Time matters: Adopting a lifespan developmental perspective on individual differences in skills, cumulative advantages, and the role of dynamic modeling approaches

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Summary

The impact of individual differences in cognitive skills and socioeconomic background on key educational, occupational, and health outcomes, as well as the mechanisms underlying inequalities in these outcomes across the lifespan, are two central questions in lifespan psychology. The contextual embeddedness of such questions in ontogenetic (i.e., individual, age-related) and historical time is a key element of lifespan psychological theoretical frameworks such as the HIstorical changes in DEvelopmental COntexts (HIDECO) framework (Drewelies et al., 2019). Because the dimension of time is also a crucial part of empirical research designs examining developmental change, a third central question in research on lifespan development is how the timing and spacing of observations in longitudinal studies might affect parameter estimates of substantive phenomena. To address these questions in the present doctoral thesis, I applied innovative state-of-the-art methodology including static and dynamic longitudinal modeling approaches, used data from multiple international panel studies, and systematically simulated data based on empirical panel characteristics, in three empirical studies.

The first study of this dissertation, Study I, examined the importance of adolescent intelligence (IQ), grade point average (GPA), and parental socioeconomic status (pSES) for adult educational, occupational, and health outcomes over ontogenetic and historical time. To examine the possible impact of historical changes in the 20th century on the relationships between adolescent characteristics and key adult life outcomes, the study capitalized on data from two representative US cohort studies, the National Longitudinal Surveys of Youth 1979 and 1997, whose participants were born in the late 1960s and 1980s, respectively. Adolescent IQ, GPA, and pSES were positively associated with adult educational attainment, wage levels, and mental and physical health. Across historical time, the influence of IQ and pSES for educational, occupational, and health outcomes remained

approximately the same, whereas GPA gained in importance over time for individuals born in the 1980s.

The second study of this dissertation, Study II, aimed to examine strict cumulative advantage (CA) processes as possible mechanisms underlying individual differences and inequality in wage development across the lifespan. It proposed dynamic structural equation models (DSEM) as a versatile statistical framework for operationalizing and empirically testing strict CA processes in research on wages and wage dynamics (i.e., wage levels and growth rates). Drawing on longitudinal representative data from the US National Longitudinal Survey of Youth 1979, the study modeled wage levels and growth rates across 38 years. Only 0.5 % of the sample revealed strict CA processes and explosive wage growth (autoregressive coefficients AR > 1), with the majority of individuals following logarithmic wage trajectories across the lifespan. Adolescent intelligence (IQ) and adult highest educational level explained substantial heterogeneity in initial wage levels and long-term wage growth rates over time.

The third study of this dissertation, Study III, investigated the role of observation timing variability in the estimation of non-experimental intervention effects in panel data. Although longitudinal studies often aim at equally spaced intervals between their measurement occasions, this goal is hardly ever met. Drawing on continuous time dynamic structural equation models, the study examines the –seemingly counterintuitive – potential benefits of measurement intervals that vary both within and between participants (often called individually varying time intervals, IVTs) in a panel study. It illustrates the method by modeling the effect of the transition from primary to secondary school on students' academic motivation using empirical data from the German National Educational Panel Study (NEPS). Results of a simulation study based on this real-life example reveal that individual variation in time intervals can indeed benefit the estimation precision and recovery of the true intervention effect parameters.

Zusammenfassung

Die Auswirkung individueller Unterschiede in kognitiven Fähigkeiten und sozioökonomischem Hintergrund für Bildung, Beschäftigung, und Gesundheit im Erwachsenenalter, sowie die Mechanismen, die Ungleichheiten in diesen Lebensbereichen zugrunde liegen, sind zwei zentrale Fragen der Lebensspannenpsychologie. Die kontextuelle Einbettung solcher Fragen in ontogenetische (d.h. individuelle, altersbezogene) und historische Zeit ist ein Schlüsselelement lebensspannenpsychologischer Modelle wie dem HIstorical changes in DEvelopmental Contexts (HIDECO) Framework (Drewelies et al., 2019). Die Zeitdimension ist zudem entscheidend für die Gestaltung empirischer Forschungsdesigns, um Veränderung und Entwicklung über die Lebensspanne hinweg zu untersuchen. Eine dritte zentrale Frage ist daher, welchen Einfluss die Auswahl von Messzeitpunkten und vor allem die Auswahl der Abstände zwischen solchen Messzeitpunkten in längsschnittlichen Studien bei der Erforschung interessierender Merkmale haben. Um diese Fragen in der vorliegenden Doktorarbeit zu beantworten, werden im Rahmen von drei wissenschaftlichen Studien innovative statistische Methoden wie statische und dynamische longitudinale Modellierungsansätze angewendet, Daten aus mehreren internationalen Panelstudien herangezogen, sowie Daten simuliert.

