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Emergency-Aid for Self-employed in the Covid-19 Pandemic: A Flash in the Pan?*

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ABSTRACT

The self-employed faced strong income losses during the Covid-19 pandemic. Many governments introduced programs to financially support the self-employed during the pandemic, including Germany. The German Ministry for Economic Affairs announced a €50bn emergency-aid program in March 2020, offering one-off lump-sum payments of up to €15,000 to those facing substantial revenue declines. By reassuring the self- employed that the government 'would not let them down' during the crisis, the program had also the important aim of motivating the self-employed to get through the crisis. We investigate whether the program affected the confidence of the self-employed to survive the crisis using real-time online-survey data comprising more than 20,000 observations. We employ propensity score matching, making use of a rich set of variables that influence the subjective survival probability as main outcome measure. We observe that this program had significant effects, with the subjective survival probability of the self- employed being moderately increased. We reveal important effect heterogeneities with respect to education, industries, and speed of payment. Notably, positive effects only occur among those self-employed whose application was processed quickly. This suggests stress-induced waiting costs due to the uncertainty associated with the administrative processing and the overall pandemic situation. Our findings have policy implications for the design of support programs, while also contributing to the literature on the instruments and effects of entrepreneurship policy interventions in crisis situations.

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https://portal.fdz- bo.diw.de/study/S0021 and in Bertschek et al. (2022).

1. Introduction

The Covid-19 pandemic led many countries in spring 2020 to temporarily close major parts of their economies, especially in the service and trade industries. Self-employed and micro-businesses (referred to as "self-employed" from now on) are major economic actors in these industries. Research shows that the self-employed suffered financially more strongly from the disruption caused by Covid-19 than other parts of the working population (Fairlie and Fossen, 2022b, Graeber et al., 2021). In Germany, for instance, about 60% of the 4 million self-employed faced sales and income losses, while only about 15% of dependently employed individuals were confronted with job or wage losses (see Kritikos et al., 2020).

However, the crisis affected the self-employed, not just economically but also from a psychological and mental health perspective. First evidence (see Torrès et al., 2022) points to a worsening of the mental health conditions among the self-employed, due in part to their financial losses (Caliendo et al., 2022b). This negatively affects their decision-making processes, showing that the economic and psychological conditions of the self-employed are closely interconnected (Wiklund et al., 2019).

Given the importance of the self-employed for the German economy and given the need to strengthen their confidence into their own abilities to keep their businesses up and running, their situation was of high concern for policy makers. Hence, at the end of March 2020, Germany introduced an emergency-aid program ("*Soforthilfe*") of €50 billion designed to financially support those self-employed facing strong revenue losses due to the imposed restrictions. The program was a one-off lump-sum grant of up to €15,000 per self-employed and was accessible between the end of March and end of May 2020. The program had not only a financial aim but also the aim of motivating the self-employed to get through the crisis. With regard to the latter, the German Minister for Economic Affairs stated at a press conference on March 10, 2020, "that we will not let any firm-owner down and that no firm should be forced to leave the market because of the Corona pandemic" (DPA 2020). Thus, *Soforthilfe* sought to quell existential fear from financial hardship, motivate the self-employed and prevent massive exits from self-employment.

In this study, we focus on the aim of the program to increase the confidence of the self-employed in the crisis and investigate how the program affected the beliefs of the self-employed that their business would survive the crisis. Previous research shows that subjective beliefs about firm survival and failure are crucial for their continuation (Khelil, 2016), as the self-employed will stop investing in their firms once they stop believing in their business survival (Ucbasaran et al., 2010). Thus, it is important to investigate whether policy measures like *Soforthilfe* achieved their aim of increasing subjective beliefs in the survival of their own business. Secondly, to understand how the program design affects, and under what conditions the use of such instruments increases, the confidence of the self-employed to survive a crisis, we also causally examine whether the speed of payment matters. Third, given that research shows that education and risk tolerance (see e.g. Van der Sluis et al., 2008, Caliendo et al., 2010, 2104, 2022a) are two important personal characteristics strongly affecting business development, we investigate how these factors influence the impact of *Soforthilfe*. These research questions are highly relevant given the huge amount of taxpayer money – €50bn – made available for this program. Typical self-employment policy measures, like Germany's various start-up subsidy programs, receive yearly budgets of less than €1bn (see e.g. Caliendo and Kuenn, 2011), clarifying that the amount made available to this program was exceptionally high.

For our analysis, we rely on a survey answered by more than 20,000 self-employed individuals in April and May 2020. Besides information on crisis related sales losses, liquidity constraints, and the willingness to apply for financial support from the emergency-aid, the survey collected information on most individual- and firm-related characteristics relevant for self-employment. As our outcome variable, we use a measure that is based on the individual assessment about the probability to "end their self-employment activities due to the Corona-crisis in the next 12 months." Research has established that subjective probability measures are an appropriate way to measure expectations (Manski, 2004), showing that these measures reflect entrepreneurial decision-making, thus impacting firm survival (Cassar, 2010, Hyytinen et al., 2014). Moreover, beyond rich information on the self-employed, we make use of the fact that the data is surveyed in real-time. To causally analyze whether the financial support instrument increased the subjective survival probability, we rely on the conditional independence assumption (CIA). Thereby, we compare self-employed who already received support from the program (the treatment group) with those who planned to apply for the program (the control group), controlling for a rich set of variables that influence the application and survival probability.

We contribute to the literature analyzing how the Covid-19 pandemic affected the self-employed (Adams-Prassl et al., 2020, Block et al., 2022, Graeber et al., 2021) in three ways. This crisis is unique and no existing research shows how public policy interventions help the self-employed deal with the psychological consequences of a truly exogenous crisis like Covid-19. Our study provides first empirical evidence on the subjectively perceived effectiveness of an emergency-aid program during the pandemic and, more broadly, on the non-monetary effects from policy interventions during economic crises, thus contributing to the literature on the non-monetary and motivational effects of public policy (Stutzer, 2020). Secondly, we investigate the impact of variations in the speed of processing the applications and paying out the emergency-aid, taking a procedural utility and administrative burden perspective on public interventions (Frey et al., 2004, Block and Koellinger, 2009). The results of our study imply that program impacts during a crisis do not just depend on its content but also on its processing speed associated, reflecting stress-induced waiting costs resulting from uncertainty (Baekgaard et al. 2021; Greco and Roger, 2003; Monat, Averill, and Lazarus, 2003). Thirdly, we analyze effect heterogeneities with respect to various individual-level variables, such as risk-tolerance or educational attainment. In that sense, our analysis is of high relevance given the ongoing debate on the right design and implementation of such policy instruments, informing governments about how specific target groups perceive the public financial support under the given conditions. With our results, we contribute more generally to the literature on SME policy in times of crises (Minniti, 2008, Belitski et al., 2022).

2. Covid-19 and Self-employment

2.1. Covid-19 in Germany and Policy Response

At the time of data collection in April and May 2020, Germany was among the countries most affected by the Covid-19 pandemic. The German government tried to stop the spreading of the virus by implementing several measures that severely affected the economy. Schools, daycare centers, shops, restaurants, and hotels were closed, except for supermarkets. A curfew was imposed, including a ban on public gatherings with more than two people. Events, including trade fairs, sports, and concerts, were cancelled; travel was restricted. During that time, a GDP decline of 9% was predicted for 2020 (IfW 2020).

To help the economy while avoiding job cuts and a long-lasting recession, the German government introduced several support programs to mitigate the consequences of the pandemic. Targeting established firms, employers could send their employees into *Kurzarbeit* (short-time work), where the Federal Employment Office covers a substantial portion of the wage costs. However, the self-employed are not covered by this instrument. To address this occupational group, the government launched the *Soforthilfe* emergency-aid of €50 billion, accessible from March 25, 2020, through the end of May 2020, of which €13.7 billion were actually spent. The self-employed could receive immediate financial assistance of up to €9,000 for businesses with up to five employees, and up to €15,000 for businesses up to ten employees - if they had acute liquidity shortfalls (Federal Ministry for Economic Affairs and Energy, 2020). However, support program funds could only be used to cover operating costs; private living costs were excluded.

2.2. Prior Research on Self-employment in the Covid-19 Pandemic

The effects of Covid-19 on self-employment attracted empirical research documenting that, during the crisis, self-employed in other countries suffered like those in Germany (see Adams-Prassl et al., 2020, Graeber et al. 2021, Belitski et al., 2022, Kalenkoski and Pabilonia, 2022), clarifying that the pandemic disrupted self-employment globally. Moreover, research points to effects on self-employed beyond economic losses: Descriptive (Torrès et al. 2022) and causal (Caliendo et al. 2022b) evidence reveals a worsening of mental health among the self-employed in the wake of pandemic-driven market distortions.

Moreover, beyond describing how the pandemic affected the self-employed, research investigates how the self-employed coped with the early stages of the pandemic and how government programs responding to this economic disruption affected the self-employed. Block et al. (2022) investigates how the self-employed managed the consequences of Covid-19 by maintaining their liquidity through the use of bootstrap-financing. Meurer et al. (2022) demonstrate how entrepreneurial online communities offered support to affected entrepreneurs. Bertschek and Erdsiek (2020) show that self-employed with a higher degree of digitalization were less affected by the crisis. With respect to government programs, various public policy instruments responding to the economic disruption and addressing the financing needs of the self-employed are identified. Fairlie and Fossen (2022a) provide a disbursement analysis of the Paycheck Protection Program and the Economic Injury Disaster Loan Program, both in the US, that aimed to help disadvantaged groups. For China, Liu et al. (2022) show the supportive role of Chinese state-owned banks for small businesses’ lines of credit, where the broad policy mix comprised loan guarantees, direct lending to SMEs, grants, and equity instruments. Belghitar et al. (2022) investigate the effects of UK governmental policies for SMEs during Covid-19 and examined their effect on the ability to survive the pandemic.

