-	−11,395
Lost job in *t* + *2*	−30	−25	−38	-/-	-/-	−93
Longitudinal sample Two-year analysis	**5,552**	**6,037**	**5,816**	-/-	-/-	**17,405**

Source: SOEPv33, survey years 2012–2016.
Note: Since the data from wave 2017 were unavailable at the time of writing, there is no information available for waves 2016 /2015 in t + 1/t + 2.

under analysis. These include the groups explicitly named in the Federal Minimum Wage Act that do not fall within its purview: the self-employed, the formerly long-term unemployed, vocational trainees, interns, and individuals below the age of 18. We also exclude all those employees working in sectors with a sector-specific minimum wage.[9] This latter group can be further differentiated depending on whether the sector-specific minimum wage is above or below €8.50 per hour. The Federal Minimum Wage Act stipulated a transitional period up to December 31, 2017, for sectors with a sector-specific minimum wage that was below the statutory minimum wage. Like the aforementioned groups, employees in this group were temporarily ineligible to receive the minimum wage and, thus, did not fall within the scope of the Minimum Wage Act. There are also some sectors with a minimum wage above the statutory minimum wage. For these employees, the statutory minimum wage, therefore, has no direct implications for their hourly wages. In principle, these employees are eligible

9 The identification was done by separating into groups according to the classification of occupations defined and published by the Federal Employment Agency. Employees from sectors such as the following were excluded: waste management, construction, roofing, facility cleaning. Special exemptions for East Germany were also taken into consideration.

to be paid the minimum wage after their sector-specific minimum wage agreements expire, but if future agreements increase their sector-specific minimum wages, this could make it more difficult to identify effects of the statutory minimum wage. For instance, the minimum wage for temporary workers was increased several times over the period under investigation. The resulting wage effects for these employees could then lead to distortions in the causal analysis. As this group falls within the scope of the statutory minimum wage legally, but not effectively, they are excluded from the analysis below. We, therefore, observe only employed people who were eligible to receive the minimum wage without any overriding sector-specific minimum wage agreements. Of the remaining observations, missing information on monthly income or working hours exclude an additional approximately 3,600 observations per year from the analysis.[10]

Longitudinal sample for one-year analysis: For the one-year analysis, with t as the reference year, we use individual information from the subsequent observation wave $(t+1)$. This allows us to identify *individual* changes in working hours, dependent on information about a person in period t. In defining the relevant longitudinal population, however, we can only consider those who took part in at least two subsequent SOEP surveys and provided all of the information required to determine hourly wages and eligibility for the minimum wage.

Labor market transitions: Some employees showed a change of labor market status and, thus, no longer fell within the scope of the Minimum Wage Act. Even though they provided all the information in $t+1$, they, therefore, had to be observed separately. Here we can distinguish two types of transitions. The first are those from one job that was covered by the minimum wage law in t to a job that was not covered by the law in $t+1$. This may have been the case, for instance, for transitions to self-employment or job changes to a sector that is exempt from the law. Since job changes like these may be a direct consequence of the introduction of the minimum wage, these transitions are taken into account into the analysis below, and the longitudinal population includes individuals in this category. The second relevant transition is job loss. Although previous research findings do not suggest that employment was cut back significantly (e. g. Bossler and Gerner 2019), it still cannot be ruled out that employees in the sample with hourly wages lower than €8.50 per hour rather than increased wages lost their jobs and, therefore, reduced their working hours

10 Those not eligible for the minimum wage can be grouped into the following categories: vocational trainees, the self-employed, employees in sectors with sector-specific minimum wages (below or above €8.50 per hour), the long-term unemployed, the working unemployed, and the non-employed.

to zero. These transitions are, by definition, not part of the “intensive margin” but can lead to distortions in the estimators. In all of the regression-based analyses, individuals with a job loss in $t+1$ are excluded.

Only the status at the specific point in time of the interview was decisive in the analysis. Job loss and labor market re-entry as well as changes in working hours over the course of the year between surveys t and $t+1$ were not taken into consideration.

Selection effects and missing socio-demographic information: Panel survey drop-outs may be subject to selection processes. Singles, migrants, the unemployed, and people with a change of job have a higher probability of dropping out of surveys (Kroh et al. 2017). To minimize possible distortions in the results due to systematic drop-outs that are dependent on observable characteristics, we control for socio-demographic characteristics and labor market information in the analysis. However, we can not consider those respondents who did not provide all of the necessary information. This leads to a further data loss of around 300 observations per year, meaning that in the end, we have around 7,000 observations available for the one-year analysis.

Longitudinal sample for two-year analysis: Along with the annual changes in working hours, it also makes sense to look at changes over two years up to the first half of 2016, as the one-year analysis is only able to measure immediate effects in the first half of the year after the introduction of the minimum wage. We are able to modify the sample defined above such that it was no longer a one-year difference (t to $t+1$) but a two-year difference (t to $t+2$) that was being observed. Building on the one-year sample, individuals must be observed in three subsequent waves of the SOEP (t, $t+1$, and $t+2$). Further data losses occur here due to panel mortality or transitions into self-employment, unemployment, or non-employment. Individuals are allowed to change their employment between t and $t+1$ $(t+2)$, for instance by switching from marginal employment to regular employment. In our causal analysis, we control for changing job characteristics to take into account potential losses of eligibility or changes in the sector, firm size or contract term. Consequently, we do not have a balanced panel sample. In 2014, this leaves us with around 5,800 observations for the two-year analysis.

4.2 Descriptive analysis

In the following, we start by describing the distribution of various socio-demographic groups across three wage segments for the base year 2014 (see Table 2).

Table 2: Percentage of subgroups in the total sample by hourly wages, 2014.

	Wage < €8.50	€8.50 ≤ Wage < €10	Wages ≥ €10	Total
Share in %				
Female	70.5	62.8	45.0	49.1
Male	29.5	37.2	55.0	50.9
East Germany	32.2	29.7	16.5	19.2
West Germany	67.8	70.3	83.5	80.8
Foreigner	16.2	17.3	7.8	9.4
German	83.8	82.7	92.2	90.6
Employed full-time	46.5	63.8	82.0	76.8
Employed part-time	15.6	17.3	15.8	15.9
In marginal employment	37.8	18.9	2.3	7.4
Observations	1,184	811	8,221	10,216

Source: SOEPv33, survey year 2014.
Notes: Calculations made use of individual weighting factors. Sectors with their own sector-specific minimum wage were not included. Calculations based on contractual working hours and the cross-sectional sample.

In total, we observe 1,184 persons in the first wage group (< €8.50 per hour), of whom, for instance, around 71 percent are female and 16 percent are not German citizens. These and other percentage values are similar in the second wage group from €8.50 to €10 per hour (women: 63 percent; foreign citizens: 17 percent). The group of individuals in marginal employment are an exception: 38 percent of individuals earning hourly wages below €8.50 per hour are in marginal employment, whereas in the second wage group only 19 percent are in marginal employment and this share even further decrease to only two percent in the third wage group (€10 per hour or more). Part-time employees (defined in the following as those with fewer than 30 hours per week) make up around 15 to 17 percent of all wage categories.

According to these figures, workers in marginal employment are found much more frequently in the low-wage group than employees who are subject to social security contributions. Furthermore, this group is subject to special rules regarding social security contributions on the employee side: those with income up to 450 euros per month are almost completely exempt. Thus, gross wages are here equivalent to net wages, with the exception of voluntary pension contributions. Due to their low number of working hours, marginal employment is often reported by parents as extra income (Bachmann et al. 2017). It is likely that the minimum wage has specific effects on marginally employed workers. After all, in contrast to employees who are subject to social security contributions, marginally employed workers have a direct incentive to limit their working hours in order to prevent their earnings from crossing the €450 threshold. As a result, we consider workers in marginal employment and employees subject to social security contributions separately in the following (Table 3).

Table 3: Hourly wages by wage segment and employment status.

	Wage < €8.50	€8.50 ≤ Wage < €10	Wage ≥ €10	Total
Employees subject to social security contributions				
Gross monthly income in euros	1,030.61	1,399.29	3,162.03	2,889.72
	(367.09)	(356.76)	(1.504.28)	(1.558.43)
Weekly working hours				
Contractual	33.83	34.91	35.77	35.57
	(10.18)	(8.68)	(7.44)	(7.78)
Actual	35.66	37.44	39.43	39.03
	(11.51)	(9.74)	(9.34)	(9.60)
Hourly wages in euros				
Contractual	7.10	9.24	20.31	18.61
	(1.10)	(0.42)	(8.47)	(8.94)
Observations	728	639	8,020	9,387
Workers in marginal employment				
Gross monthly income in euros	355.42	357.47	383.05	362.78
	(92.78)	(89.36)	(85.15)	(90.91)
Weekly working hours				
Contractual	13.46	8.90	7.00	10.94
	(4.68)	(2.82)	(2.49)	(4.84)
Actual	13.71	9.47	7.99	11.44
	(4.89)	(3.52)	(3.38)	(5.01)
Hourly wages in euros				
Contractual	6.27	9.08	13.69	8.69
	(1.20)	(0.39)	(5.63)	(4.29)
Observations	456	172	201	829

Source: SOEPv33, survey year 2014.
Notes: Standard deviations in parentheses. Sectors with a sector-specific minimum wage were not included. Calculations are based on the cross-sectional sample using individual weighting factors.

The average gross monthly wages of the three wage groups differ significantly, as expected. Employees subject to social security contributions with hourly wages below €8.50 earned average gross monthly wages of €1,030 in

2014. In the middle and upper wage groups, they earned close to €1,400 and €3,160, respectively. However, not only their monthly wages but also their working hours differed. In the group of employees subject to social security contributions, average contractual weekly working hours were around 33.8 in the first wage group and around 35 hours in the second and third wage groups. Average contractual hourly wages were around €18.60 overall, but varied widely from almost €7.10 in the lowest and around €20.30 in the highest wage group.