Die erste Studie, Studie I, untersuchte die Bedeutung jugendlicher Intelligenz (IQ), Noten (GPA) und des sozioökonomischen Status der Eltern (pSES) für Bildung, Beschäftigung und Gesundheit im Erwachsenenalter über ontogenetische und historische Zeit hinweg. Um mögliche Auswirkungen historischer Veränderungen im 20. Jahrhundert auf diese Beziehungen zu untersuchen, zog die Studie Daten aus zwei repräsentativen amerikanischen Kohortenstudien, den National Longitudinal Surveys of Youth 1979 und 1997, deren Teilnehmer in den späten 1960er bzw. 1980er Jahren geboren wurden, heran. Höhere Intelligenz, bessere Noten und ein höherer sozioökonomischer Status hatten einen positiven Einfluss auf den Bildungsstand, Einkommen sowie psychische und physische

Gesundheit im Erwachsenenalter. Im Laufe der historischen Zeit blieb der Einfluss von IQ und pSES für die verschiedenen Lebensbereiche im Erwachsenenalter relativ gleich, während Schulnoten für die jüngere Kohorte an Bedeutung gewannen.

Die zweite Studie, Studie II, hatte zum Ziel, die Akkumulation früher Vorteile als Mechanismus für die Entwicklung individueller Unterschiede und Ungleichheiten über die Lebensspanne hinweg zu untersuchen. Dynamische Strukturgleichungsmodelle (DSEM) werden als vielseitiges und flexibles statistisches Rahmenmodell vorgeschlagen, um Akkumulationsprozesse in Bezug auf Gehaltsniveaus und Gehaltswachstum zu operationalisieren und sie damit empirisch testbar zu machen. Gestützt auf repräsentative Längsschnittdaten der US National Longitudinal Survey of Youth 1979 modellierte die Studie Gehälter und deren Wachstumsraten über 38 Jahre hinweg. Nur 0,5 % der Stichprobe zeigten explosives Wachstum (autoregressive Koeffizienten AR > 1), die Mehrheit der Personen wies logarithmische Gehaltsverläufe über die Lebensspanne hinweg auf. Jugendliche Intelligenz und das höchste Bildungsniveau im Erwachsenenalter erklärten erhebliche Heterogenität im Einstiegsgehalt und langfristigem Gehaltswachstum.

Die dritte Studie, Studie III, untersuchte die Rolle von variierenden Zeitintervallen zwischen Messzeitpunkten für die Schätzung nicht-experimenteller Interventionseffekte in Paneldaten. Obwohl Längsschnittstudien oft gleichmäßig verteilte Intervalle zwischen ihren Messzeitpunkten anstreben, wird dieses Ziel kaum erreicht. Basierend auf zeitkontinuierlichen, dynamischen Strukturgleichungsmodellen untersuchte die Studie daher den potenziellen Nutzen von Messintervallen, die sowohl innerhalb als auch zwischen Teilnehmenden einer Studie variieren. Die Methode wurde anhand empirischer Daten des deutschen Nationalen Bildungspanels (NEPS) und der Modellierung des Effekts des Übergangs von der Grundschule in die Sekundarstufe (als nicht-experimentelle Intervention) auf die akademische Motivation der Schülerinnen und Schüler veranschaulicht. Die Ergebnisse einer Simulationsstudie, die auf diesem realen Beispiel basiert, zeigen, dass individuelle Variation in Zeitintervallen einen positiven Einfluss auf die Schätzgenauigkeit der wahren Interventionseffektparameter haben kann.