3. Impact of the Aid Program on the Subjective Survival Probability

3.1. Baseline Effect

Self-employed have expectations about the financial and nonfinancial goals of their business activities and base their investment decisions on these expectations (Gimeno et al., 1997). In the context of a crisis like the Covid-19 pandemic, their subjective evaluation about the extent they will be able to achieve their own aims (possibly set before the crisis) by further running their businesses is crucial for the decision between continuing their business or closing it (Hyytinen et al., 2014). The assessment of these expectations about future prospects influences the effort they put into the venture, affects their investment decisions, and, ultimately, the decision over firm survival (Ucsbasaran et al., 2013). If individuals believe that they will be able to attain their goals, they will invest in their businesses, thus remaining in the market (Koellinger et al., 2007; Ayala and Manzano, 2014; Li et al., 2021). If individuals expect that they will no longer be able to realize their goals, they will stop investing in their firms, leading to firm closure (Ucsbasaran et al., 2010; Ayala and Manzano, 2014). Khelil (2016, p. 76) defines failure among self-employed as a condition when the self-employed enter “into a spiral of a psychological state of disappointment” and argues that “in the absence of economic or psychological support, entrepreneurs are forced to exit from their entrepreneurial activities.” The self-employed might even close their business despite an excellent financial situation if they hold negative subjective beliefs about the future. Therefore, how the self-employed perceive their future prospects is particularly important in the context of an economic crisis.

During the pandemic, the self-employed were among the most affected occupational groups, especially those in the hotel and restaurant business, tourism industry, retail, cultural, and events sector as well as all industries requiring personal contact. For them, the policy measures to contain the pandemic meant a *de facto* temporary inability to work, where they could not generate revenues to cover their operating expenses and living costs. Such conditions of financial hardship may have negative second order effects. Financial scarcity can be linked with behavior of financial avoidance and with changing assessments of future gains in the form of an increase in discounting of future gains and losses (Hilbert et al., 2022a, 2022b). In case the self-employed decides to move away from this occupational form, it might also impact the effectiveness of their job search (Gerards and Welters, 2022), as subsequent financial hardship may limit their cognitive resources, thereby preventing them from making deliberate decisions.

Further, the self-employed also confronted a loss of procedural utility otherwise derived from self-employment (Frey et al., 2004). The self-employed in these affected industries were collectively sent into a “psychological state of disappointment” with negative effects on their subjective beliefs about business survival. This was true at the beginning of the pandemic, when it was unforeseeable for how long the pandemic and its containment measures would last. The “state of disappointment” in combination with the experience of financial hardship is likely to negatively influence the assessment of their business future.

Deemed at a high risk of business closure, the emergency-aid aimed to provide economic support against insolvency covering the fixed business costs that continued to accrue despite no or low revenues. Further, given the statement of the Minister for Economic Affairs that attracted a lot of public attention and enjoyed a broad reception among the self-employed, the emergency-aid provided motivational support encouraging the self-employed to remain in business. Public discussion on the emergency-aid was guided by one question: did the program affect the subjective belief of the self-employed of not being “abandoned”? In that sense, the emergency-aid program aimed at counteracting negative assessments of the self-employed about the future of their businesses and at improving their expectations about the subjective survival probability of their businesses by easing potential financial hardships. We hypothesize:

H1: Receiving financial support from the emergency-aid positively affected the subjective belief of the self-employed that their firms will survive the pandemic.

3.2. Moderating Factors

3.2.1 Severity of the Crisis by Industry

As a first moderating factor, we differentiate between industries according to the degree the crisis affected them. The reason is that a program following a "watering-can principle" that does not consider individual needs, often has only limited effects (Wunsch and Lechner, 2008; Grashof, 2021). We posit that the effect of the emergency-aid program depends on how severe the crisis hit the respective self-employed and how severe the individual need was (Caliendo and Kuenn, 2011). Self-employed who were only weakly hit by the crisis and received the financial support are not expected to have a higher subjective survival probability compared to individuals who were weakly hit by the crisis but did not receive the support. In this range, we expect deadweight losses among those who obtained the financial support. In contrast, among self-employed who were strongly hit by the crisis and received the financial support, we expect that they will assess the survival probability of their businesses higher than individuals who were strongly hit by the crisis but did not yet receive support. We hypothesize:

H2a: The positive effect of the emergency-aid on the subjective belief of the self-employed that their firms will survive the pandemic is stronger for those self-employed in strongly versus weakly affected industries.

3.2.2 Level of Education

Research shows that education levels increase the business performance of the self-employed and firm survival (e.g. Parker and van Praag, 2006; Van der Sluis et al., 2008). It correlates with an individual’s cognitive abilities to identify and exploit entrepreneurial opportunities (Hartog et al., 2010) and with an individual’s adaptability to changing environments (Stasielowicz, 2020). Research finds that individuals with higher cognitive abilities achieve better financial outcomes (Tang, 2021) and have lower unemployment risks (Vélez-Coto et al., 2021). For this study, we posit that strong cognitive abilities are needed to successfully master crisis situations like the pandemic. The emergency aid may help to cover the running costs of the business on short-term basis but to cope with the long-term impacts of the crisis, the affected self-employed must have the capacity and willingness to adapt their products, services, and business model. Such changes require strong cognitive abilities. Seeing education level as a proxy for cognitive ability (Berry, Gruys, and Sackett, 2006), we argue that the better educated self-employed are able to react more flexibly to exogenous shocks associated with high uncertainty, putting them into a better position to benefit from the emergency-aid. In that sense we use education level as a proxy for cognitive abilities. We hypothesize:

H2b: The positive effect of the emergency-aid on the subjective belief of the self-employed that their firms will survive the pandemic is stronger for those self-employed with a high versus low level of education.

3.2.3 Risk Tolerance

The subjective belief of whether one’s own business will survive a crisis also depends on one’s risk tolerance. Research shows that risk tolerance is not only one of the most important personality characteristics affecting decision making, behavior, and survival of the self-employed (Brandstätter, 1997; Hansemark, 2003; Brown et al., 2011; Caliendo et al. 2009, 2010, 2012, 2022a; Caliendo and Kritikos, 2012; Urbig et al., 2012; Willebrands et al., 2012), but also the effectiveness of public policy measures (Fairlie and Holleran, 2012). Staying in the market at a time when it is unclear how long government restrictions will be in place increases failure risk as ongoing costs and missing sales may exceed the financial support the individuals received. Thus, it is risky to remain in the market; risk tolerance is expected to play a significant role in the sense that more risk tolerant self-employed are more likely to positively assess their survival when they receive financial support than less risk tolerant ones because the former ones will derive a higher utility from the financial support (Kihlstrom and Laffont, 1979).[1] We hypothesize:

H2c: The positive effect of the emergency-aid on the subjective belief of the self-employed that their firms will survive the pandemic is stronger for those self-employed with a high versus low level of risk tolerance.

3.2.4 Speed of Payment and Waiting Time

We argue that the effect of the emergency-aid on the subjective belief of the self-employed about their firm survival depends on the perceived administrative burdens of the program, particularly the speed of payment and the associated waiting time. Public administration research describes administrative burden as "an individual's experience of policy implementation as onerous" (Burden et al., 2012, p. 742). Formal and informal practices shape how the benefits and costs of state programs are perceived. In this regard, time and 'waiting for the state' (Carswell et al., 2019) are shown to increase the non-monetary costs associated with state programs and the perceived administrative burdens (Holler and Tarshish, 2022). Waiting is associated with temporal uncertainty leading to stress. This situation is unbearable for many self-employed during crises like the Covid-19 pandemic. Self-employed as an occupational group are typically proactive (Neneh, 2019) and do not want to wait to improve their economic situation. To summarize, we propose that the intended positive effect of the emergency-aid to increase the belief of the self-employed about the survival of their firms and to send the signal that the government does not want to let anybody down in such a crisis situation reduces with a long waiting time and the associated uncertainty of waiting. We hypothesize:

H2d: The positive effect of the emergency-aid on the subjective belief of the self-employed that their firms will survive the pandemic is stronger for those self-employed who quickly receive the payment versus those who have to wait a long time.

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[1] Please note that we cannot exclude that the level of risk tolerance is, *per se*, affected by such shocks; see Dalton et al., (2020) and Harrison et al., (2022).

4. Data

4.1. Description of the Estimation Sample

Data was collected via an online-survey between April 7 and May 4, 2020. The survey gathered information about the consequences of the pandemic for the self-employed alongside their individual and firm characteristics. It included questions on whether the self-employed were eligible for government support as well as whether they applied for and already received it. It recorded the exact days of the respondent's emergency-aid application as well as its approval or denial. The survey was administered via the Verband der Gründer und Selbstständigen Deutschland e.V. (VGSD) and other self-employment associations.

We collected data from 27,262 respondents. To arrive at the estimation sample matching our research question, we excluded respondents who live outside Germany or with inconsistent application data (e.g. application dates before the policy intervention). Second, we exclude respondents with missing information for the variables needed in our propensity score matching. Third, we excluded people for whom we do not have a subjective belief of their firm surviving the Covid-19 pandemic (our outcome variable). The final sample comprises 16,859 self-employed individuals.

4.2. Individual and Firm Characteristics

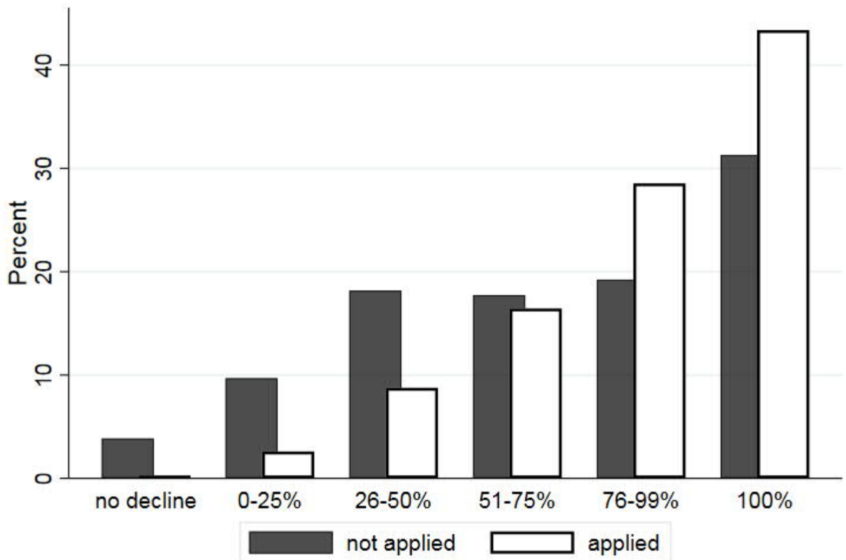
We describe our sample, starting with individual and firm characteristics. Table A1 in Appendix A.1 shows descriptive statistics for the whole sample and the subsamples used in the propensity score matching analysis. Respondents have a median age of 50 years, men comprise half of the respondents, and education levels are relatively high, with 61% of the individuals holding a university degree. About 90% of the respondents work full-time.