Within the lowest wage group hourly wages changed substantially between 2014 and the following years. As discussed in more detail in Burauel et al. (2019), the increase in contractual hourly wages was more pronounced for the treatment group than for the control group. Nevertheless, the change was below the necessary increase to imply full compliance.

Among workers in marginal employment, the picture is somewhat different: average gross monthly wages were around €360 and varied little across the three wage groups. However, individuals who earned below €8.50 per hour with an average of around 13.5 hours per week worked more than marginally employed workers in the second and third wage groups (around 8.9 and 7 hours, respectively). Here, too, hourly wages varied relatively widely between €6.30 and €13.70 across the groups.[11]

5 Causal analysis

Based on the findings reported above of differences between employees subject to social security contributions and workers in marginal employment, we study these groups separately in the following causal analysis.

11 In interpreting the results, it should be borne in mind that the observation numbers are low, especially in the higher wage groups. If additional data are required in t + 1 or t + 2, the sample size decreases further. The results of the subsequent causal analysis, therefore, refer to the working sample included, potentially challenging the generalizability of the findings. To control for potential selection effects due to individuals who lost jobs, individual probabilities of remaining employed were estimated using a DiD approach (see Bonin et al. 2018, p. 90f). Here we found that individuals with wages below €8.50 showed a significantly lower probability in general of being observed in employment one or two years later, but their probability of being employed did not change after the introduction of the minimum wage.

5.1 Effects on employees subject to social security contributions

For a cohesive illustration, we present the DiD approach following eq. (2) in simplified form in Table 4. Here, we show the change in weekly working hours and the relative growth rate in the one-year sample, separating treatment and control groups.

Table 4: Average change in weekly working hours between 2014 and 2015 in treatment and control groups, employees subject to social security contributions only.

	Change in contractual working hours			Change in actual working hours		
	Observations	**Abs. (in h/week)**	**Logarithm. (*100)**	**Observations**	**Abs. (in h/week)**	**Logarithm. (*100)**
Wage < €8.50	437	−1.55	−5.70	429	−0.93	−3.47
		(7.38)	(26.19)		(8.10)	(27.14)
€8.50 ≤ Wage < €10	435	−0.34	−1.21	432	−0.34	−1.26
		(4.60)	(15.81)		(6.32)	(18.32)
Difference		−1.21***	−4.48***		−0.59	−2.20

Source: SOEPv33, survey years 2014–2015.
Notes: Standard deviations in parentheses. The differences presented in the last row are tested for their difference from zero, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ represent the resulting significance level. No weighting factors are used. Contractual working hours were used for the assignment to groups. Absolute values are given. Calculations are based on the longitudinal sample. Not all employed people reported their actual hours worked in addition to their contractual working hours. The observations, therefore, were reduced by a few cases if actual hours worked were examined as the dependent variable.

In the treatment group, the number of weekly working hours declined by an average of 1.6 hours per week between 2014 and 2015 and, thus, more than in the control group (around 0.3 hours per week). Based on the assumption that this development would have occurred in the control group even without the minimum wage reform, the minimum wage reduced contractual working hours by the difference between the two averages, that is, by 1.2 hours per week. This effect is statistically significant.

Effects on working hours may, however, be dependent on the level of the outcome variable at the time of the minimum wage introduction. Slight changes in working hours might be enough for marginally employed workers to adapt to the minimum wage, for instance, whereas more substantial changes might occur among full-time employees. To control for these kinds of non-linear relationships, we can look not just at the absolute change in working hours but also at the logarithmic change ($\ln(h_{it+1}/h_{it}) \times 100$). The corresponding difference between treatment and control group then yields the percentage change of hours worked due to the minimum wage introduction. Here, the data show that contractual working hours fell overall by around 4.5 percent due to the minimum wage. For actual working hours, the results show an absolute and relative difference between the treatment and the control group, but this is not statistically significant.

This mean value analysis assumes that treatment and control groups do not differ with the exception of their respective wages. In order to measure the actual effect of the minimum wage as precisely as possible, we take the following variables into consideration in the regressions below: age, gender, marital status, nationality (German/foreign), occupational qualification, number of children in the household (below the age of 16), and place of residence. Job characteristics include information on part-time employment,[12] contract term, company size in terms of number of employees, and sector. Finally, we take into account information on job changes, including changes in minimum wage eligibility, changes in contract limit, company size, and sector. Through the inclusion of the previous year (2013) we are also able to test to what extent the common trend assumption is fulfilled, that is, whether working hours experienced similar developments in the treatment and control group prior to the minimum wage introduction. As the model takes several years into account, we add a last control vector that captures general time trends using a year dummy for 2014.

Table 5 presents the results of the regression analysis with all of the control variables for contractual working hours of employees subject to social security contributions who have been eligible to receive the minimum wage. In order to control for non-linear relationships, we use the logarithmic change in working hours from t to $t+1$ instead of the absolute change. Thus, as mentioned in Section 3, coefficients have to be interpreted as percent changes of hours worked. In the first column, we give the result of the base estimation, which contains only

12 Controlling for part-time employment may be a `bad control' as the dummy is partially related with our outcome variable. We include the dummy despite these concerns due to the substantial differences between full- and part-time workers (e. g. preferences, time contraints, and multiple employment). These differences are likely to results in a heterogeneous probability to change employment and working hours which would affect our treatment effect. Yet, column (2) and (3) in Table 5 indicate that the impact of the part-time dummy has only minor consequences on our estimation.

Table 5: DiD regressions for employees subject to social security contributions: effect of minimum wage on the increase in working hours, one-year analysis.

	Contractual working hours				Actual working hours	
	(1)	(2)	(3)	(4)	(5)	(6)
DiD 2014–2015	−4.49***	−4.58***	−5.05***	−5.12***	−2.21	−2.53
	(1.46)	(1.47)	(1.45)	(1.44)	(1.58)	(1.55)
DiD 2013–2014	−1.37	−1.50	−1.48	−1.55	0.49	0.55
	(1.31)	(1.34)	(1.35)	(1.34)	(1.51)	(1.53)
year 2014	0.96	0.93	1.03	0.69	1.95	1.41
	(1.17)	(1.18)	(1.17)	(1.21)	(1.41)	(1.44)
Socio-demographics:						
Age (in years)		0.01	−0.03	−0.03		−0.03
		(0.05)	(0.05)	(0.05)		(0.06)
Female		−0.06	−1.69	−1.83*		−3.05***
		(0.93)	(1.07)	(1.08)		(1.12)
Married		−1.42	−1.77	−1.84*		−1.38
		(1.09)	(1.09)	(1.09)		(1.14)
Child in household		0.89	−0.02	0.03		0.49
		(0.99)	(0.98)	(0.98)		(1.07)
East Germany		1.69	2.93***	2.73**		1.60
		(1.04)	(1.07)	(1.07)		(1.15)
Not German citizen		−0.40	0.38	0.63		−0.54
		(1.63)	(1.62)	(1.62)		(1.82)
Level of education:						
Vocational training		0.95	1.22	1.25		1.48
		(1.36)	(1.35)	(1.35)		(1.61)
University education		0.34	0.67	0.25		1.21
		(2.30)	(2.28)	(2.29)		(2.39)
Job characteristics:						
Part-time			8.60***	8.68***		6.43***
			(1.55)	(1.54)		(1.66)
Limited-term contract			−1.02	0.40		2.49
			(1.49)	(1.81)		(1.95)
Company size:						
Fewer than 20 employees			0.63	0.64		1.03
			(1.22)	(1.22)		(1.37)
More than 200 employees			1.69	1.71		2.82**
			(1.26)	(1.27)		(1.41)
Sector:						
Primary sector			1.30	0.77		1.43
			(1.76)	(1.83)		(2.40)
Sales, transport, logistics			−1.39	−0.99		−0.16
			(1.09)	(1.13)		(1.38)

(*continued*)

Table 5: (*continued*)

	Contractual working hours				Actual working hours	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Service sector			−2.26	−2.23		−0.45
			(1.69)	(1.69)		(1.77)
Public administration			−2.04	−1.82		−0.00
			(1.59)	(1.63)		(1.79)
Other			−0.19	−0.34		1.31
			(2.74)	(2.79)		(2.65)
Change in						
Eligibility				−1.76		−3.15
				(2.30)		(2.47)
Job				0.25		0.46
				(1.48)		(1.64)
Contract term				−3.84*		−4.77**
				(2.03)		(2.32)
Company size				−2.33**		−2.61**
				(1.02)		(1.10)
Sector				1.60		2.41
				(1.76)		(1.95)
Constant	−2.18**	−3.20	−2.36	0.60	−3.21***	0.24
	(0.88)	(2.44)	(2.62)	(3.27)	(1.10)	(3.67)
Observations	1,848	1,848	1,848	1,848	1,827	1,827
Adj. R2	0.004	0.004	0.027	0.031	−0.000	0.016

Source: SOEPv33, survey years 2013–2015.
Notes: Robust standard errors in parentheses, clustered at the individual level with * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. No weighting factors are used. The reference group in specifications (4) and (6) is male, married, and has no children below the age of 16 in the household, works full-time with a permanent contract in a medium-sized company in the manufacturing sector, graduated from an intermediate secondary school, has German citizenship, lives in the federal states of the former East Germany, and did not report a change of job. All coefficients are given in %. To determine hourly wages, we used contractual working hours. Calculations based on the longitudinal sample. The reference year in all specifications is 2013.

the interaction terms and year indicators. Columns (2) to (4) successively add the following control variables: socio-demographic variables, job characteristics, and job changes. The control variables for gender, place of residence, part-time work, and indicators for changes in contract term and company size have a significant effect on working hours but are of less interest here as our focus is on identifying the causal effect of the minimum wage reform.