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Introduction and Theoretical Background

1 Introduction and Theoretical Background

We human beings develop and change continuously from our conception to old age (Baltes et al., 2006; Staudinger & Lindenberger, 2003). Although each developmental period of the lifespan, such as childhood, adolescence, adulthood, and old age, has its own developmental agenda, they are all closely interconnected with each other (Baltes et al., 2006; Patton & Spry, 2021). International large-scale assessments and longitudinal panel data, such as the US National Longitudinal Surveys (Cooksey, 2018), the German Socioeconomic Panel Study (Goebel et al., 2019), and the German National Education Panel Study (Blossfeld et al., 2009), have long focused on investigating individuals' long-term development across the lifespan, addressing the prediction of and change in educational, competence-, work-, family-, and health-related outcomes. These studies' aims are to both monitor differences between individuals in certain outcomes, such as educational attainment, income, or mental and physical well-being, and to learn about factors affecting such differences, that is, to identify the mechanisms that bring about differential lifespan developmental trajectories (Blossfeld et al., 2009; Blossfeld & von Maurice, 2011; Cooksey, 2018).

Psychological, social, and economic antecedents in lifespan development

To illustrate, we may consider two friends, Agnes and Tim, who know each other from early childhood. They went to the same primary school, became friends, transitioned to high school together, and graduated together when they were 18 years old. After graduation, they lost track of each other, but met up again 20 years later. When they share their stories, they find out that Agnes went on to finish a university degree after high school, and today lives in an affluent neighborhood in their hometown after returning from several jobs abroad, and is financially well-off as an executive in a medium-sized company. Tim, on the other hand, started working right after graduating from high school. Although he considered attending college, the fees were too high, and unlike Agnes's parents, his parents would not financially support him. He went on to work as a freelance musician, took Spanish classes at the local community college, and now lives across town in the city's pleasant but not-so-wealthy suburbs. Although they are both content with their lives and would not wish to change their circumstances, together they try to figure out why their educational and wage trajectories were so different. They think back to their families. Agnes came from a slightly more socioeconomically advantaged background than Tim, although not by far. In high school, Agnes excelled with straight As, while Tim's grades were usually in the average range. They laugh when they remember how many hours Agnes spent studying, when it took Tim five minutes to copy her homework afterwards. Skipping a few years forward, they remember their salaries in the year 2000, because it was a significant year to both of them. At this time, Tim had worked for five years, whereas Agnes had just started her first job after graduation from university. She earned 200 US Dollars more a month than Tim at that time. Not much later, however, she changed jobs frequently and managed to earn much more than him in a short period of time. They now wonder: Did their family background affect their trajectories? Would Tim have attended university if his parents had provided financial assistance, or was he content to pursue other interests because he never liked formal learning in the first place? Was it Agnes's intelligence and perseverance that later manifested in their different formal educational achievements and income? Was it their different income levels at an early point in their careers that led to Agnes earning significantly more than Tim over the next decades? Or, finally, was Agnes fortunate because she had chosen to improve her skills in the growing field of computer science, whereas Tim had chosen to work as an English-Spanish translator, a declining sector since the introduction of artificial intelligence and online translation?

One of the foundations of contemporary developmental theories is the understanding that human development evolves through reciprocal interactions between individuals and their contexts (Drewelies et al., 2019; Lövdén et al., 2010). To understand development across the lifespan, it is thus crucial to take into account both individual resources, such as cognitive skills, socioemotional characteristics, and family background, as well as individuals' social relationships, institutional embeddedness, and the specific historical time in which a person lives (Blossfeld et al., 2009; Drewelies et al., 2019; OECD, 2015; Spengler et al., 2015). These contexts usually work together in complex structures to shape individual characteristics or behaviors, and are shaped by them in reverse (Drewelies et al., 2019).