We were interested in the respondents' willingness to take risk. For measuring risk tolerance, we follow Dohmen et al. (2011), who test and find support for the behavioral relevance of single measures for risk tolerance in a field experiment, and Nieß and Biemann (2014), who investigate risk tolerance in the context of self-employment and who also operationalize risk tolerance based on a single-item measure using such a question. Accordingly, we use an item where respondents indicated their willingness to take occupational risks on a 5-point scale ranging from 1 (complete unwillingness) to 5 (complete willingness). We group answers into three categories: low-risk tolerance (1/2); medium-risk tolerance (3); and high-risk tolerance (4/5); finding that the reported risk tolerance levels are approximately uniformly distributed among self-employed. With regard to industry distribution, 41% of the respondents are from the cultural, entertainment, and recreation sector, followed by information and communication (12%), education (12%), and health (7%). The share of solo self-employment is relatively high: 79% of the respondents have no employees. We control for this imbalance in propensity score matching. Respondents also report their self-employment experience: 81% of the respondents have more than five years of self-employment experience, 56% have more than ten years.

4.3. Financial Loss due to the Covid-19 Pandemic

Before the main analysis, we provide some insights into the data. Figure 1 summarizes the financial situation of the self-employed during the pandemic, distinguishing between respondents who applied for the emergency-aid and those who did not. Figure 1 reveals that the revenue decline due to the Covid-19 pandemic was more pronounced among those who applied for the support program than those who did not. Similarly, applicants experienced higher monthly financial losses on average and report impending insolvency (see Appendix, Figures A1 and A2).

Figure 1: Revenue decline due to the Covid-19 pandemic



Note: Figure 1 provides information on the distribution of the revenue decline due to the Covid-19 at the beginning of the pandemic in 2020 among respondents (16,859 observations). The black bars indicate the distribution of respondents who did not apply for the support program, the white bars of respondents who did apply for the support program.

Table 1 reports that a large share of respondents faced substantial declines in their revenues due to the pandemic; still, individual economic sectors were affected in very different ways. The hotel and restaurants industry as well as the arts, recreation, and cultural industry were hit particularly hard by the economic lockdown. In these industries, the majority of applicants report that they had no revenues at all, with 90% having to compensate for declining revenues of more than 75%. With respect to their future prospects, applicants and non-applicants appear to form similar expectations. In spring 2020, the majority of the self-employed expected financial hardship to continue for about half a year (see Appendix, Figure A3) and was weakly optimistic about their firm surviving the pandemic over the next 12 months (see Appendix, Figure A4).

Table 1: Revenue decline by industry

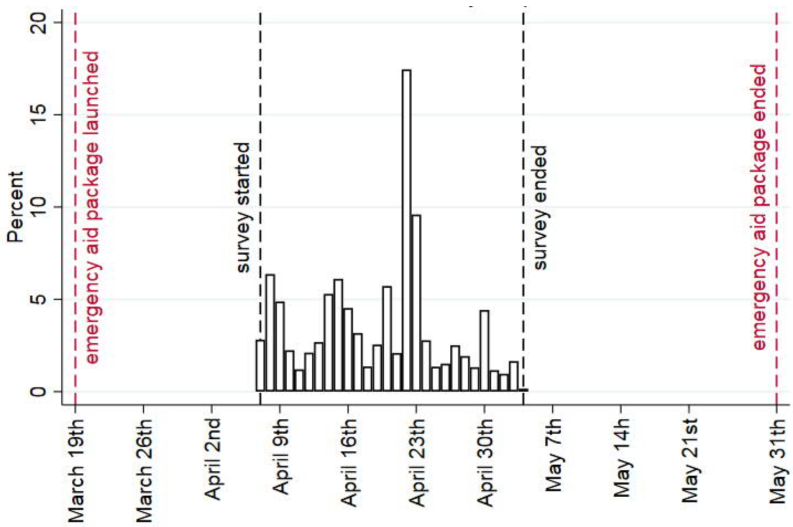
Share of respondents within each industry with a revenue decline due to the Covid-19 pandemic of…				
	Applicants		Non-applicants	
Industry	76 to 99%	100% (no more revenue)	76 to 99%	100% (no more revenue)
Manufacturing	0.28	0.21	0.18	0.11
Trade, repair of motor vehicles	0.33	0.29	0.18	0.19
Hotels and restaurants	0.27	0.64	0.10	0.70
Information and communications	0.36	0.19	0.23	0.12
Professional services	0.28	0.32	0.17	0.27
Other services	0.23	0.30	0.11	0.27
Education	0.31	0.45	0.23	0.40
Health care and social services	0.31	0.23	0.16	0.28
Arts, recreation, cultural activities	0.26	0.55	0.20	0.44
Other	0.26	0.42	0.17	0.32

Note: Table 1 provides information on the industries of respondents who indicated a decline in revenue by "76 to 99%" or "100% (no more revenue)." Columns (1) and (2) display the information on respondents who did apply for the support program, Columns (3) and (4) on respondents who did not apply.

4.4. Emergency-Aid Program

Germany's federal program started on March 25, 2020. Some federal states started similar programs earlier than the federal government: the earliest was Bavaria on March 19, 2020. From April 1, 2020 all state and federal level programs were merged into one single program. Figure 2 shows the survey within the time-frame of the emergency-aid program. The survey began three weeks after the start of the emergency program and was online for nearly four weeks until May 4, 2020. Applications for the program could be made until May 31, 2020. A subsequent support program that was designed for SMEs, less for self-employed, and which could only be applied for through a tax advisor ("Übergangshilfe I") was started on July 8, 2020. When the emergency-aid program ended, the next program was not yet foreseeable.

Figure 2: Distribution of survey responses over time



Note: Figure 2 provides information on the distribution of completed interviews during the field phase of the conducted survey in 2020 (27,262 completed interviews).

Table 2 provides an overview of the respondents' application status in our sample and a description of the non-applicants regarding their plans to apply later on. We observe 9,885 applicants in our sample, of which two-thirds successfully applied for the emergency-aid program and 58% had received the payment at the time of the survey. Processing averaged 7.5 days with half of the applicants receiving their payment within 5 days. At the time surveying, one-third of the applicants were still awaiting a decision. Rejection rates were low.

Table 2: Number of applicants vs. non-applicants

	N	% of whole sample
Number of applicants	**9,885**	**59%**
… with application approved	6,376	38%
… with payment received	5,754	34%
av. duration in days from application to payout (median/mean)	*5 / 7.5*	
…waiting for decision	3,268	19%
av. number of days waiting (median/mean)	*15 / 15.8*	
…with application rejected	241	1%
Number of non-applicants	**6,974**	**41%**
… planning to apply	1,013	6%
… unsure whether to apply or not	2,933	17%
… decided not to apply	3,028	18%

Note: Table 2 provides information on respondents of the estimation sample who did and did not apply for the emergency-aid program at the time of their interview.

Figure A5 in the Appendix illustrates the distribution of applications and payouts over time, showing that most applications were made within the first three weeks after the program was launched.

5. Estimation Strategy

5.1. The Identification of Treatment Effects

We investigate how much the emergency-aid program increased the subjective probability of the self-employed to remain self-employed over the following 12 months despite the Covid-19 pandemic. To estimate treatment effects, we rely on the Roy (1951) – Rubin (1974) model with two potential outcomes, Y_1 and Y_0, and a binary treatment variable D_i equal to one if the individual receives the treatment and equal to zero otherwise. Since the counterfactual outcome is not observable, i.e., we do not observe the outcome of the treated if they were not treated and vice versa, we cannot estimate the individual treatment effect. Instead, we rely on population averages and consider the average treatment effect of the treated defined as

$$ATT = E[Y_1 \mid D = 1] - E[Y_0 \mid D = 1]$$

and the average treatment effect of the sample population. This is composed of the average treatment effect of the treated (ATT) and the average treatment effect of the untreated (ATU) weighted by their respective proportions in the sample π and $(1- \pi)$:

$$\begin{aligned} ATE &= E[Y_1] - E[Y_0] = ATT + ATU \\ &= \pi\,(E[Y_1 \mid D = 1] - E[Y_0 \mid D = 1]) + (1- \pi)(E[Y_1 \mid D = 0] - E[Y_0 \mid D = 0]) \end{aligned}$$

Approximating the unobservable average outcome of the treated under no treatment $E[Y_0 \mid D = 1]$ by the observable average outcome of the control group, $E[Y_0 \mid D = 0]$, leads to selection bias since $E[Y_0 \mid D = 1]$ usually does not equal $E[Y_0 \mid D = 0]$ in nonexperimental data, as individuals self-select into treatment and might differ from the control group along some dimensions. The same applies for $E[Y_1 \mid D = 0]$. We overcome this by assuming conditional independence, i.e., conditional on observable characteristics X, the potential outcome is independent of treatment assignment, obtaining

$$ATT = E[Y_1 \mid X, D = 1] - E_X[E[Y_0 \mid X, D = 0] \mid D = 1]$$

and

$$\begin{aligned} ATE = {} & E[Y_1 \mid X, D = 1] - E_X[E[Y_0 \mid X, D = 0] \mid D = 1] \\ & + E_X[E[Y_1 \mid X, D = 1] \mid D = 0] - E[Y_0 \mid X, D = 0] \end{aligned}$$

The outer expectation $E_X[\ .\ |\ D = .]$ conveys that individuals in the comparison group are matched to treated units such that the mean distribution of the covariates in the matched control group resembles that of the treatment group for the calculation of the ATT and vice versa for the ATU (Caliendo and Kopeining, 2008). Furthermore, we assume overlap with $0 < Pr(D = 1|X) < 1$ for all X, meaning that individuals with the same values for X have a positive probability of being treated and untreated, i.e., there is no determinism in treatment assignment based on the covariates. We apply propensity score matching to reduce the dimensionality of the covariates to a single balancing score, P(X), based on which individuals from the control group are matched to the treatment group for the ATT and vice versa for the ATU.