The first line shows the causal effect of the minimum wage reform on average contractual working hours of employees who are subject to social security contributions and are eligible for the minimum wage according to the minimum wage law (see the coefficients from “DiD 2014–2015”). Contractual working hours in the treatment group have decreased by an average of 4.5 percent relative to the control group since the introduction of the minimum wage. This effect is statistically significant at the 1 percent level. The inclusion of sociodemographic control variables changes the effect negligibly (column (2)). Adding job characteristics in column (3) also causes only marginal changes in the strength of the effects and significance levels. The effect, thus, varies little with possible selection controls. The same is true when controlling for various changes in employment in column (4). The effect resulting from the most extensive specification in column (4) of just below 5.1 percent corresponds to a 1.7 hours reduction in average weekly working hours ($33.8\,\frac{hours}{week} \star -5.1\% = -1.72\,\frac{hours}{week}$).

The results of the regression analysis for actual hours worked are found in columns (5) and (6) in Table 5. Column (5) relates to the basis specification without control variables, whereas in column (6) all control variables were included. Here, as before, a negative effect is found, which (similarly to the previous specifications) becomes slightly stronger through the inclusion of control variables. However, at –2.5 percent, the effect is weaker than with contractual working hours and slightly below the 10 % significance level ($p = 0.103$). The results, thus, suggest that actual hours worked have decreased less sharply than contractual working hours. But, using the change in the difference between actual and contractual hours as dependent variable of our model does not reveal diverging trends between both time concepts (see Bonin et al. 2018: 107ff). From this perspective, overtime has, thus, not changed due to the minimum wage. The different result may result from a higher variance in actual hours.

The second line presents the test of the common trend assumption (see the coefficients in “DiD 2013–2014”). The placebo test is negative in all specifications but insignificant, which suggests that developments did not differ among the groups prior to the introduction of the minimum wage. From this perspective, we find no evidence that would contradict the common trend assumption.

In the Appendix, Table 10 presents the estimation for various subsamples. While some groups have small sample sizes, which plausibly sometimes yields insignificant treatment effects, the subgroup analysis makes clear that the reduction in working hours was the strongest in groups with lower wages on average, i. e. those with low or no training, women and migrants. Furthermore, including in the analysis only those individuals who truly experienced a wage increase, shows a stronger adaptation in hours. Table 10 also raises some concerns regarding the common trend assumption. For men as well as young people (18–24 years) the subgroup analysis indicates that those earning less than

€8.50 in 2013 differ significantly from the control group with respect to their hours' volatility already prior to the reform. Male and young low-wage employed seem to differ structurally from the control group before the minimum wage was introduced. The common trend assumption does, thus, not hold for every subgroup, not allowing to interpret the results in these groups as causal.

To study possible changes in the second half of 2015 and the first half of 2016, we also analyze the two-year effects from 2014 to 2016. As in the previous estimates, the period of time prior to the introduction of the minimum wage (2012 to 2014) can be used for a placebo test. Table 6 presents the

Table 6: DiD regressions for employees subject to social security contributions – minimum wage effect on working hours increases – two-year analyses.

	Contractual working hours		Actual hours worked	
	(1)	(2)	(3)	(4)
One-year difference				
DiD 2014–2015	−3.75**		−1.47	
	(1.56)		(1.68)	
DiD 2013–2014	−0.01		1.06	
	(1.35)		(1.72)	
Two-year difference				
DiD 2014–2016		−1.54		−1.27
		(1.87)		(2.04)
DiD 2012–2014		−7.99*		−2.80
		(4.50)		(2.01)
Constant	−1.86	−1.54	−3.91	−8.72*
	(3.33)	(1.87)	(4.17)	(4.69)
Control variables				
Year dummy for 2014	yes	yes	yes	yes
Socio-demog. information	yes	yes	yes	yes
Job characteristics	yes	yes	yes	yes
Change of job	yes	yes	yes	yes
Observations	1,364	1,288	1,349	1,271
Adj. R2	0.027	0.041	0.011	0.033

Source: SOEPv33, survey years 2012–2016.
Notes: Robust standard errors in parentheses, clustered at the individual level with * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. No weighting factors are used. The reference group is male, married and has no children below the age of 16 in the household, works full-time with a permanent contract in a medium-sized company in the manufacturing sector, graduated from an intermediate secondary school, has German citizenship, lives in the federal states of the former East Germany, and did not report a change of job. All coefficients are given in %. To determine hourly wages, we used contractual working hours. Calculations based on the longitudinal sample. The reference year in Column (1) and (3) is 2013; in Column (2) and (4) it is 2012.

results. In this case, the dependent variable is defined as the relative change in working hours between t and $t+2$.

The two-year analysis requires that respondents be observed in three successive years, which reduces and changes the sample. Thus, in column (1) in Table 6, the one-year estimate was replicated with the two-year sample using all of the control variables. The effect is around − 3.8 percent and is significant at the 5 percent level and similar in qualitative terms to the results in Table 5 (column (4)). Thus, there does not seem to be a systematic difference in the results between the two-year and one-year samples.

In column (2), we estimate the effect from 2014 to 2016. This effect is approximately − 2.5 percent and is statistically insignificant. This suggests that the introduction of the minimum wage reduced contractual working hours in 2015 but did not continue to do so in 2016. Results are, thus, in line with the firm level evidence from Bossler and Gerner (2019). The low effect size in 2016 relative to 2015 and the insignificance of the 2016 coefficients may have occurred, however, for non-economic, “technical” reasons, including the fact that working hours probably vary more widely at the individual level over two years than over one year, and that the two-year analysis contains fewer observations. In addition, the placebo test from the previous period (2012–2014) indicates that the common trend assumption does not hold in this specification, i. e. employees with wages below €8.50 per hour have a different trend in their working hours than the employed above the considered threshold.

The analysis can also be repeated for actual working hours. In column (3) we replicate the one-year estimation from Table 5. The estimator for the treatment effect between 2014 and 2015 remains insignificant. The same is true for the effect from 2014 to 2016 in column (4). This suggest that there was no significant change in actual hours worked either in 2015 or in 2016 due to the introduction of the minimum wage, although the “technical” effects should be kept in mind.

5.2 Effects on marginally employed workers

The estimates presented above are repeated for workers in marginal employment (Table 7). The results should, however, be treated very cautiously because of the very low numbers in the control group (N = 66 in the longitudinal sample). We again use the change from 2013 to 2014 as a placebo test.

We first look at the change in contractual and actual working hours from 2014 to 2015. As was the case with employees who are subject to social security contributions, the treatment effect (see the coefficient in “DiD 2014–2015”) is

Table 7: DiD regressions for workers in marginal employment – minimum wage effect on the increase in working hours – one-year analysis.

	Contractual Working Hours				Actual Hours Worked	
	(1)	(2)	(3)	(4)	(5)	(6)
DiD 2014–2015	−6.61	−7.68	−8.65	−11.10*	−2.54	−6.78
	(5.63)	(5.49)	(5.88)	(5.81)	(6.02)	(6.30)
DiD 2013–2014	−4.20	−6.02	−6.66	−6.07	−3.09	−4.44
	(6.25)	(6.02)	(5.87)	(5.86)	(6.93)	(6.66)
Constant	8.87	79.72***	78.20***	72.63***	8.76	65.25***
	(5.52)	(15.61)	(16.33)	(16.26)	(6.15)	(17.85)
Control variables						
Year dummy for 2014	yes	yes	yes	yes	yes	yes
Sociodemographic information		yes	yes	yes		yes
Job characteristics			yes	yes		yes
Change of job				yes		yes
Observations	530	530	530	530	529	529
Adj. R^2	−0.002	0.064	0.073	0.111	−0.005	0.092

Source: SOEPv33, Survey years 2013–2015.
Notes: Robust standard errors in parentheses, clustered at the individual level with * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. No weighting factors are here. The reference group in columns (4) and (6) is male, married and has no children below the age of 16 in the household, works full-time with a permanent contract in a medium-sized company in the manufacturing sector, graduated from an intermediate secondary school, has German citizenship, lives in the federal states of the former East Germany, and did not report a change of job. All coefficients are given in %. To determine hourly wages, we used contractual working hours. Calculations based on the longitudinal sample. The reference year in all specifications is 2013.

negative, but here it is insignificant—potentially due to the relatively low numbers of observation. With our additional control for change of job chracteristics in column (4), we identify a weakly significant treatment effect of –11.1 percent, but only for contractual working hours.

The treatment effects vary considerably in quantitative terms across the different specifications, which suggest strong selection within this group. The more precisely this selection is taken into account in the estimations using control variables, the more precisely the originary effect of the minimum wage can be identified. Ultimately, the findings also suggest that many workers in marginal employment have reduced their contractual working hours with the introduction of the minimum wage, probably in order to stay below the €450 threshold. However, the association is weak, the case numbers are small, and there is no evidence of a significant effect in actual working hours (see also Table 11 in the Appendix for the two-year analysis).

5.3 Robustness analyses

In the following section, we test the robustness of the effects on working hours described above against two factors. First, our information on working hours and monthly income, which we use as the outcome variable and treatment identifier, may be subject to measurement error. Second, the DiD approach used here requires us to assume that the control group—individuals with wages between €8.50 and €10 per hour—were not influenced by the minimum wage, and, thus, that no spillover effects occurred. We address both of these critical points for our analysis below to assess their impact on the explanatory power of the results above.

5.3.1 Robustness against measurement error

If the working hours and monthly wages reported in SOEP are subject to measurement error, it is possible that individuals have been grouped into the wrong wage segments. If the errors in grouping are systematic, the measured effects of the minimum wage would also be distorted. Table 8, therefore, presents three robustness tests each for the one- and two-year analyses (Panel A and B) and for contractual and actual working hours (columns (1) to (3) and (4) to (6)). The tests are only for employees subject to social security contributions. The specifications presented use all of the control variables defined above.