Modeling and measuring lifespan development and change

After some time, Agnes and Tim continue their talk. Agnes raises another point. One of their former classmates, Hugo, somehow defied the odds. Although he did not perform well in school, and his parents were certainly not rich, he went on to college and successfully pursued a PhD. Nobody would have expected that. Was it thus even possible to draw general conclusions about how particular factors, such as your family background or grades, affect your subsequent life? Was it different for everyone? Or, did exceptions like Hugo just prove the rule? In light of this discussion, Tim tells Agnes that he has been participating in a national household panel study for many years, which tries to investigate these and similar questions. Every year, he receives a questionnaire in which he is asked about his income, education, and health. Agnes gets excited. Such regular tracking could potentially explain more about what happens in between your adolescence and your adult life. They then discuss how such changes from one life phase to another actually work. Is it time that brings about the changes from one life phase to another, as in the phrase "Time heals all wounds"? Or is it actually all the little steps and decisions that you make from day to day, month to month, or year to year that then inform your future decisions and eventually form your life's trajectory? Later on, Tim grudgingly admits that some things never change. Although he usually receives the survey's questionnaire in February, he normally waits a few weeks before filling it out. He sometimes returns it in March, sometimes in April, and once he did not return it until July. This sparks a new set of questions for Agnes. Wasn't it that as a freelancer, Tim would not earn the same amount each month? Wouldn't his earnings be higher in April than in July when people are more likely to be on vacation? What would the consequences be of not reporting his wages at the same time each year? On the one hand, it may have appeared that his wage had changed from one year to another, while in fact it had not. On the other hand, if he reported it the same month each year, it would appear to be constant throughout the year's cycle, which was not the case either. They wonder how a researcher conducting a study would handle such a situation. Should you only accept responses from your participants at the same time each year? But wouldn't you miss out on some interesting information if you did? And then, would it matter if the participants' responses were sometimes nine, sometimes fifteen months apart? At this point, they laugh and shake their heads.

Although the discipline of psychology often aims for universally applicable results for a population, it is widely acknowledged that people differ substantially from each other in terms of their individual characteristics, behaviors, or reactions to certain situations (Baltes et al., 2006; Cattell, 1952; Nesselroade & Ghisletta, 2003; Thorndike, 1914). To account for such individual differences when modeling trajectories, we need to apply statistical techniques that include random effects. Here, effect estimates are assumed to follow a distribution rather than being a single average point estimate for all persons (see e.g., Driver & Voelkle, 2018a). Other interesting approaches are for example quantile regression analysis, where quantile-specific coefficients for a dependent variable are estimated (e.g., Firpo et al., 2009; Koenker & Hallock, 2001). Furthermore, in recent years, dynamic models have been (re-)emphasized as useful tools in the psychological field (e.g., Hamaker et al., 2018; Voelkle et al., 2018). If we know that individual differences in an outcome exist, dynamic models can be applied to learn more about the underlying mechanisms that bring about these differences or inequalities. They do so by linking present levels of an outcome to prior levels of the outcome (Voelkle et al., 2018). Dynamic structural equation models are an example of these dynamic modeling approaches (e.g., Hamaker et al., 2018; McArdle, 2007; Voelkle et al., 2012). In their advanced form, they can accommodate random effects (Driver & Voelkle, 2018a; Hamaker et al., 2018). Similarly, a relatively new form of estimating dynamic relationships in psychological research is on the basis of continuous time models (Driver & Voelkle, 2018a; van Montfort et al., 2018; Voelkle et al., 2012). These allow the separation of the measurement process (i.e., when and in which intervals repeated measurements take place) from the actual process of interest (i.e., how a phenomenon develops over time; Oud & Delsing, 2010). This can be advantageous when working with panel data that regularly have time intervals that vary within and between individuals (Voelkle & Oud, 2013).

The present doctoral thesis

In my doctoral thesis, I will address the overarching questions raised by Agnes and Tim in their discussion. In particular, I (together with my collaborators) will investigate how adolescent skills contribute to the development of vital life outcomes across the lifespan, and how different classes of statistical models can help us to represent and understand developmental change processes and the evolution of inequality in a population. I do so by following three research strands. These research strands will be discussed within the HIDECO (Historical changes in developmental contexts) framework of developmental psychology (Drewelies et al., 2019), which is one of the first models in the field of psychology that actively takes into account the importance of individual-related contexts but also the historical time an individual lives in. In the first research strand, which I cover in Study I, I investigated the extent to which individual differences in vital adult life outcomes such as mental and physical health, education, income, and occupation can be attributed to individual differences in adolescent intelligence (IQ), grade point average (GPA), and parental socioeconomic background. Here, I focused on how historical changes in the socioeconomic environment in the 20th century might have affected these relationships between adolescent characteristics and adult life outcomes (Research Question 1). Furthermore, in addition to investigating average relationships, I followed up on the question of individual differences by examining whether individuals with different relative statuses (e.g., high vs. low) in the examined life outcomes and their relationships to adolescent IQ, GPA, and socioeconomic background were affected differently by historical changes (Research Question 2). To do so, I compared data from two representative US birth cohorts of 15- and 16-year-olds, one of them born in the early 1960s (National Longitudinal Survey of Youth, 1979), the other in the early 1980s (National Longitudinal Survey of Youth, 1997).