5.2. Estimation Procedure

5.2.1 Outcome Variable

The aim of the emergency-aid program was to avoid firm closures by the self-employed whose economic survival was threatened by the Covid-19 pandemic. Beyond the financial support, an important aspect was that the aid program intended to reassure the self-employed that the government 'would not let them down' and that they could maintain their venture despite the crisis. Thus, the question is whether the program achieved this goal by increasing their belief in being able to successfully navigate the businesses through the crisis. The psychological aspect is particularly important in the context of the self-employed. Moreover, the analysis of the subjective survival probability using matching techniques helps to identify the perceived utility of the program by the self-employed, without running into the problem of intentional misreporting.

Therefore, we examine changes in the subjective survival probability of self-employed individuals in spring 2020. Respondents are asked to assess the likelihood of quitting self-employment within the coming year due to the pandemic. We use this information to construct our outcome variable, capturing the subjective survival probability of the respondents' ventures ranging from 1 ("very unlikely") to 5 ("very likely"). Appendix Figure A4 shows the distribution of the variable in our sample, distinguishing between applicants and non-applicants. For our treatment analysis, we reduce it to a binary variable with categories 5 ("very likely") and 4 ("rather likely") equaling one; the remaining categories equal zero: 3 ("neutral"), 2 ("rather unlikely"), and 1 ("very unlikely"). The binary variable allows for an intuitive interpretation of the results, since the ATT coefficients can be directly interpreted as changes in survival probability. To check the sensitivity of our results vis-à-vis the reduced explanatory variable, we conduct robustness checks using the original ordinal variable as dependent variable; results are very similar (Section A.4.2 in the Appendix).

5.2.2 Treatment Variable

We asked respondents to indicate whether they had applied, or planned to apply, for the emergency-aid program. Possible answers are 1 ("yes, I applied"), 2 ("I am planning to apply"), 3 ("I am not sure yet"), and 4 ("I will not apply"). We combine this question with information on their application's status ranging from 1 ("approved"), over 2 ("declined") to 3 ("I am waiting for a decision"). We also have information on the payment status for those individuals with approved application, obtaining information on the respondents' application status for the emergency-aid program, illustrated in Table 3.

Table 3: Definition of the treatment and control group

<table>
<tr><td>Survey Question</td><td>Q30: Did you apply for the emergency assistance (grant) from the federal or state government?</td><td>Q33: What is the status of your application?</td><td>Q35: Has the aid already been paid out …?</td></tr>
<tr><td rowspan="7">Answering Options</td><td rowspan="4">Yes, I applied</td><td rowspan="2">Accepted</td><td>Yes …</td></tr>
<tr><td>No …</td></tr>
<tr><td>Declined</td><td rowspan="5"></td></tr>
<tr><td>I am waiting for a decision</td></tr>
<tr><td>I am planning to do so</td><td rowspan="3"></td></tr>
<tr><td>I am not sure yet</td></tr>
<tr><td>No, I won't</td></tr>
</table>

Treatment Group

Control Group

Note: Table 3 provides information on the definition of the applied treatment and control groups in the main matching model of this paper. The dark grey shaded panel indicates the definition of the treatment group. The light grey shaded panel indicates the definition of the control group.

We are interested in the subjective survival probability of individuals receiving the emergency-aid. Respondents falling in this category are defined as the treatment group (dark grey shaded panel in column (3) of Table 3; N=5,743). Individuals 'who did not apply' are not suitable for the control group as their reasons for not applying are quite diverse and they probably differ from the treatment group along several (unobserved) dimensions (Table A2 in the Appendix). Instead, we follow Sianesi (2004), and Fredriksson and Johansson (2008) in using respondents who are planning to apply for the control group (light grey shaded panel in columns (2) of Table 3). The advantage is that respondents who are inclined to apply, share important characteristics with those who have already applied regarding their financial situation and their firm's characteristics, etc., compared to individuals who did not apply or do not intend to apply.

Respondents who are planning to apply might still differ from the treatment group in that their need for support is less urgent. One explanation could be that they were either (a) financially less affected by the crisis or (b) had alternative sources of finance, e.g., own financial reserves or support through alternative government programs. Furthermore, there might be other endogeneity issues between applicants and those who were only planning to apply in terms of optimism about the future with respect to how quickly the crisis would end. Among other variables influencing selection into treatment (see Section 5.2.3), we address these issues in the propensity score matching algorithm by controlling for revenue decline, for estimated time to insolvency after accounting for financial reserves, for transfers from the basic income scheme, and, with respect to differences in optimism, by controlling for the expected duration of financial hardship due to the crisis as expressed by the individuals. [2] While these factors should be the main reasons for postponing applications, we cannot rule out that other, unobservable factors are present. If so, we would underestimate the emergency program's treatment effect, i.e. if the control group's decision to postpone applications is associated with higher survival probabilities than the counterfactual survival probabilities of the treatment group.

We further exclude respondents whose application was successful but to whom the aid was not paid out when they were surveyed (Table 3, question 35). These individuals cannot be easily classified as in the treatment or control group. Knowing how much financial support they will receive, they might be close to the treatment group as they anticipate the lump-sum payment. However, having not yet received the financial support, they might be more conservative in their expectations because it remains unclear whether

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2 Other government programs (e.g. BAFA-subsidy, KfW-loans) were not designed for the self-employed but targeted larger firms, which explains the very low response rate. Therefore, in the majority of the cases, financial support from alternative government programs beyond the emergency-aid program and the basic-income scheme does not explain the control group's decision to postpone the application. We control for transfers from the basic income scheme in our estimation. In addition, as a robustness check, we estimate an alternative model controlling for further government support programs in the propensity score matching. The results are largely the same and available upon request from the authors.

they will receive the payment and because the exact date of the payout is still uncertain; meaning, they must bridge the time financially. If this effect dominates, including them in the treatment group would negatively bias the average outcome of the treatment group. Furthermore, we decided against using individuals waiting for a decision (question 33 in Table 3) as a control group, since the average time that has elapsed since their application (15 days, see Section 4.4, Table 2) exceeds the average processing time (7.5 days), thus suggesting their applications somehow differ from average (e.g., their cases are complicated). Here it is unclear how the uncertainty about the approval date affects their expectations about their future prospects.

As we are interested in the treatment effect for all self-employed targeted by the emergency fund, we estimate both the ATT and ATE. It is reasonable to believe that the majority of the self-employed who planned to apply are also eligible for the emergency-aid (Table 2 shows a rejection rate of 2.4%; 241 of 9,885). It can be assumed that many of them would have joined the program (Sianesi, 2004).

5.2.3 Propensity Score Matching

We apply propensity score matching to match treated and untreated individuals based on a set of covariates that are likely to affect the application for the emergency-aid and the respondents' expectations about their firms' prospects.

First, we control for *personal characteristics*, including well-known variables influencing entrepreneurial decision and survival, like the respondent's age (Kautonen et al., 2014) and gender (Verheul et al., 2012). Similarly, we control for the respondents' self-employment experience by accounting for the number of years spent in self-employment (Parker, 2018). As discussed in Section 3.2, various studies show that entrepreneurs' education and risk tolerance levels influence their business performance and survival. We include a binary variable on education and measure the self-employed respondents' risk tolerance on a scale from 1 (low risk-tolerance) to 5 (high risk-tolerance), where previous research emphasizes that individuals with high risk tolerance are, at the maximum, risk neutral (see Dohmen et al., 2011).

We further control for several *business-related characteristics* that likely influence selection into treatment and the outcome variable. We include information as to whether the self-employed work full-time or part-time in their firms and whether they have employees. Prior research documents different survival probabilities for these groups in comparison to other self-employed persons (de Vries et al., 2019). Moreover, we expect full-time self-employed (in contrast to part time self-employed) and solo self-employed (in contrast to self-employed with employees) to be more vulnerable to revenue decreases during the Covid-19 pandemic and, therefore, more likely to apply for emergency-aid. We further consider the firm's degree of digitalization by having asked the respondents to indicate their ventures' level of digitalization before the pandemic started on a 5-point Likert scale. We expect that more digitalized firms adapt their service provision to the requirements of the containment measures more easily (Bertschek and Erdsiek 2020). We also account for imbalances in the industry structure between treatment and control groups by including a set of industry fixed effects that indicate the main industry of the respondent's firm as the impact of the Covid-19 crisis differs across industries.

Prior research shows that the *financial situation*, like wealth, living costs, and household income, is an important determinant of entrepreneurial behavior and success (Hurst and Lusardi, 2004; Parker and Van Praag, 2006). Therefore, we control for the respondents' monthly private cost of living. Second, we measure whether they received financial support from the basic-income scheme to account for other sources of income that might influence both the likelihood to apply for the program and the survival probability. Third, we use information on how their firms were affected by the crisis, as more strongly affected individuals might be more prone to apply for financial support (thus, influencing their probability of treatment). Notably, we asked respondents to indicate how many months their ventures would be able to maintain solvency given their current revenue and cost situations, and account for reported revenue decreases due to the Covid-19 pandemic.