Exclusion of interval around the minimum wage: Since the treatment group is a binary variable, measurement errors are relevant when persons are assigned a false treatment status as a result. The probability of this is largest for those who are paid close to the minimum wage threshold. For this reason, we exclude individuals from the analysis in columns (1) and (4) whose wages were close to the minimum wage threshold. Concretely, we create an interval around the minimum wage of (€8.50 ± 5.0% *€8.50) and exclude Individuals who lay within this band (€8.075 to €8.925) from the analysis.

The effects are somewhat stronger after excluding these employees than in the base estimations for the one-year analysis (Panel A). This was to be expected, as the persons excluded here from the treatment group would have had the lowest wage increases in order to exceed the critical value of €8.50, meaning that their wage costs changed the least and, thus, working hours

Table 8: DiD regressions for employees subject to social security contributions – robustness test.

	Contractual working hours			Actual hours worked		
	(1)	(2)	(3)	(4)	(5)	(6)
	5 % interval	Wage > €5	Hours > 20	5 % interval	Wage > €5	Hours > 20
Panel A: One-Year Analysis						
DiD 2014–2015	−6.27***	−4.51***	−5.17***	−3.81**	−2.23	−3.00**
	(1.71)	(1.44)	(1.35)	(1.79)	(1.57)	(1.52)
DiD 2013–2014	−1.19	−1.62	−1.84	0.62	0.36	0.85
	(1.65)	(1.38)	(1.30)	(1.85)	(1.56)	(1.47)
Constant	1.46	−1.30	0.07	0.82	−2.09	−3.61
	(3.89)	(3.65)	(3.37)	(4.18)	(4.06)	(3.77)
All control variables	yes	yes	yes	yes	yes	yes
Observations	1,392	1,770	1,734	1,375	1,751	1,738
Adj. R^2	0.031	0.031	0.027	0.026	0.017	0.015
Panel B: Two-Year Analysis						
DiD 2014–2016	−5.05**	−1.60	−4.17**	−4.07*	−1.11	−2.92
	(2.33)	(1.90)	(1.95)	(2.41)	(2.05)	(2.06)
DiD 2012–2014	−3.84*	−1.69	−1.63	−4.93**	−2.93	−2.63
	(2.25)	(1.84)	(1.83)	(2.48)	(1.99)	(1.96)
Constant	−5.95	−7.47	−6.04	−8.07	−7.71	−6.69
	(5.24)	(471)	(4.77)	(5.33)	(4.92)	(4.99)
All control variables	yes	yes	yes	yes	yes	yes
Observations	969	1,238	1,221	956	1,222	1,219
Adj. R^2	0.044	0.039	0.026	0.025	0.034	0.016

Source: SOEPv33, Survey years 2012–2016.
Notes: Robust standard errors in parentheses, clustered at the individual level with * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. No weighting factors are used. The reference group in columns (4) and (6) is male, married and has no children below the age of 16 in the household, works full-time with a permanent contract in a medium-sized company in the manufacturing sector, graduated from an intermediate secondary school, has German citizenship, lives in the federal states of the former East Germany, and did not report a change of job. The reference year in Panel A is 2013, in Panel B it is 2012. All coefficients are given in %. To determine hourly wages, we used contractual working hours. Calculations based on the longitudinal sample.

adjustments must have remained low. For the two-year analysis (Panel B), the treatment effect is twice as high as in the base analysis and highly significant. One can assume that measurement errors plays a role in the base scenario in the two-year analyses as described above and, thus, no clear causal effect can be identified. Additionally, the placebo test indicates a violation of the common trend assumption. Similar to Table 6, indviduals earning less than €8.50 do, thus, structurally differ from those earning more than €8.50.

Exclusion of low hourly wages: Due to the different reporting times in the data used, measurement inaccuracies may also result in very low hourly wages. To test whether very low hourly wages drove the estimation results, we exclude individuals who report hourly wages of less than €5 in columns (2) and (5). Again, the results show that the identified treatment effects are relatively robust. Although the coefficients are reduced, this can be attributed to the fact that those who really did have lower wages played the driving role in the effects. The picture is similar for marginally employed workers. Interestingly, the results also show that the common trend assumption is not rejected in general within the two years perspective. Excluding those with very small wages increases the comparability between treatment and control group.

Exclusion of low working hours: Finally, we consider the possibility that working hours information from employees with low working hours may be subject to measurement error. This may be due to the fact that part-time employees can have rather variable working time, meaning that the discrepancy between monthly income and average working hours is higher. As a result, those with fewer than 20 hours per week in t are excluded from the analysis (columns (3) and (6)). Again, the estimations are robust to this restriction. In actual working hours, however, there is an increase in the statistical significance. The imprecisions mentioned above in actual hours worked, thus, appear to occur primarily among employees with low numbers of working hours, thereby ensuring that this outcome variable remains below the level of significance. This suggests that the effects are slightly underestimated.

Overall, we can summarize that the estimations are robust to possible measurement errors. If measurement errors do have an effect, the identified treatment effects appear to skew towards zero. The main results should, thus, be interpreted as a lower bound.

5.3.2 Robustness to spillovers

The causal identification is based on the assumption that the introduction of a statutory minimum wage did not result in an adjustment effect in the selected control group. Specifically, those who earned more than €8.50 in 2014 are not allowed to experience any changes in their working hours in response to the minimum wage. This assumption is countered by the possibility of spillover effects, which have been identified in empirical analyses of data from countries including the USA and Germany (e. g. Neumark et al. 2004; Aretz et al. 2013). Such studies illustrate the concern towards potential spillover effects and raise the question whether the selected control indeed is unaffected by the minimum wage. Hence, an analysis of potential spillover effects is necessary.

With regard to working hours, the sign of spillover effects cannot be determined ex ante. Reductions in hours could also affect employees of companies in higher wage segments by absorbing increasing wage costs in the lower segment. The effects on working hours discussed above would be underestimated in this case, as the control group would not correctly represent the counterfactual scenario. But substitution effects could also have a counter-effect on this if employees were paid according to their marginal productivity. As individuals with wages below €8.50 become more expensive, their work could be substituted for by people who (according to economic theory) are more productive and are, therefore, paid more than €8.50 per hour. In this case as well, the selected control group would misrepresent the counterfactual scenario, which would lead to a general overestimation.

The existing literature strongly suggests that spillover effects occur primarily close to the minimum wage threshold. We, therefore, compare the control group with a second, alternative control group: employees with hourly wages between €10.00 and €11.50, under the assumption that these are as similar as possible to the base control group. If the wage group from €8.50 to €10 was not affected by the minimum wage, we assume that there should be no differences in the change in working hours between the control group and the additional group.

The interpretation of the treatment indicators also remains similar to the previous one in this estimation: DiD coefficients have to be interpreted in relation to the reference group "€8.50 ≤ wage < €10" (Table 9). The second, additional group "€10 ≤ wage < €11.50" now has to be examined in reference to the control group "€8.50 ≤ wage < €10". If there were spillover effects during the period of time in which the minimum wage was introduced, it is likely that we would find a significant deviation in the change in working hours in the newly added group.

When the estimation is expanded to include the group defined above, the results for the treatment group remain de facto unchanged. Between 2014 and 2015, we see a significant effect for contractual working hours. The treatment effect remains insignificant in the two-year analysis. For employees with wages between €10 and €11.50, however, no significant effects could be identified. They report identical changes in working hours over the period under examination to the group with wages between €8.50 and €10 per hour (see the coefficients "Spillover DiD"). This robustness test, thus, does not suggest the existence of significant spillover effects.

Table 9: DiD regressions for employees subject to social security contributions – spillover effects.

	One-Year Analysis		Two-Year Analysis	
	(1)	(2)	(3)	(4)
	Contractual working hours	Actual hours worked	Contractual working hours	Actual hours worked
Group: wage < €8.50				
DiD 2014–2015	−5.10***	−2.46		
	(1.43)	(1.55)		
DiD 2013–2014	−1.65	0.46		
	(1.33)	(1.52)		
DiD 2014–2016			−2.57	−1.09
			(1.94)	(2.04)
DiD 2012–2014			−1.55	−2.69
			(1.84)	(1.97)
Group: €10 ≤ Wage < €11.50				
Spillover DiD 2014–2015	−0.27	0.17		
	(1.06)	(1.26)		
Spillover DiD 2013–2014	1.15	2.07		
	(1.21)	(1.41)		
Spillover DiD 2014–2016			1.09	1.68
			(1.53)	(1.70)
Spillover DiD 2012–2014			2.04	2.88*
			(1.36)	(1.55)
Constant	−1.67	−2.40	−6.62*	−6.87*
	(2.66)	(3.03)	(3.59)	(3.91)
All control variables	yes	yes	yes	yes
Observations	2,762	2,732	1,941	1,919
Adj. R^2	0.029	0.012	0.053	0.041

Source: SOEPv33, survey years 2012–2016.
Notes: Robust standard errors in parentheses, clustered at the individual level with * p < 0.1, ** p < 0.05, *** p < 0.01. No weighting factors are used. The reference group in columns (4) and (6) is male, married and has no children below the age of 16 in the household, works full-time with a permanent contract in a medium-sized company in the manufacturing sector, graduated from an intermediate secondary school, has German citizenship, lives in the federal states of the former East Germany, and did not report a change of job. All coefficients are given in %. To determine hourly wages, we used contractual working hours. Calculations based on the longitudinal sample. The reference year in Column (1) and (2) is 2013; in Column (3) and (4) it is 2012.