The second research strand, which I address in Study II, refers to the question of how the large inequalities in life outcomes (such as educational attainment and wages) observed in Study I actually come about. A prominent concept on the generating mechanisms behind growing lifespan inequality is called cumulative advantages. I examined how the mechanism of cumulative advantage could be operationalized and mapped onto a statistical framework to make it empirically testable (Research Question 3). I did so by utilizing multivariate wage time-series of individuals across a period of 38 years. Then, I examined to what extent individual differences in individuals' adolescent IQ, GPA, socioeconomic status, and adult highest levels of education predicted differential initial wage levels and wage growth rates across the lifespan (Research Question 4). To tackle these research questions, I used representative repeated-measures wage time-series data from the US National Longitudinal

Survey of Youth 1979 cohort. I proposed hierarchical dynamic structural equation models (DSEM) to empirically investigate cumulative advantage processes. The DSEM framework not only allows one to model autoregressive (wage) dynamics, but to also include random effects estimates to account for differences in wage dynamics between individuals. Such between-person heterogeneity in individuals' dynamics can then be modeled conditional on third variables, such as skills, socioeconomic status, and education.

In the third research strand, which I cover in Study III, I examine how we can model intervention effects on ongoing developmental processes when the time intervals between measurement occasions vary between participants in a longitudinal study. This is especially relevant to panel data with many individuals, as often not everyone can be measured at the exact same point in time each measurement wave; the time intervals between measurements in this case vary both within and between individuals ("individually varying time intervals"; IVTs). With reference to the story above, Study III thus also addresses the "problem" caused by Tim's inconsistent response behavior when he participates in the household panel. How can we ensure that such observation timing variability does not bias the parameter estimates we obtain for an (intervention) effect of interest? And, taking it a step further, might we even profit from IVTs when estimating intervention effects from panel data (Research Question 5)? To examine this research question, I draw on data from the German National Educational Panel Study (NEPS) to model the transition from primary to secondary school as a non-experimental intervention that affects students' academic motivation over time. I do so by making use of continuous time (CT) dynamic structural equation models. In a subsequent simulation study based on the empirical parameters and sample characteristics (sample size N, number of time points T) of the original NEPS data, I examine varying degrees of individual variation in time intervals between measurement occasions and how they affect estimation precision and recovery of the true underlying parameters.

In the next chapters, I will first present the dissertation's theoretical foundation (Chapter 1). I will first define lifetime development and developmental change as they apply to the thesis (Section 1.1). I will then introduce Drewelies et al.'s (2019) HIDECO framework, which serves as the thesis's guiding framework (Section 1.2). Building on this foundation, I will introduce the theoretical background for the first and second research strands, namely how individual differences in resources and skills affect individuals' lives, how historical circumstances affect such developments, and how the theoretical mechanism of cumulative advantage explains growing population inequality over time (Section 1.3). Section 1.4 introduces methodological perspectives on developmental change across the lifespan. It introduces the third research strand by providing an overview of panel studies as distinct data environments for learning about developmental change and introducing time as a crucial dimension for the statistical analysis of developmental change. I highlight the role of time in static and dynamic longitudinal models and discuss the importance of time intervals and their relationship to effect sizes in discrete and continuous time models. The next part (Section 1.5) summarizes the goals of the current doctoral thesis. The theoretical foundation of the thesis is followed by Study I (Chapter 2), Study II (Chapter 3), Study III (Chapter 4), and the General Discussion (Chapter 5). In the General Discussion, the key findings are summarized in relation to the proposed research questions (Section 5.1). They are then discussed in light of the theoretical foundation and beyond by giving additional overarching discussion points (Section 5.2). Finally, I discuss strengths, limitations, and directions for future research (Section 5.3), as well as implications for policy and practice (Section 5.4).

1.1 Lifespan development: Definitions, measurement, and relevance

In what follows, I will outline several concepts and definitions that are fundamental to the current dissertation. Every concept will appear in some form or another throughout the dissertation, and this chapter seeks to provide a common ground for how each one is used and defined in this thesis.