We include two variables affecting the outcome variable, i.e. how the self-employed assess their *future prospects*. Respondents were asked about their expectations regarding the duration of the pandemic and of the financial hardship it will cause. Thus, we ensure that matched individuals from the treatment and control groups have similar expectations about the future and that differences in the subjective survival probability are not caused by different perceptions about the crisis endurance. Furthermore, we control for the calendar week that each individual was surveyed, since assessments of future prospects might depend on progression of the crisis and related containment measures.[3]

Finally, the measures taken by the government in reaction to the Covid-19 crisis also differed across the 16 German federal states. To capture these differences and other

[3] At the beginning of May 2020, which coincides the end of the survey (see Figure 2), the German government announced that it would relax some of the containment measures by the mid of May; for instance, restaurants would be allowed to reopen and cultural events could take place in the open air.

regional differences in socio-economic structure and its impact on self-employment across Germany, we include *region fixed effects* for the federal state where the respondents' firm is located. Table A1 in the Appendix summarizes the covariates and compares their realized value distribution between the unmatched sample versus the treatment and control groups within the matched sample.

To ensure overlap, we trim the matching sample to observations within the region of common support using the max(min{P(X)|D=1, P(X|D=0)} and min(max{P(X)|D=1, P(X|D=0)} condition at the tails of propensity score distribution (see Section A.3 in the Appendix). We use an Epanechnikov kernel to construct a weighted average of the control units for the calculation of the counterfactual outcome, with kernel bandwidth chosen by cross-validation. The advantage of the kernel matching estimator over other techniques is that we use information from a range of control units instead of relying on a small set of matching partners in the close neighborhood of the treated unit. This is relevant in our case as the control group is smaller than the treatment group, thus, requiring high replacement rates for neighborhood matching, potentially causing inefficient ATT estimates (Caliendo and Kopeining, 2008). As a robustness check, we re-estimate our main results with different matching estimators (Section A.4.1 in the Appendix). We bootstrap standard errors for the average treatment effects based on B=1,999 replications.

6. Econometric Results

6.1. Main Results

Table 4 shows the estimated average treatment effects for the whole treatment group, both for a trimmed model applying the min-max-criterion and for a conservative trimming model with an upper bound of 0.95. On average, the emergency-aid moderately increases the subjective survival probability among those self-employed who received financial support by 6.5 percentage points, the effect is significant at the 1%-level (Table 4, column 1), confirming hypothesis 1. Comparing this effect to support measures that sought to increase the survival of start-ups (see, e.g. Caliendo and Kuenn, 2011; Caliendo et al., 2016), these studies find of about the double effect size. In this context, it must be considered that the emergency-aid consisted only of a one-time lump-sum payment, while start-up subsidies comprised repeated payments for several months.

As some observations (n=422) remain unused in the matching process, we further analyze the robustness of the effect size in Section 6.2, also shedding more light on heterogeneous effects between subgroups.

Table 4: ATT for the main sample

	Trimming approach	
	min/max	min / .95
ATT	0.065**	0.058**
SE	(0.023)	(0.021)
p-value	0.004	0.006
Common support	[0.107,0.996]	[0.107,0.950]
N matched	6,284	5,174
N unmatched	422	15
N out of common support	50	1,567
N total	6,756	6,756

Note: Table 4 provides information on the ATT for the main sample. Column (1) displays the estimation result for the matching model with min-max-criterion, Column (2) for the matching model with trimming at propensity score level of .95. Propensity scores for the treated and comparison groups are estimated using probit regression based on the baseline specification including information on respondents' socio-demographics, business demographics, crisis performance indicators, and risk attitudes. Matching is performed using non-parametric kernel matching with an Epanechnikov kernel to estimate balancing weights. Standard errors are bootstrapped with B=1,999 replications (*p<.05 **p<.01 *** p<.001).

One might be concerned that the upper bound is still close to unity and, therefore, includes respondents with a nearly perfect prediction of being treated. Excluding persons from the treatment group who have propensity scores close to 1 does not substantially alter the results (Table 4, column 2). However, the conservative model discards a large number of treated units, questioning whether the estimated effect is still representative of the treated individuals. Therefore, we focus on the min-max-criterion in the subsequent analyses.

If we include the hypothetical effect on the control group, i.e., changes in the subjective survival probability of the respondents who are planning to apply for the emergency fund (if they did and received the payment), we obtain an average treatment effect of the whole sample population of 6.4%, which is virtually identical to the ATT.

Table 5: ATE for the main sample

	Trimming approach	
	min/max	min / .95
ATE	0.064**	0.058**
SE	(0.020)	(0.019)
p-value	0.002	0.003
Common support	[0.107,0.996]	[0.107,0.950]
N matched	6,284	5,174
N unmatched	422	15
N out of common support	50	1,567
N total	6,756	6,756

Note: Table 5 provides information on the ATE for the main sample. Column (1) displays the estimation result for the matching model with min-max-criterion, Column (2) for the matching model with trimming at propensity score level of .95. Propensity scores for the treated and comparison groups are estimated in the same way as in Table 4. Standard errors are bootstrapped with B=1,999 replications. (*p<.05 **p<.01 *** p<.001).

6.2. Effect Heterogeneities

The ATT in the main sample measures the average program effect across all individuals who received financial support from the emergency-aid fund. We are further interested in knowing whether some individuals benefitted more than others based on their exposure to the crisis, their personal characteristics, or the application process.

6.2.1 Effect by Industries

The impact of governmental measures to contain the pandemic differed across industries. Some industries suffered from revenue declines more strongly than others (see Table 1). Therefore, we explore heterogeneous treatment effects between industries and estimate the average treatment effect within the particularly affected industries – under which we subsume hotels and restaurants as well as arts, recreation, and cultural activities – against less affected industries, comprising manufacturing, repairing of motor vehicles, trade, information and communications, professional services, education, health and social care, and other services.

Table 6: ATT by industry

	Industries	
	severely affected by the crisis	**less affected**
ATT	0.101**	0.022
SE	(0.034)	(0.036)
p-value	0.003	0.549
N matched	3,235	3,353
N unmatched	15	1
N out of common support	74	78
N total	3,324	3,432

Note: Table 6 provides information on the ATT, comparing respondents from industries particularly affected by the crisis with respondents from less affected industries. Column (1) displays the estimation result for respondents from industries particularly affected by the crisis, Column (2) for respondents from less affected industries. Propensity scores for the treated and comparison groups are estimated in the same way as in Table 4. Standard errors are bootstrapped with B=1,999 replications. (*p<.05 **p<.01 *** p<.001).

On average, the emergency-aid increased the subjective survival probability of the self-employed in strongly affected industries by 10.1 percentage points (Table 6), whereas the survival probability in the other industries was – on average – unaffected (hypothesis 2a). Note that the reference category is quite heterogeneous. Therefore, an insignificant overall effect does not mean that single industries within this category did not benefit from the emergency aid. Limits in the sample size preclude more detailed analysis. From a policy perspective, the support program appears to have predominantly improved the subjective survival probability for self-employed whose sectors were hit hard by the crisis.

6.2.2 Effect by Level of Education

Since the self-employed's level of education affects entrepreneurial performance and survival, we distinguish between persons with university degree and without. Results listed in Table 7 support hypothesis 2b. The emergency-aid program has a strong and significant effect, increasing the subjective survival probability by 10.4 percentage points among those self-employed with a university degree, but no effect among persons without such degree.

Table 7: ATT by education level

Education		
	university degree	**no university degree**
ATT	0.104***	0.042
SE	(0.031)	(0.039)
p-value	0.001	0.291
N matched	3,808	2,672
N unmatched	47	41
N out of common support	70	118
N total	3,925	2,831

Note: Table 7 provides information on the ATT comparing respondents with a university degree to respondents without one. Column (1) displays the estimation result for the subsample of respondents with university degree. Column (2) displays the estimation result for the subsample of respondents without university degree. Propensity scores for the treated and comparison group are estimated in the same way as in Table 4. Standard errors are bootstrapped with B=1,999 replications (*p<.05 **p<.01 *** p<.001).

6.2.3 Effect by Risk Attitude

Since the self-employed's willingness to take risks affects their decision behavior and firm results – including income (Hvide and Panos, 2014) and survival (Caliendo et al., 2010) – we distinguish between subgroups reporting different levels of risk tolerance.

Table 8: ATT by risk attitude

Risk attitude			
	Low risk tolerance	**Medium risk tolerance**	**High risk tolerance**
ATT	**-0.005**	**0.031**	**0.053**
SE	(0.046)	(0.046)	(0.043)
p-value	0.910	0.509	0.215
common support	[0.196,0.980]	[0.220,0.995]	[0.258,0.995]
N matched	1,583	2,374	2,288
N unmatched	126	1	140
N out of common support	123	38	83
N total	1,832	2,413	2511

Note: Table 8 provides information on the ATT comparing respondents with various levels of risk tolerance. Column (1) displays the estimation result for respondents with low, Column (2) for respondents with medium, Column (3) for respondents with high risk-tolerance. Propensity scores for the treated and comparison group are estimated in the same way as in Table 4. Standard errors are bootstrapped with B=1,999 replications (*p<.05 **p<.01 *** p<.001).

As Table 8 shows, we do not find a significant effect of risk tolerance: the support from the emergency aid did not measurably increase the subjective survival probability of the more risk tolerant self-employed, thus not confirming hypothesis 2c.

6.2.4 Effect by Speed of Payment

We also investigate whether temporal aspects in processing and disbursing the emergency-aid affect the subjective survival probability. We consider how the speed of payment influenced the effect among the treated individuals by sorting treated individuals into two groups: (i) those whose applications were processed within 5 days (compared to an average of 7.5 days, Section 4.4, Table 2), denoted as fast, and (ii) those waiting for more than 5 days for their applications to be processed, denoted as slow.

The results, confirming hypothesis 2d, are listed in Table 9. For the self-employed whose applications were processed fast, the subjective survival probability increases by 6.3 percentage points on average, while we find no significant effect for individuals whose applications were processed slowly. It appears that the speed with which the aid was granted and paid out measurably affects subjective survival probability.