6 Conclusion

In this paper, we examine the causal effect of the German minimum wage introduction on the number of hours worked. We, thus, focus on the intensive margin of employment effects, rather than on the number of employed people. The results present a consistent picture: comparing employees subject to social security contributions with hourly wages below €8.50 prior to the reform (treatment group) with employees subject to social security contributions with hourly wages between €8.50 and €10 prior to the reform (control group), we find a significant reduction in contractual working hours in the treatment group relative to the control group of 5 percent on average from 2014 to 2015. These findings are robust across various subgroups of employees who are eligible to be paid the statutory minimum wage.

These findings shows that the potential side effects of a minimum wage are not limited to the extensive margin only. According to calculations by the German Federal Statistical Office (Destatis, 2016), as of April 2014, around 1.8 million full-time and part-time employees who were eligible for the statutory minimum wage under the new minimum wage law were being paid less than €8.50 per hour. As the average contractual working hours for this population, as calculated above, amount to 33.8 hours per week, the effect of a −5.1 percent reduction in aggregated contractual working hours is equivalent to approximately 3.1 million working hours per week. For comparison: 3.1 million working hours per week are worked by 79,000 full-time employees with 39 contractual weekly working hours.

Given the low number of observations on marginally employed, it is not possible to provide a conclusive answer for this particular group. If one examines the difference between actual and contractual working hours, however, the results show that contractual working hours have been reduced more than actual hours worked. This could be an indication that overtime or moonlighting has increased over the course of implementing the new minimum wage. Unfortunately, the corresponding questionnaire of the SOEP changed across the considered waves. Consequentily, it is not possible to look more closely into these issues.

The empricial investigation has some caveats. For specific groups of employed as well as in the two-year analysis until 2016 the common trend assumption is rejected. The applied difference-in-difference approach, hence, does not allow a causal interpretation. Small sample sizes in some subgroups additionally need to be taken into account and call for a cautious interpretation of the effects. Furthermore, selection issues could hamper the identification of significant effects in the mid-run: Changes into unemployment, for instance, cannot be controlled for by the presented model. This is a concern especially for low-wage earners, who are highly volatile in their employment. In addition, potential measurement errors for the self-reported working hours and monthly gross income need to be kept in mind as well, as they could cause a bias of the estimated treatment effects towards zero. Especially in this respect, futher analysis are needed which compare the wage and hours information from the SOEP with data potentially less prone to measurement issues, e. g. administrative data or employer surveys.

In the scope of this paper, we have not been able to identify whether the reduction in working hours has been driven by labor demand or supply. The SOEP provides a question on the preferred working hours (taking the corresponding income changes into account). With this information, it would be possible to analyze the labor supply perspective. However, it is not straightforward how the results of such an analysis are to be interpreted. Consequently, analyzing which labor perspective drives our findings is beyond the scope of our analysis and constitutes an interesting research question for future studies.

Overall, we can conclude that the introduction of the minimum wage had a negative effect on the intensive margin of the employment effects in the short run, namely the number of hours worked on average in 2015. While the results presented here need to be interpreted cautiously with the aforementioned limitations in mind, various robustness tests provide evidence that the identification is robust to several potential sources of error.

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A Appendix

Table 10: DiD regressions – effect of the minimum wage on the increase in contractual working hours by subgroups.

	DiD 2014–2015		DiD 2013–2014		Observations
Total sample	−5,12***	(1.44)	−1.55	(1.34)	1,848
Full-time employees	−5.49***	(1.44)	−2.08	(1.37)	1,401
Part-time employees	−6.27	(4.10)	0.19	(3.73)	447
18 ≤ Age < 25	−1.46	(4.94)	−7.41*	(4.00)	160
25 ≤ Age < 55	−5.46***	(1.66)	−0.59	(1.61)	1,427
55 ≤ Age	−5.59	(3.69)	−4.66	(2.89)	261
No voc. training or univ. education	−6.22*	(3.31)	−4.44	(3.27)	411
Vocational training	−5.48***	(1.64)	−0.69	(1.47)	1,258
University education	1.54	(6.31)	−1.97	(6.63)	179
Living in West Germany	−6.04***	(2.19)	−2.64	(1.91)	1,083
Living in East Germany	−4.13***	(1.54)	0.02	(1.82)	765
Men	−4.08*	(2.35)	−4.73***	(1.77)	623
Women	−5.59***	(1.75)	−0.44	(1.83)	1,225
German citizens	−5.01***	(1.53)	−0.97	(1.45)	1,541
Foreign citizens	−6.02	(4.44)	−4.25	(3.68)	307
Wage increase to comply with Minimum Wage Act	−8.21***	(2.00)	−1.70	(1.35)	1,586

Source: SOEPv33, Survey years 2013–2015.
Notes: Robust standard errors in parentheses, clustered at the individual level with * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. No weighting factors are used. Each line is an independent specification and reduces the representation to two coefficients. All regressions include the year dummy for 2014 and all control variables. The reference group for the estimation of the total sample is male, married and has no children below the age of 16 in the household, works full-time with a permanent contract in a medium-sized company in the manufacturing sector, graduated from an intermediate secondary school, is a German national, lives in the federal states of the former East Germany, and did not report a change of job. The reference year in all specifications is 2013. All coefficients are given in %. Coefficients of the specification “total sample” are based on column (4) in Table 5, including the years 2013 and 2014 in the estimation. Calculations based on the longitudinal sample.

Table 11: DiD regression for workers in marginal employment – minimum wage effect on the increase in working hours – two-year analysis.

	Contractual working hours		Actual hours worked	
	(1)	(2)	(3)	(4)
One-year difference				
DiD 2014–2015	−3.05		1.46	
	(6.89)		(7.58)	
DiD 2013–2014	−8.21		−8.06	
	(5.41)		(6.29)	
Two-year difference				
DiD 2014–2016		−13.47		−13.42
		(8.17)		(8.49)
DiD 2012–2014		−11.98		−5.23
		(7.69)		(8.26)
Constant	87.79***	54.68*	73.03***	60.85*
	(22.70)	(28.81)	(24.55)	(31.05)
Control variables				
Year dummy for 2014	yes	yes	yes	yes
Sociodemographic information	yes	yes	yes	yes
Job characteristics	yes	yes	yes	yes
Change of job	yes	yes	yes	yes
Observations	348	345	348	342
Adj. R^2	0.083	0.102	0.086	0.131

Source: SOEPv33, Survey years 2012–2016.
Notes: Robust standard errors in parentheses, clustered at the individual level with * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. No weighting factors are used. The reference group in columns (4) and (6) is male, married and has no children below the age of 16 in the household, works full-time with a permanent contract in a medium-sized company in the manufacturing sector, graduated from an intermediate secondary school, has German citizenship, lives in the federal states of the former East Germany, and did not report a change of job. The reference year in Column (1) and (3) is 2013; in Column (2) and (4) it is 2012. All coefficients are given in %. To determine hourly wages, we used contractual working hours. Calculations based on the longitudinal sample.

Chapter 7

Conclusion

This dissertation is motivated by two different aspects on the implementation of successful labor market policies (LMP). First, it is necessary to understand the current labor market situation and mechanisms in order to design a programme that addresses the underlying issue rather than merely the symptoms. Second, evaluating implemented LMPs gives way to analyze the actual effects of the LMP and whether ex-post adjustments are required.

The first part of this thesis focuses on the status quo of the training investment decision of the working population. As technological and global developments in the labor market call for regular skill updates, work-related training has received much attention and economists found training investments to be overall beneficial (e.g. Bartel, 1995; Frazis and Loewenstein, 2005; Melero, 2010; Konings and Vanormelingen, 2015). Nevertheless, participation rates have been observed to be low among the working population, e.g. in Germany below 40%. In an attempt to increase such take-up rates, implementing an LMP may be considered. To this end, it is important to understand why participation is lacking. The large body of literature that investigates the determinants of training (e.g. Lynch, 1992; Oosterbeek, 1998; Bassanini *et al.*, 2007; Maximiano, 2012) has so far left non-cognitive traits widely neglected. However, various non-congnitive traits such as personality traits and economic preferences have been recognized to influence decisions in the labor market (e.g. locus of control and risk preferences, see Cobb-Clark, 2015; Heckman and Montalto, 2018). Consequently, chapters 2 to 4 combine these two strands of literature and ask whether and how the non-congitive traits of workers influence their decision to invest into work-related training. This information can then help derive suggestions on how to increase the take-up rate of work-related training.

Indeed, the empirical evidence presented suggests that the traits locus of control, risk attitudes, and job satisfaction play a significant role in the training investment decision: First, chapter 2 presents evidence that internal workers are more likely to participate in training and that they have a higher expectation to receive a pay raise in the future. This relationship is highly driven by general training, as no significant relationships can be found for specific training. Finally, participation in any type of training is positively related to wages in $t + 1$. However, the return to training is independent of the worker's locus of control, reinforcing the previous findings that the systematic difference in participation rates for internals and externals can be attributed to different return expectations. Based on these findings, an information based LMP may be sufficient to increase the training participation rate among external workers: externals should be made aware of the potential returns to training which has the potential of boosting their training motivation.

Second, in chapter 3, risk attitudes are found to be relevant as well. On average, risk-seeking individuals are more likely to participate in training. This implies that on average the working population views training as a risky investment rather than an insurance against labor market shocks. However, when only focusing on workers with uncertain employment relationships or limited access to public insurance schemes the insurance mechanism becomes relevant, effectively making training investments more attractive to risk-averse workers as well. As with locus of control, the distinction between general and specific training reveals to be pivotal: Since the returns to specific training largely accrue to the firm rather than the worker, the relationship between the worker's risk attitude and specific training participation is insignificant, while it is highly significant for general training. Due to the opposing mechanisms, it is important to first identify those workers for whom the uncertainty in the labor market is a dominating concern. For these workers, an informative LPM about the potentially insuring role of training could motivate them to participate. On the other hand, for those workers, who regard training as a risky investment, financial support might decrease the perceived risk of training and could increase the take-up rate of risk-averse individuals.