Table 9: ATT by speed of payment

	Speed of payment	
	fast (up to 5 days)	slow (more than 5 days)
ATT	0.063*	0.038
SE	(0.032)	(0.024)
p-value	0.049	0.110
N matched	4,457	3,042
N unmatched	2	1
N out of common support	72	19
N total	4,531	3,062

Note: Table 9 provides information on the ATT comparing treated respondents whose applications were processed within 5 days with treated respondents waiting for more than 5 days for their applications to be processed. Column (1) displays the estimation result for the “fast” sample, Column (2) for the “slow” sample. Propensity scores for the treated and comparison group are estimated in the same way as in Table 4. Standard errors are bootstrapped with B=1,999 replications (*p<.05 **p<.01 *** p<.001).

7. Discussion and Conclusions

The Covid-19 pandemic severely affected the self-employed. Many countries implemented financial support programs designed to help the self-employed survive the Covid-19 crisis. We investigate the effect of the German emergency-aid program, for which €13.7bn was spent. Launched at the end of March 2020, self-employed individuals could apply for lump-sum payments of up to €15,000 to cover firm-related operating costs. We investigate the motivational effect of this program by analyzing its impact on the subjective survival probability of the self-employed. To evaluate whether the program achieved its goal of reassuring the self-employed, we use rich data of more than 20,000 self-employed collected in spring 2020 and implemented a propensity score matching analysis comparing self-employed who received the grant with those who planned to apply for it.

We find that the emergency-aid program had only moderate effects on the subjective probability to remain self-employed in the subsequent months, with these positive effects being stronger in industries that were severely affected by the crisis. We reveal further heterogeneity effects that are informative for the future design of such policy instruments: the speed of payment significantly affects how recipients perceive the financial support and influences its desired impact. Support granted within five days had significant effects, while payments granted with more delay did not.

Stronger effects are also observed among individuals who are higher educated. This result is consistent with evidence that the ability to adapt to unforeseen shocks increases with education (Stasielowicz, 2020) and that individuals with higher education are more likely to develop plans for alternative scenarios for their future. The higher educated self-employed might also be better able to develop ideas on business restructuring to survive the crisis because they are more likely opportunity-oriented (Simón-Moya et al., 2016). Moreover, they might interpret the emergency program as a signal that the government would continue support, reflecting positive relationships between educational attainment and trust in the government (Foster and Frieden, 2017).

These observations are highly relevant for the further design of such policy instruments and have three implications: First, the program, which spent an enormous amount of taxpayers' money, was only moderately effective at reassuring self-employed that they would get through the crisis. Effect sizes, however, are greater for self-employed from industries that were hit especially hard. Thus, future design of such instruments should have stricter access conditions by introducing thresholds levels. That would save taxpayers' money and ensure that the access to such programs is limited to those who are hit hard. Second, the analysis of our real-time data-set reveals that the processing speed of applications is key to the success of the instrument. It clarifies the importance of well-prepared administrative structures being able to process large numbers of applications within short time-periods. Third, we should also point to limitations in the use of financial aid mentioned in the introduction. As the support could only be used to cover fixed business expenses, we speculate that effects might have been stronger if lump-sum payments could also have been used to cover living expenses. Overall these results clarify how such instruments could be designed more effectively and more efficiently with respect to achieving their aims in the future.

Our study comes with some limitations: Not having accounting data, we cannot draw any conclusions with respect to the firms' productivity levels and the subsidization of weak firms (see Belghatir et al., 2022). Economic crises can accelerate shakeouts by forcing unproductive firms to leave the market, thus reallocating resources from low- to high-productive firms. In this context, government support policies might run the risk of disturbing processes of market restructuring toward more efficient resource usage. However, the Covid-19 pandemic hit certain industries irrespective of the firms' productivity level. Therefore, it was impossible for governments to identify high-performers.

Second, we cannot exclude that, in our matching approach, an unobserved bias remains. Therefore, despite our very rich set of covariates, we do not claim that these reflect all factors that might have remained unobserved. Third, another important limitation is that we have only single-item measures with respect to risk tolerance and the subjective survival probability. Although this approach is already used in the literature, future research should incorporate multi-item approaches.

More broadly, this article contributes to the understanding of motivational effects from public policy interventions during economic crises (Dolan and Galizzi, 2015). Self-employed individuals are well suited for this analysis, as their beliefs about future economic prospects concern their own business and can directly affect economic behavior; that is, the continuation and performance of their business at the micro-level as well as the industry's condition at the meso-level. In this respect, it would be interesting to complement our study with future investigations on firm survival. This would allow for shedding light on relationships between expectations and outcomes.

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Online Appendix

1 Tables

Table A1: Summary statistics

	Whole Sample		Matched sample		Treatment Sample		Control Sample	
Variables and categories	%	N	%	N	%	N	%	N
Risk tolerance								
Low risk tolerance	29%	4,894	27%	1,832	26%	1,512	32%	320
Medium risk tolerance	36%	5,993	36%	2,413	36%	2,050	36%	363
High risk tolerance	35%	5,972	37%	2,511	38%	2,181	33%	330
Monthly living costs (in €								
Up to 500	2%	413	1%	85	1%	58	3%	27
501 to 1,000	16%	2,632	14%	932	13%	773	16%	159
1,001 to 1,500	26%	4,304	26%	1,730	26%	1,487	24%	243
1,501 to 2,000	22%	3,790	24%	1,618	25%	1,411	20%	207
2,001 to 2,500	14%	2,352	15%	997	15%	855	14%	142
2,501 to 3,000	8%	1,423	9%	604	9%	511	9%	93
3,001 to 3,500	5%	771	5%	327	5%	268	6%	59
3,501 to 4,000	3%	451	3%	182	3%	144	4%	38
4,001 to 4,500	1%	211	1%	100	2%	89	1%	11
4,501 to 5,000	2%	279	1%	100	1%	81	2%	19
More than 5,000	1%	233	1%	81	1%	66	1%	15
Sales decline due to pandemic								
No decline or increase	2%	296	0%	31	0%	15	2%	16
Up to 25%	6%	933	3%	200	3%	153	5%	47
26% to 50%	13%	2,134	10%	680	9%	520	16%	160
51% to 75%	17%	2,862	17%	1,142	17%	968	17%	174
76% to 99%	25%	4,163	28%	1,921	29%	1,660	26%	261
100%	38%	6,471	41%	2,782	42%	2,427	35%	355
Estimated time to insolvency								
No separate business account	9%	1,601	9%	621	10%	554	7%	67
Already insolvent	26%	4,366	25%	1,668	24%	1,402	26%	266
One month	16%	2,742	19%	1,273	19%	1,094	18%	179
Two months	16%	2,627	17%	1,164	17%	995	17%	169
Three months	15%	2,487	16%	1,060	16%	901	16%	159
Four to six months	12%	1,997	11%	731	10%	603	13%	128
More than 6 months	6%	1,039	4%	239	3%	194	4%	45
Gender								
Male	48%	8,121	52%	3,532	53%	3,017	51%	515
Female	51%	8,665	47%	3,201	47%	2,711	48%	490
Diverse	0%	73	0%	23	0%	15	1%	8
Age								
Up to 39 years	22%	3,759	24%	1,591	23%	1,348	24%	243
40 to 49 years	28%	4,714	28%	1,923	29%	1,647	27%	276
50 to 59 years	37%	6,211	36%	2,443	36%	2,089	35%	354
60 years and more	13%	2,175	12%	799	11%	659	14%	140
Education								
Other	21%	3,524	22%	1,512	23%	1,324	19%	188
Professional education	18%	3,042	20%	1,319	20%	1,150	17%	169
University degree	61%	10,293	58%	3,925	57%	3,269	65%	656
Federal state								
Baden-Württemberg	10%	1,625	11%	710	10%	572	14%	138
Bavaria	17%	2,789	9%	621	8%	463	16%	158
Berlin	11%	1,828	19%	1,298	22%	1,241	6%	57