Third, in chapter 4 dissatisfied workers are found to be less likely to participate in work-related training than satisfied workers. This implies that on average dissatisfied workers disregard their duties in the context of updating their skill set. However, when zooming in on training courses that serve the purpose of preparing the worker for a new position or promotion and when focusing on workers who express an increased likelihood of quitting the current position, an increased likelihood of participating in training is also evident for dissatisfied workers. Hence, training is also viewed as a steppingstone to leaving the dissatisfactory situation. Finally, the job satisfaction measure proves to be a complex one, as there are multiple facets which a worker can be satisfied or dissatisfied with at the same time. When taking a closer look at such facets, e.g. the satisfaction with pay, evidence suggests that workers are also inclined to participate in training to improve the dissatisfactory situation rather than simply leaving it. Due to this complexity of the job satisfaction measure, a diverse and individual approach appears more promising than a simple “one size fits all” LMP. Consequently, firms might seek out closer contact with their workers in order to figure out which dissatisfactory situations arise. With regular, open and honest dialogues it might be more straightforward to figure out which problems can be solved with training.

In conclusion, the first part of this dissertation provides evidence that traits and attitudes of the worker play an important role in the training decision process. Different traits, such as an external locus of control, can contribute to a lower willingness to invest into work-related training. LMPs centered around information interventions may prove useful to increase the take-up rates. The three chapters also highlight the importance of tailoring the LMP to the specific channel: depending on the targeted trait, a different set of information is valuable. This dissertation also points towards potential future work in the context of work-related training, as further non-cognitive skills of the worker could be important, e.g., time preferences, grit, and resilience. Additionally, an assessment of the returns to mandatory vs. optional training would be useful in understanding whether mandatory training can yield similar positive returns to optional training. If this is indeed the case, mandatory training could be explored as a potential channel to target workers with a lower willingness to participate in training.

The second part of this thesis evaluates the introduction of the national minimum wage in Germany in 2015. The years leading up to this introduction were accompanied by a lengthy discussion about the pros and cons of the minimum wage. The chance of protecting workers from poverty and reducing inequality was stressed (Bosch, 2007; Kalina and Weinkopf, 2014), while concerns about negative employment and welfare effects were voiced (Knabe *et al.*, 2014; Bachmann *et al.*, 2014). An evaluation of the effects of the minimum wage on the labor market ensures the opportunity to adjust the minimum wage policy if necessary.

Consequently, chapters 5 and 6 analyze the effects of the minimium wage on the hourly wages, monthly earnings, and working hours. First, a positive effect on hourly wages can be detected, both descriptively and causally. Considering how the LMP is targeted directly towards the hourly wages, this finding indicates that the minimum wage is indeed implemented successfully. However, this analysis also provides evidence that the wages were not increased sufficiently for all workers: a large share of low-income workers still did not receive the minimum wage in the years 2015 and 2016. This finding points to the issue of non-compliance and demands more rigorous monitoring and sanctioning to ensure the implementation of the minimum wage in all firms. The second main finding is a decrease in the working hours of the low income workers, where the decrease is more prominent in contractual rather than actual working hours. This points towards overtime being prominent. This is only a concern if the overtime remains unpaid, as overtime is also subject to the minimum wage. However, the combination of increased hourly wages and decreased (contractual) working hours results in overall unchanged monthly earnings. This would imply that the overall economic situation of the low-income workers has remained unchanged. Fortunately, when looking at the two-year affects up to 2016, the increase in hourly wages continues, while no decrease in working hours can be observed. This then results in an increase in monthly earnings. Consequently, an adjustment period appears to have been required for the firms and workers to react to the intervention in the labor market.

Overall, the provided results in the second part of this dissertation provide an optimistic picture of the minimum wage effects as (with some delay) improvements of the economic situation of low-income workers are evident. However, there are limitations to the optimism, as the enforcement was lacking, leaving some low-income workers behind. Consequently, it is advised to adjust the monitoring and sanctioning in the context of the minimum wage enforcement. Additionally, the results must be interpreted with a favorable business cycle in mind. This may have promoted a positive development of the labor market after the minimum wage introduction. Hence, continued evaluations in the medium and long term are necessary. In this context, as has been done by e.g. Bachmann *et al.* (2020) and Pestel *et al.* (2020), it is also important to consider and evaluate the increases of the minimum wage in 2017, 2019, and 2020 (Mindestlohnkommission, 2016, 2018).

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List of Abbreviations

CPS	Current Population Survey
CRRA	Constant Relative Risk Aversion
DTADD	Differential Trend Adjusted Difference-in-Differences
GDP	Gross Domestic Product
HILDA	Household, Income and Labour Dynamics in Australia Survey
IAB	Institute for Employment Research
ISCO	International Standard Classification of Occupations
LMP	Labor Market Policies
LoC	Locus of Control
ME	Marginal Effects
MLD	Mean Log Deviation
NACE	Nomenclature statistique des Activités Economiques dans la Communauté Européenne
NEPS	National Educational Panel Study
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Squares
SD	Standard Deviation
SOEP	Socio-Economic Panel

German Summary

Arbeitsmarktprogramme (AMP) haben in vielen Ländern an Popularität gewonnen, da sie sich für gezielte Interventionen in vielen Bereichen des Arbeitsmarktes und der Integration in diesen eignen (Auer and Leschke, 2005; Crépon and Van Den Berg, 2016). Solche Programme zielen oft darauf ab, die Beschäftigungsfähigkeit der Erwerbsbevölkerung zu erhalten und zu verbessern (Olivetti and Petrongolo, 2017; International Labour Office, 2020), oder die Wiedereingliederung von Arbeitslosen zu fördern (Brown and Koettl, 2015). Inzwischen werden AMP international vielfältig und flexibel eingesetzt, wobei OECD Länder im Schnitt 1,1% des Bruttoinlandsprodukt in AMP investieren (OECD, 2022). Diese hohen Ausgaben unterstreichen den internationalen Ruf der AMP, aber auch die Notwendigkeit einer rentablen Kosten-Nutzen-Analyse bei jedem durchgeführten AMP.

Hierfür sind zwei Punkte von zentraler Bedeutung. Erstens ist es wichtig, den Status Quo des Arbeitsmarktes zu verstehen bevor ein AMP konzipiert wird: Welche nachteilige Situation ist auf dem Arbeitsmarkt aktuell vorherrschend und welche Mechanismen führen zu dieser Problematik? Das Verständnis der zugrundeliegenden Zusammenhänge ermöglicht es, gut informierte politische Empfehlungen zu geben und somit geeignete AMP zu implementieren. Zweitens ist nach der Umsetzung von AMP eine gründliche Evaluation ihrer Wirksamkeit erforderlich, bei der geprüft wird, ob die umgesetzten AMP ihre ursprünglichen Ziele erfolgreich erreichen und ob unbeabsichtigte Nebeneffekte (z.B. Spillover-Effekte) auftreten. Mit regelmäßigen Auswertungen der AMP können Rückschlüsse gezogen werden, wie die Fortführung der Programme gestaltet werden sollte (Auer and Leschke, 2005).

Die vorliegende Dissertation knüpft an beide Punkte an. Dabei befasst sich der erste Teil dieser Arbeit mit dem Status quo der Weiterbildungsinvestitionsentscheidungen der Erwerbsbevölkerung. Da technologische und globale Entwicklungen auf dem Arbeitsmarkt eine regelmäßige Aktualisierung der Qualifikationen erfordern, hat die berufsbezogene Weiterbildung in der ökonomischen Literatur viel Aufmerksamkeit erhalten. Das Gesamtbild dieser Literatur zeichnet ein positives Bild über die Effektivität von Weiterbildungsinvestitionen, da solche Kurse z.B. mit erhöhter Produktivität and Löhnen einhergehen (Bartel, 1995; Frazis and Loewenstein, 2005). Dennoch sind die Teilnahmequoten in der Erwerbsbevölkerung niedrig, z.B. liegen sie in Deutschland unter 40%. Um diese Teilnahmequoten zu erhöhen, kann die Einführung eines AMP in Betracht gezogen werden. Zu diesem Zweck ist es wichtig zu verstehen, warum die Teilnahme so gering ist. In der umfangreichen Literatur, die sich mit den Determinanten der Weiterbildungsbeteiligung befasst (z.B. Lynch, 1992; Oosterbeek, 1998; Bassanini *et al.*, 2007; Maximiano, 2012), wurden nicht-kognitive Merkmale bisher weitgehend vernachlässigt. Es wurde jedoch erkannt, dass verschiedene nicht-kognitive Merkmale wie Persönlichkeitsmerkmale und ökonomische Präferenzen die Entscheidungen auf dem Arbeitsmarkt beeinflussen (z.B. Locus of Control (Kontrollüberzeugung) und Risikopräferenzen, siehe Cobb-Clark, 2015; Heckman and Montalto, 2018). Die Kapitel 2 bis 4 kombinieren daher diese beiden Literaturstränge und beschäftigen sich mit der Frage, ob und wie die nicht-kognitiven Eigenschaften von Arbeitnehmer*Innen ihre Entscheidung, in berufsbezogene Weiterbildung zu investieren, beeinflussen. Aus diesen Informationen können dann Vorschläge abgeleitet werden, wie die Teilnahmebereitschaft arbeitsbezogener Weiterbildungen mit AMP erhöht werden kann.

Hierbei befasst sich Kapitel 2 mit dem Persönlichkeitsmerkmal Locus of Control (Kontrollüberzeugung). Personen mit einem internalen Locus of Control sind davon überzeugt, dass ihre Arbeitsmarkterfolge direkt von ihren eigenen Handlungen abhängen, während Personen mit einem externalen Locus of Control Erfolge und Fehlschläge auf Schicksal, Glück oder andere Personen zurückführen. Im theoretischen Modell wird argumentiert, dass internale Personen einen höheren Ertrag von Weiterbildungen erwarten (z.B. in Form von erhöhten Löhnen), weswegen sie auch eine höhere Teilnahmebereitschaft haben als externale Personen. In Anlehnung an Becker (1962), wird zwischen Kursen unterschieden, bei denen die vermittelten Fähigkeiten in vielen Firmen anwendbar sind ("firmenübergreifende Kurse") oder nur in der aktuellen Firma Anwendung finden ("firmenspezifische Kurse"), wobei die Arbeitnehmer*Innen einen höheren Ertrag von firmenübergreifenden Kursen erzielen können. Folglich wird ein positiver Zusammenhang zwischen Locus of Control und den erwarteten Erträgen von firmenübergreifende Kursen vermutet, aber kein solcher Zusammenhang bei firmenspezifischen Kursen. Daraus folgt auch nur bei firmenübergreifenden Kursen ein positiver Zusammenhang zwischen Locus of Control und der Teilnahmewahrscheinlichkeit.

Eine empirische Überprüfung dieser Hypothesen erfolgt mit den repräsentativen Daten des deutschen Sozio-oekonomischen Panels (SOEP). Dabei wird ein starker positiver Zusammenhang zwischen Locus of Control und der Teilnahmewahrscheinlichkeit von firmenübergreifenden Kursen festgestellt, aber keinen Zusammenhang bei firmenspezifischen Kursen. Ferner wird gezeigt, dass diese Ergebnisse sehr robust sind, z.B. gegenüber Änderungen der Definition von firmenübergreifenden und -spezifischen Kursen. Dies deutet daraufhin, dass die Unterscheidung zwischen firmenübergreifenden und -spezifischen Weiterbildungskursen von grundlegender Bedeutung ist, um die Anreize für die Teilnahme an solchen Kursen zu verstehen. Schließlich werden empirische Belege für den zugrundeliegenden Mechanismus geliefert: Internale Personen haben höhere Erwartungen hinsichtlich der Wahrscheinlichkeit einer Lohnerhöhung nach Teilnahme an firmenübergreifenden Kursen, nicht aber bei firmenspezifischen Kursen. Abschließend zeigt sich, dass die Lohnentwicklung nach Kursteilnahme nicht vom Locus of Control abhängt. Dies bestärkt die Ergebnisse, dass Locus of Control die erwarteten Erträge von (firmenübergreifenden) Kursen beeinflusst und damit auch die Teilnahmebereitschaft.

Diese Ergebnisse deuten darauf hin, dass ein externaler Locus of Control zu einer Unterinvestition in berufsbezogene Weiterbildung beitragen kann. Da Locus of Control die subjektiven Überzeugungen über den Nutzen der Weiterbildung mit der Weiterbildungsentscheidung verknüpft, könnte die Information über den Nutzen der Weiterbildung nützlich sein, um die Motivation der externalen Arbeitnehmer*Innen zur Teilnahme zu erhöhen.

Im Anschluss wird in Kapitel 3 die Rolle der Risikopräferenz detailliert analysiert. Weiterbildungskurse können als riskante Investition interpretiert werden, z.B. wenn der Ertrag des Kurses ungewiss ist. Alternativ können solche Kurse als Versicherungsinvestition angesehen werden, mit der das Risiko von Arbeitsmarktschocks verringert wird. In beiden Fällen wird vermutet, dass die Risikopräferenz bei der Investitionsentscheidung berücksichtig werden sollte. Wenn das Investitionsrisiko der Weiterbildung überwiegt, sagt das theoretische Modell voraus, dass risikoscheue Arbeitnehmer*Innen weniger investieren. Im Gegenzug wird erwartet, dass die Teilnahmerate für risikoscheue Arbeitnehmer*Innen höher ist, wenn die vorherrschende Rolle der Weiterbildung die Versicherung gegen Arbeitsmarktschocks ist. Auch hier wird zwischen firmenübergreifenden und firmenspezifischen Kursen unterschieden (Becker, 1962) und argumentiert, dass die Beziehung zwischen Risikoeinstellung und Weiterbildungsinvestitionen von firmenübergreifenden statt firmenspezifischen Kursen bestimmt wird, aufgrund der Nullrendite von firmenspezifischen Kursen.

Die empirische Analyse mit dem SOEP zeigt einen positiven Zusammenhang zwischen der Risikoaffinität und der Teilnahmewahrscheinlichkeit an Kurses. Dieses Ergebnis deutet darauf hin, dass für die erwerbstätige Bevölkerung im Schnitt das Risiko der Rendite gegenüber dem Versicherungsnutzen der Weiterbildung überwiegt. Allerdings gilt dieses Ergebnis nur für firmenübergreifende Kurse, nicht für firmenspezifische Kurse. Die Ergebnisse werden mit verschiedenen Robustheitsanalysen untermauert. Zusätzlich zeigt sich, dass manche Teilgruppen mehr Wert auf den Versicherungsmechanismus legen, z.B. Personen mit einem befristeten Arbeitsvertrag. Daher wird festgestellt, dass die Stärke des Verhältnisses zwischen Risikoeinstellung und Weiterbildungsinvestitionen vom Kontext abhängt, da das Risiko einer Weiterbildung allgegenwärtig ist, während der Versicherungsnutzen wahrscheinlich auf bestimmte Untergruppen, z.B. die kürzlich Arbeitslosen, konzentriert ist.

Diese Ergebnisse geben Aufschluss darüber, wie die Risikoeinstellung die Entscheidung zur Teilnahme an einer Weiterbildung beeinflussen kann. Untergruppen, die weitgehend vom Versicherungsmechanismus profitieren, könnten über die Vorteile der Kurse aufgeklärt werden. Im Gegensatz dazu könnten risikoscheue Personen, die es vorziehen, die Risiken der Weiterbildung nicht auf sich zu nehmen, zur Teilnahme ermutigt werden, indem sie über das tatsächliche Risiko der Weiterbildung informiert werden (falls möglich) oder indem (Teile) der Kosten übernommen werden (durch das Unternehmen oder im Rahmen eines AMP).

Schließlich fokussiert sich Kapitel 4 auf die Arbeitszufriedenheit der Arbeitnehmer*Innen. Da eine hohe Zufriedenheit nicht kontinuierlich gewährleistet werden kann (Rusbult *et al.*, 1988), ist es von zentraler Bedeutung, zu verstehen, welche Folgen Unzufriedenheit mit sich zieht. Psychologen kategorisieren die Verhaltensreaktion von Arbeitnehmer*Innen auf Unzufriedenheit am Arbeitsplatz in (i) Verlassen des Arbeitsplatzes (exit), (ii) Verbesserung der unzufriedenen Situation (voice), (iii) Treue zum Unternehmen und Ertragen der Unzufriedenheit (loyalität) und (iv) Vernachlässigung von Pflichten (neglect) (Farrell, 1983; Jodlbauer *et al.*, 2012). Das theoretische Modell in diesem Kapitel sagt eine U-förmige Beziehung zwischen Arbeitszufriedenheit und Kursteilnahme voraus, sofern die unzufriedenen Arbeitnehmer*Innen planen, die Stelle zu verlassen oder die Situation zu verbessern. Im Gegensatz dazu entsteht ein insgesamt positiver Zusammenhang, falls die Unzufriedenheit zu Vernachlässigung der Pflichten führt.

Zur empirischen Untersuchung werden Daten des Household, Income and Labour Dynamics in Australia Survey (HILDA) verwendet. Die Ergebnisse deuten auf eine insgesamt positive Beziehung hin, was bedeutet, dass unzufriedene Arbeitnehmer*Innen im Durchschnitt mit Nachlässigkeit reagieren und weniger bereit sind, in Weiterbildungen zu investieren. Diese Ergebnisse bleiben auch bei verschiedenen Robustheitsüberprüfungen stabil. Allerdings nehmen unzufriedene Arbeitnehmer*Innen vermehrt an Kursen teil, wenn diese Kurse Chancen auf eine Beförderung oder neue Stelle erhöhen oder wenn die Arbeiternehmer*innen eine hohe Intention äußern, die aktuelle Stelle zu verlassen. Dies deutet darauf hin, dass der Plan, den Arbeitsplatz zu verlassen, die Kursteilnahmebereitschaft bei Unzufriedenheit erhöht. Abschließend wird Evidenz geliefert, dass Arbeitnehmer*Innen bei Unzufriedenheit auch versuchen, die Situation zu verbessern: Wenn der Ursprung der Unzufriedenheit tatsächlich mit Kursen verbessert werden kann (z.B. die Löhne), so steigt auch bei den Unzufriedenen die Bereitschaft an Kursen teilzunehmen. Dies unterstreicht die Komplexität der Arbeitszufriedenheit sowie die Notwendigkeit, die Quelle der Unzufriedenheit zu berücksichtigen.

Diese Ergebnisse deuten darauf hin, dass unzufriedene Arbeitnehmer*Innen im Durchschnitt weniger bereit sind, in Weiterbildung zu investieren. Es könnte für Firmen von Vorteil sein, ihre Arbeitnehmer*Innen zu ermutigen, ihre Unzufriedenheit zu äußern, um geeignete Schritte zur Verbesserung der Situation, z.B. durch Weiterbildung, zu ermitteln. Aufgrund der Komplexität des Konzepts der Arbeitszufriedenheit sind jedoch weitere Forschungsarbeiten erforderlich, um evidenzbasierte Empfehlungen für AMP zu geben.