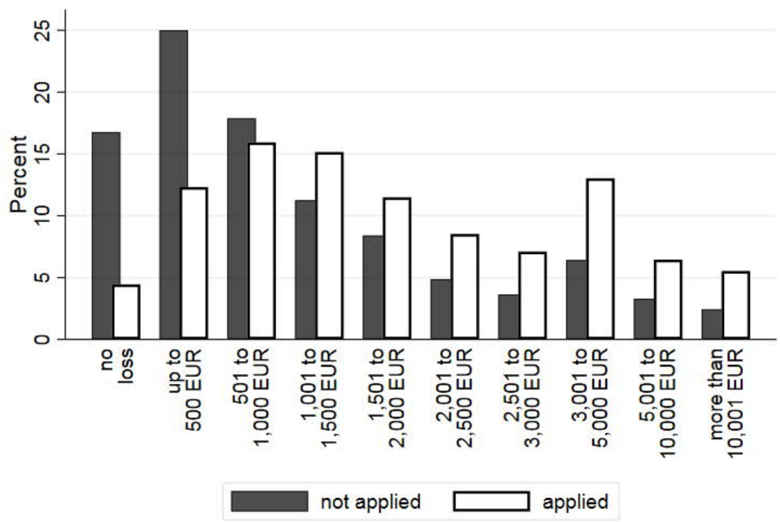
Brandenburg	3%	430	2%	154	2%	137	2%	17
Bremen	1%	143	0%	31	0%	23	1%	8
Hamburg	5%	903	6%	430	6%	352	8%	78
Hesse	8%	1,329	6%	405	5%	298	11%	107
Mecklenburg-Western Pomerania	1%	199	1%	48	1%	41	1%	7
Lower Saxony	8%	1,279	6%	374	5%	296	8%	78
North Rhine-Westphalia	21%	3,502	29%	1,957	31%	1,761	19%	196
Rhineland Palatinate	4%	725	2%	148	2%	89	6%	59
Saarland	1%	103	0%	26	0%	20	1%	6
Saxony	5%	881	4%	276	4%	232	4%	44
Saxony-Anhalt	1%	247	1%	53	1%	42	1%	11
Schleswig-Holstein	3%	584	2%	142	2%	107	3%	35
Thuringia	2%	292	1%	83	1%	69	1%	14
Duration of self-employment								
0 to 4 years	19%	3,271	17%	1,138	17%	954	18%	184
5 to 10 years	25%	4,193	24%	1,651	25%	1,416	23%	235
11 to 20 years	33%	5,569	34%	2,313	34%	1,960	35%	353
21 to 30 years	17%	2,889	19%	1,281	19%	1,093	19%	188
More than 30 years	6%	937	6%	373	6%	320	5%	53
Industry category								
Manufacturing	6%	963	6%	390	6%	330	6%	60
Trade; repair of motor vehicles	2%	419	2%	161	3%	151	1%	10
Accommodation and food service	2%	328	3%	172	3%	162	1%	10
Information and communication	12%	2,032	10%	654	9%	532	12%	122
Professional services	8%	1,266	6%	401	6%	322	8%	79
Other service activities	5%	923	4%	245	3%	191	5%	54
Education	12%	2,026	11%	774	11%	643	13%	131
Human health and social work act.	7%	1,255	6%	435	6%	351	8%	84
Arts, entertainment and recreation	41%	6,921	48%	3,260	50%	2,845	41%	415
Other	4%	726	4%	264	4%	216	5%	48
Level of digitization								
(continuous scale from 1 to 5)								
Mean (std. dev)	2.89	(1.17)	2.86	(1.14)	2.87	(1.14)	2.85	(1.17)
Part-time/full-time self-employed								
Part-time	11%	1,806	5%	312	4%	204	11%	108
Full time	89%	15,053	95%	6,444	96%	5,539	89%	905
Solo self-employed								
No	21%	3,564	24%	1,629	25%	1,408	22%	221
Yes	79%	13,295	76%	5,127	75%	4,335	78%	792
Application for basic security ("Hartz IV")								
I will not apply	83%	13963	80%	5398	80%	4599	79%	799
I applied	8%	1312	8%	553	9%	519	3%	34
I plan to apply	9%	1584	12%	805	11%	625	18%	180
Expected duration of financial hardship								
no hardship	1%	252	1%	40	1%	32	1%	8
1 to 3 months	20%	3,343	17%	1,156	17%	956	20%	200
4 to 6 months	40%	6,751	41%	2,744	40%	2,304	43%	440
7 to 9 months	15%	2,498	16%	1,109	17%	961	15%	148
10 to12 months	15%	2,606	17%	1,124	17%	981	14%	143
More than one year	8%	1,409	9%	583	9%	509	7%	74
Survey week								
April 6 – April 12, 2020	20%	3,310	17%	1,156	16%	920	23%	236
April 13 – April 19, 2020	26%	4,335	25%	1,674	24%	1,406	26%	268
April 20 –April 26, 2020	41%	6,831	43%	2,916	44%	2,513	40%	403
April 27 – May 4, 2020	14%	2,383	15%	1,010	16%	904	10%	106

Table A2: Reasons for not applying for the emergency aid program

Reasons	share of those who did not apply
Others	0.10
I think I am not eligible	0.23
I would need further information	0.04
An application was not possible yet	0.02
Server overloaded	0.01
I am waiting until conditions become more clarified	0.14
Not enough time	0.01
Revenue decline will occur later	0.14
Unsettled by threatened consequences for providing incorrect information	0.13
I am not in financial difficulties yet	0.18

2 Figures

FigureA1: Monthly financial loss during the crisis



FigureA2: Duration of solvency without government support

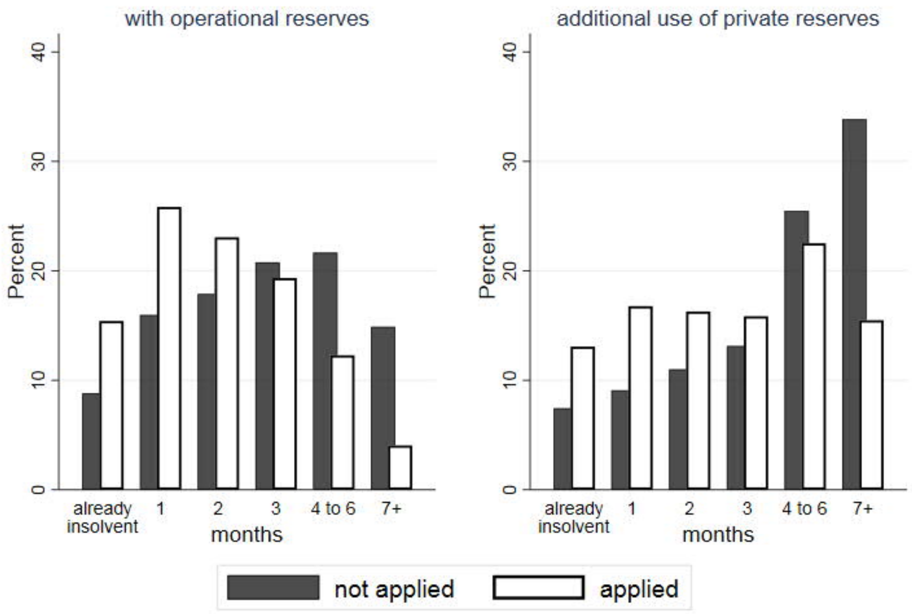


Figure A3: Expected duration of financial hardship due to the Covid-19 pandemic

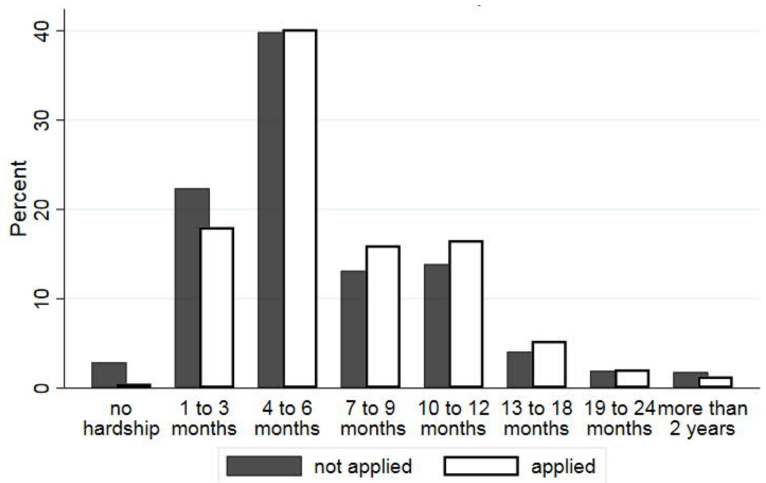


Figure A4: Subjective probability of occupational survival during the next 12 months

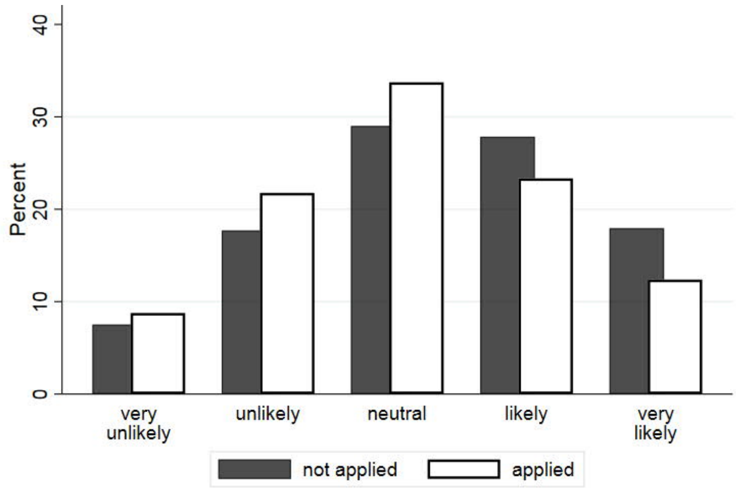
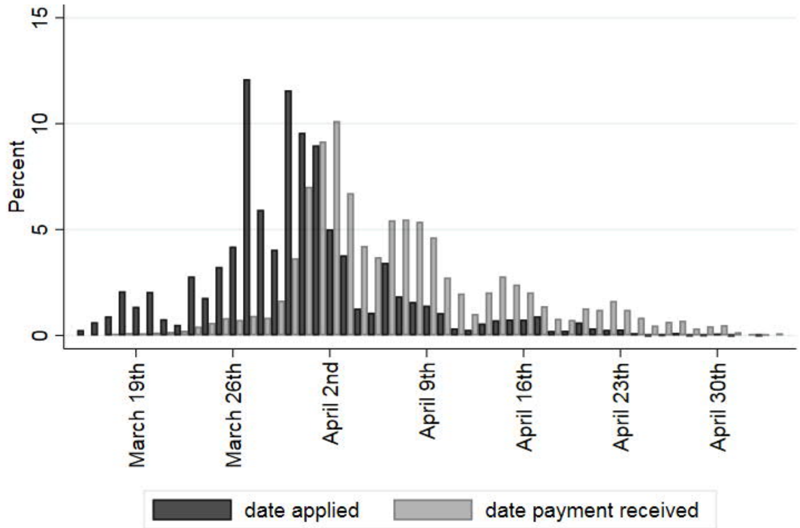


Figure A5: Timing of the application process



A.3 Matching Quality

We operationalize the categorical variables X by a set of dummy variables resulting in a total of 66 variables in the propensity score matching. To verify the matching quality, we calculate the standardized bias according to Rosenbaum and Rubin (1985), finding that the number of variables with absolute standardized biases above 5% and the mean absolute standardized bias are substantially reduced after matching (Table A3, rows 1-5 and 7), with a mean value below 5% being generally considered a successful bias reduction (Caliendo and Kopeining, 2008). One can also rely on two measures developed by Rubin (2001) to separately analyze the matching effect on bias reduction and variance. To analyze bias reduction, Rubin suggests comparing the number of standard deviations between the means of the covariate distributions for the treatment and control groups -- usually referred to as Rubin's B – arguing that standard deviations should be less than half a standard deviation apart after matching, preferably close to one-quarter. We obtain a value of 0.26, showing that we successfully reduced the bias between treatment and control groups (Table A3, row 8). Since there is a well-known trade-off between bias reduction and variance (Caliendo and Kopeining, 2008), we analyze Rubin's R, the ratio between the propensity score's variances in both groups, before and after the matching.