Zusammenfassend liefert der erste Teil dieser Dissertation Evidenz dafür, dass nicht-kognitive Merkmale und Einstellungen der Arbeitnehmer*Innen eine wichtige Rolle bei der Weiterbildungsentscheidung spielen. Verschiedene Merkmale, wie z.B. ein externaler Locus of Control, können zu einer geringeren Bereitschaft beitragen, in arbeitsbezogene Weiterbildung zu investieren. AMP, die sich auf Informationsmaßnahmen konzentrieren, können sich als nützlich erweisen, um die Teilnahmebereitschaft zu erhöhen. In den drei Kapiteln wird auch deutlich, wie wichtig es ist, das AMP auf den jeweiligen Mechanismus zuzuschneiden: Je nach betrachteter Eigenschaft ist eine andere Art von Informationen sinnvoll. Diese Dissertation weist auch auf potenzielle künftige Arbeiten im Zusammenhang mit berufsbezogener Weiterbildung hin, da weitere nicht-kognitive Fähigkeiten der Arbeitnehmer wichtig sein könnten, z.B. Zeitpräferenzen. Darüber hinaus wäre eine Bewertung der Effektivität von obligatorischen im Vergleich zu freiwilligen Kursen nützlich, um zu verstehen, ob obligatorische Kurse eine ähnlich Effektivität wie freiwillige Kurse aufweisen. Sollte dies der Fall sein, könnten obligatorische Weiterbildungskurse als potenzielle Maßnahme untersucht werden, um die Teilnahmebereitschaft zu erhöhen.

Der zweite Teil dieser Arbeit evaluiert die Einführung des flächendeckenden Mindestlohns in Deutschland im Jahr 2015, welches einen erheblichen Eingriff in den Arbeitsmarkt darstellt. Ziel war es, die Bruttostundenlöhne von Geringverdiener*Innen zu erhöhen. Allerdings waren die Jahre vor dieser Einführung von einer langen Diskussion über das Für und Wider des Mindestlohns begleitet. Betont wurde die Chance, Arbeitnehmer*Innen vor Armut zu schützen und Ungleichheit zu verringern (Bosch, 2007; Kalina and Weinkopf, 2014), während Bedenken über negative Beschäftigungs- und Wohlfahrtseffekte geäußert wurden (Bachmann *et al.*, 2014; Knabe *et al.*, 2014). Eine Evaluierung der Auswirkungen des Mindestlohns auf den Arbeitsmarkt gewährleistet die Möglichkeit, die Mindestlohnpolitik bei Bedarf anzupassen.

Entsprechend wird in Kapitel 5 analysiert, ob das Hauptziel des Mindestlohns erreicht wurde: Es werden empirisch mit dem SOEP die Auswirkungen der Einführung auf die Stundenlöhne und die monatlichen Verdienste in den zwei Jahren nach der Mindestlohneinführung ermittelt. Hierbei wird zuerst eine umfassende deskriptive Analyse der Lohnveränderungen präsentiert. Insgesamt ergibt sich ein konsistentes Bild eines erhöhten Lohnwachstums in den zwei Jahren nach der Einführung des Mindestlohns. Dabei ist der Anteil der Personen, die weniger als 8,50 Euro verdienten, zwischen 2014 und 2016 zwar gesunken, aber nicht auf 0%. So ist die Nichteinhaltung des Mindestlohns in den ersten zwei Jahren nach dessen Einführung ersichtlich. Anhand eines differenziellen trendbereinigten Differenz-in-Differenzen Ansatzes wird ein kausaler Anstieg des Lohnwachstums aufgrund der Mindestlohneinführung für Personen identifiziert, die vor der Einführung des Mindestlohns weniger als 8,50 Euro verdienten. Auch hier bestätigt sich, dass der Anstieg nicht ausreicht, um Löhne oberhalb der Mindestlohngrenze zu gewährleistet. Im Weiteren wird überprüft, ob sich die wirtschaftliche Situation von Niedriglohnbezieher*Innen ingesamt durch die Mindestlohneinführung verbesserten. Allerdings kann im Jahr 2015 keine Auswirkung auf die monatlichen Verdienste festgestellt werden. Erst bei der Zweijahresanalyse zwischen 2014 und 2016 kann ein Anstieg der Monatsverdienste aufgrund der Mindestlohneinführung identifiziert werden. Folglich scheint eine Anpassungsphase erforderlich gewesen zu sein, damit die Unternehmen und Arbeitnehmer*Innen auf den Eingriff in den Arbeitsmarkt reagieren konnten.

Schließlich werden Hetereogenitäts- und Robustheitsanalysen durchgeführt. Hierbei zeigen sich aufgrund unterschiedlicher Anreize heterogene Auswirkungen für geringfügig Beschäftigte und zwischen Voll- und Teilzeitbeschäftigten. Außerdem gibt es keine Hinweise darauf, dass Personen, die etwas mehr als 8,50 Euro verdienten, direkt vom Mindestlohn betroffen waren. Das deutet darauf hin, dass es weder negative noch positive Spillover-Effekte gab.

Insgesamt belegen diese Ergebnisse, dass der Mindestlohn das Wachstum der Stundenlöhne erfolgreich erhöht hat, während die Auswirkungen auf die Monatsverdienste verzögert eingetreten sind. Darüber hinaus deuten die Ergebnisse darauf hin, dass die Durchsetzung des Mindestlohns unzureichend war, da ein großer Teil der Beschäftigten im Jahr 2016 immer noch weniger als die Lohnuntergrenze erhielt.

Eine der Hauptsorgen im Zusammenhang mit der Einführung des Mindestlohns waren die erwarteten negativen Auswirkungen auf die Beschäftigung (Knabe *et al.*, 2014; SVR, 2013). Folglich wurde den allgemeinen Beschäftigungseffekten in der Literatur viel Aufmerksamkeit geschenkt, wobei entweder keine (Ahlfeldt *et al.*, 2018) oder negative Auswirkungen (Caliendo *et al.*, 2018; Schmitz, 2017) auf die Gesamtbeschäftigung ("extensive Marge") festgestellt wurden. Ein weiterer möglicher Nebeneffekt auf die Beschäftigung ist jedoch eine Veränderung der “intensiven Marge”, bei der die Arbeitszeiten der Beschäftigten auf die Mindestlohneinführung reagieren. Daher wird in Kapitel 6 die Auswirkungen des Mindestlohns auf die Arbeitszeiten analysiert.

In der empirischen Kausalanalyse werden dafür die SOEP-Daten für die Jahre 2012 bis 2016 verwendet und ein einfacher Differenz-in-Differenzen-Ansatz angewendet. Hier werden zunächst nur sozialversicherungspflichtig Beschäftigte betrachtet. Für diejenigen, die vor der Einführung weniger als 8,50 Euro pro Stunde verdienten, zeigt sich eine signifikante Verringerung der Arbeitszeiten im Jahr 2015. Dieser Rückgang fällt für vertragliche Arbeitszeiten stärker aus als für tatsächliche Arbeitszeiten, was darauf hindeutet, dass sich die Überstunden durch die Einführung des Mindestlohns nicht verändert haben. Darüber hinaus wurde über einen Zeitraum von zwei Jahren bis 2016 kein Rückgang der Arbeitsstunden festgestellt. Diese Ergebnisse ergänzen das Bild aus Kapitel 5, da ein Anstieg der Stundenlöhne bei gleichzeitiger Verringerung der Arbeitszeiten zu konstanten Monatsverdiensten im Jahr 2015 führte. Da die Arbeitszeiten im Jahr 2016 jedoch nicht weiter gesunken sind, sehen wir hier einen leichten Anstieg der Monatsverdienste.

Im Anschluss werden die geringfügig Beschäftigten ebenfalls analysiert. Aufgrund der Befreiung von Sozialversicherungsbeiträgen für Beschäftigungen mit einem Einkommen von bis zu 450 Euro pro Monat haben geringfügig Beschäftigte einen direkten Anreiz, ihren Monatsverdienst auf 450 Euro zu begrenzen. Folglich ist davon auszugehen, dass sie in Reaktion auf die Einführung des Mindestlohns ihre Arbeitszeit reduzieren. In der Tat zeigt sich für diese Gruppe ein stärkerer negativer Effekt, allerdings sind diese Ergebnisse statistisch schwach, was höchstwahrscheinlich auf die geringe Anzahl von Beobachtungen zurückzuführen ist.

Schließlich werden zwei kritische Punkte der Analyse untersucht. Zum einen wird nachgewiesen, dass die Ergebnisse in Bezug auf mögliche Messfehler robust sind. Zum anderen lassen sich keine Spillover-Effekte auf die Arbeitszeit derjenigen Arbeitnehmer*Innen identifizieren, die vor der Einführung etwas mehr als 8,50 Euro verdienten. Dies bestärkt die kausale Interpretation der Ergebnisse.

Insgesamt vermitteln die im zweiten Teil dieser Dissertation vorgelegten Ergebnisse ein optimistisches Bild von den Auswirkungen des Mindestlohns, da (mit einiger Verzögerung)

Verbesserungen der wirtschaftlichen Lage von Arbeitnehmer*Innen mit niedrigem Einkommen zu beobachten sind. Der Optimismus hält sich jedoch in Grenzen, da die Durchsetzung des Mindestlohns unzureichend war und einige Arbeitnehmer*Innen nicht direkt von dem Mindestlohn profitierten. Daher ist es ratsam, die Überwachung und Sanktionierung im Zusammenhang mit der Durchsetzung des Mindestlohns anzupassen. Außerdem müssen die Ergebnisse vor dem Hintergrund einer günstigen Konjunkturlage interpretiert werden. Dies könnte eine positive Entwicklung des Arbeitsmarktes nach Einführung des Mindestlohns begünstigt haben. Daher sind weitere mittel- und langfristige Evaluierungen notwendig. In diesem Zusammenhang ist es wichtig, wie bereits in den Studien Bachmann *et al.* (2020) und Pestel *et al.* (2020) geschehen, auch die Erhöhungen des Mindestlohns in den Jahren 2017, 2019 und 2020 zu berücksichtigen und zu bewerten (Mindestlohnkommission, 2016, 2018).

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