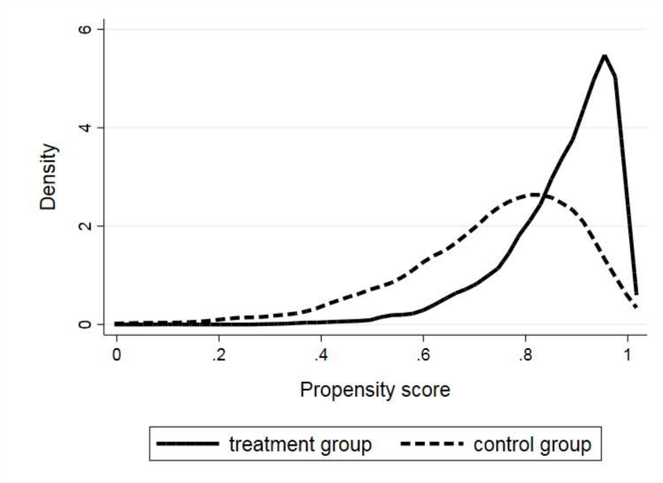
TableA3: Matching quality

	Before matching	After matching
Number of variables		
….with absolute standardized bias of		
0 to less than 1%	4	14
1 to less than 3%	12	29
3 to less than 5%	11	15
5 to less than 10%	17	7
more than 10%	22	1
… in total	66	66
Mean absolute standardized bias in %	6.8	2.1
Rubin's B	1.01	0.26
Rubin's R	0.94	1.28
(Re-)estimation of the propensity score: Pseudo- R^2	0.14	0.01

Ideally, the ratio should be close to one and not exceed [0.5; 2] (Rubin 2001). Table A3 row 9 illustrates that the bias reduction is indeed accompanied by an increase in variance from 0.94 to 1.28; however, the obtained ratio in variances is still close to 1. Finally, re-estimating the propensity score after matching obtains a Pseudo-R^2 of 0.01, meaning that the remaining variation in the treatment participation after matching cannot be explained with the covariates, i.e., there are practically no systematic differences in the distribution of covariates between the treated and controls after matching (Table A3, row 10). To sum up, the various measures indicate that the matched sample is balanced and, conditional on the covariates, potential outcomes are independent of treatment.

In addition to conditional independence, we require that the propensity score distributions of the treated and untreated overlap; i.e. there is no propensity score P(X) perfectly predicting treatment or non-treatment. Figure A6 shows the propensity score distribution for both groups. As expected, the distribution of the treatment group is left-skewed with treated individuals having a higher probability of being treated than the untreated. However, we find sufficient common support for the approximate interval of [0.11;0.99] and – importantly -- there are no holes; i.e., we do not observe areas out of common support within the interval [0.11;0.99], which otherwise would invalidate our trimming approach based on the min-max-criterion.

Figure A6: Common support



A.4 Robustness Checks

A.4.1 Nearest-Neighbor-Matching

To verify whether our results are sensitive to the choice of the matching algorithm, we repeat the analysis with a propensity score based on nearest-neighbor-matching with two neighbors and replacement. Results are listed in Table A4, columns (1) and (2), and are quite similar to those obtained under the Epanechnikov kernel estimator both in terms of size effect and efficiency.[4] The average treatment effect amounts to 6.9 percentage points against 6.5 percentage points in the main analysis, and the average treatment effect of the treated is 6.8 percentage points with nearest-neighbor matching against 6.7 percentage points in the main analysis. Apparently, using more observations from the control group as matching partners under the kernel estimator marginally increases efficiency without biasing the results. Imposing a caliper of 0.05 does not substantially alter the result (Table A4, columns (3) and (4)).

Table A4: Nearest-Neighbor-Matching with two neighbors and replacement

NN2-Matching				
	without trimming		Caliper 0.05	
	ATE	ATT	ATE	ATT
treatment effect	0.069	0.068	0.072	0.074
SE	(0.022)	(0.024)	(0.022)	(0.025)
p-value	0.002	0.005	0.001	0.003
N matched	6756	6756	6738	6738
N out of common support	0	0	18	18
N total	6756	6756	6756	6756

Notes: Robust standard errors were estimated following Abadie and Imbens (2016).

[4] We calculate analytical standard errors following Abadie and Imbens (2016), since Abadie and Imbens (2008) show that bootstrapping does not provide consistent standard errors in the case of nearest-neighbor matching with a fixed number of neighbors and replacement. Note that trimming is less relevant with nearest-neighbor matching since only the two closest observations are used, whereas kernel matching also uses information from faraway control units, depending on the bandwidth chosen.

A.4.2 Ordinal outcome variable

The original outcome variable that we use to measure the subjective survival probability is an ordinal variable ranging from 1 (“very unlikely”) to 5 (very likely”). In the main analysis, we recode the variable to obtain a binary variable that can be directly interpreted as probability by setting categories 5 (“very likely”) and 4 (“rather likely”) equal to one, and the remaining categories 3 (“neutral”), 2 (“rather unlikely”), and 1 (“very unlikely”) equal to zero. To verify whether the results are sensitive to the definition of the binary variable, we re-estimate the treatment effects with the original variable. The results, listed in Table A5, show a robust positive effect both for the ATE and the ATT. However, the interpretation of the magnitudes is less intuitive, as receiving financial support from the emergency fund increases the survival perception by 0.192 units on average on a scale from 1 to 5. Since the ordinal variable contains more variation across individuals, the treatment effects are more efficiently estimated, supporting our conclusion that the emergency program had a measurable effect on the self-employed persons’ occupational survival probability, even though the magnitude of the effect is moderate.

Table A5: Ordinal outcome variable

	Ordinal outcome variable	
	ATE	**ATT**
treatment effect	0.188	0.192
SE	(0.052)	(0.058)
p-value	0.000	0.001
common support	[0.107,0.996]	[0.107,0.996]
N matched	6284	6284
N unmatched	422	422
N out of common support	50	50
N total	6756	6756

Notes: Standard errors are bootstrapped with B=1,999 replications. The propensity score is estimated with the Epanechnikov kernel matching algorithm applying the min-max trimming criterion. The outcome variable is the subjective probability to stay self-employed over the next 12 months coded as 1 (“very unlikely”), 2 (“likely”), 3 (“neutral”), 4 (“likely”), and 5 (“very likely”).

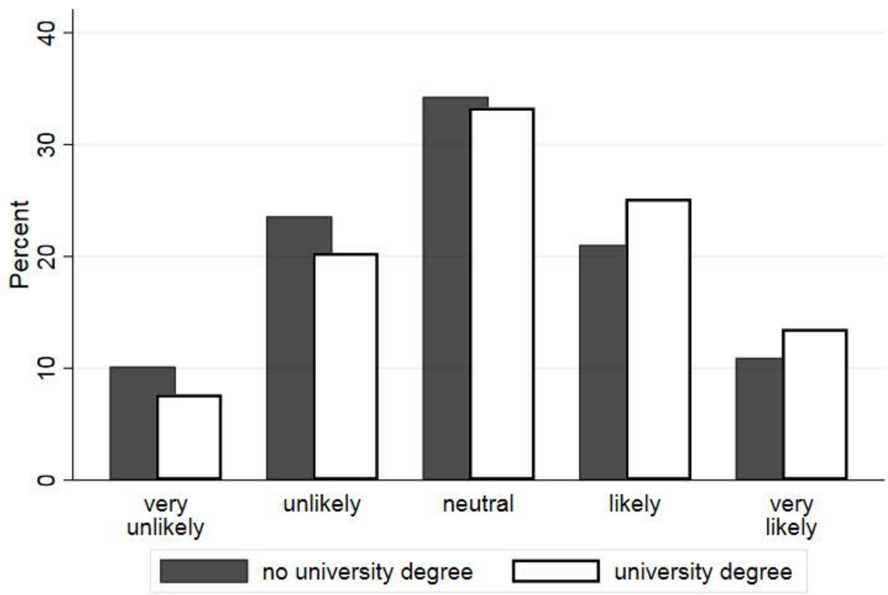
Table A6 lists the results for the heterogeneity analysis, which are in line with the binary model with an exception for the level of education. The intuition for the diverging result between ordinary and binary outcome variable is the following: While the support program increased the survival rate for both groups, it only shifted the perceived survival for people with a university degree rate to category 4 (“likely”) and 5 (“very likely”); see also categories 1 to 3, Figure A7).

Table A6: Heterogeneity analysis with ordinal outcome variable

	Ordinal outcome variable		
	ATT	**SE**	**N matched**
education			
university degree	0.223**	(0.078)	3808
no university degree	0.220*	(0.106)	2672
industry exposure to the crisis			
particularly affected	0.286***	(0.080)	3235
less affected	0.080	(0.098)	3353
application processing speed			
fast (up to 5 days)	0.186*	(0.085)	4457
slow (more than 5 days)	0.124	(0.063)	3042
risk tolerance			
low	-0.063	(0.109)	1583
medium	0.150	(0.108)	2413
…high	0.194	(0.121)	2511

*Notes: p-values : *** p < 0.001, ** 0.001 < p < 0.01, * 0.01 < p < 0.05. Standard errors were bootstrapped with B=1,999 replications. The propensity score was estimated with the Epanechnikov kernel matching algorithm applying the min-max trimming criterion. The outcome variable is the subjective probability to stay self-employed during the next 12 months coded as 1 ("very unlikely"), 2 ("likely"), 3 ("neutral"), 4 ("likely"), and 5 ("very likely")*

Figure A7: Subjective survival probability among applicants by education level



Literature to the Appendix

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