Lifespan psychology. Lifespan developmental psychology, today often referred to as lifespan psychology, studies individual development (i.e., ontogenesis) from conception to old age (Baltes et al., 2006; Staudinger, 2001). A central assumption in lifespan psychology is the malleability and adaptability of psychological functioning and behavior across the lifespan. Whereas it was earlier believed that individual development stops when a person reached adulthood (maturity), we now know that ontogenesis spans the entire lifespan and involves lifelong adaptation processes (Baltes et al., 2006; Lindenberger, 2001; Staudinger, 2001). Development is considered a developing system that comprises complex multidimensional and multifunctional dynamics. Due to selective adaptation, various components of the developing system may evolve at different rates, in different directions, for different reasons, and they may exhibit both continuities and discontinuities (Staudinger, 2001). In taking a person-centered (holistic) approach, this dissertation considers an individual as a system and seeks to learn more about lifespan development by describing and linking different age periods or developmental stages into a single, sequential pattern of lifetime individual development (Baltes et al., 2006; Magnusson & Stattin, 2006). Lifespan psychology has also always considered historical changes important for individual development. Because of the lifelong malleability of psychological functioning and behavior, individuals may adapt and react to changes in the historical environment (Drewelies et al., 2019; Lindenberger, 2001; Schaie, 1996). This implies that individuals with the same (cognitive, socio-emotional, socio-economic, etc.) prerequisites may develop differently because of historic changes in a population’s life circumstances (e.g., economic conditions).

Intra- and interindividual differences. As per the American Psychological Association, individual differences can be considered “traits or other characteristics by which individuals may be distinguished from one another" (APA Dictionary of Psychology, 2023). The term of individual differences is thus closely linked to the notion of inter- and intraindividual differences as well as intraindividual change. Drawing on Cattell's (1952) three-dimensional data frame of individuals, variables, and occasions, interindividual differences are differences that are observed across individuals for each variable at one occasion. Intraindividual differences are differences across variables for one individual at one occasion, and intraindividual change refers to sampling across occasions for one (or more) variables for one individual, that is, changes within the same person in one or more variables when the person is assessed repeatedly (Buss, 1974). In terms of ontogenesis, the way in which individuals develop might differ in some domains across the lifespan. This thesis will especially focus on interindividual differences and intraindividual change, as well as interindividual differences in intraindividual change. For example, the way cognitive skills develop from childhood to adulthood can differ between individuals, as well as their impact on future life outcomes. Agnes may reveal higher cognitive skills at age 6 compared to Tim; this reflects an interindividual difference. If we assessed Agnes and Tim repeatedly and examined the growth rates of their cognitive skills development up to age 18, we could study intraindividual change in cognitive skills for each of them over time, as well as possible interindividual differences in this intraindividual change. Other dimensions of interindividual differences in intraindividual change in developmental research include for instance levels of variation in an outcome in Agnes's or Tim's trajectories (Ram & Gerstorf, 2009).

Cognitive skills and socioemotional characteristics. Following the Organization of Economic Cooperation and Development (OECD), skills may be defined as the "ability and capacity to carry out processes and be able to use one's knowledge in a responsible way to achieve a goal" (OECD, 2019, p. 2). Importantly, a holistic view of competency includes the mobilization of information, skills, attitudes, and values to handle complex demands. Skills are a component of this idea (OECD, 2019). Cognitive skills can be thought of as a set of thinking strategies that allow individuals to use language, numbers, reasoning, and learned information. They include verbal, non-verbal, and higher-order thinking skills and are often measured by academic achievement or intelligence test scores (Duckworth & Yeager, 2015; OECD, 2019). Closely linked to the notion of skills is the concept of "lifelong learning." Akin to the assumption of malleable psychological functioning in lifespan psychology, skills are seen to be malleable across the lifespan (Kautz et al., 2014). Socioemotional characteristics encompass personality traits, such as conscientiousness and neuroticism, as well as characteristics such as empathy, emotional stability, perseverance, the ability to communicate, academic motivation, and being a responsible student (OECD, 2015, 2019; Roberts et al., 2007; Soto et al., 2022; Spengler et al., 2015). Importantly, there is an ongoing debate concerning whether or which of these characteristics can be framed as skills. Socioemotional characteristics are, similar to cognitive skills, malleable across the lifespan (Bleidorn et al., 2022; Roberts et al., 2003, 2017). However, they are usually assessed using self-report measures rather than behavioral tasks, which is frequently viewed as not accurately representing the concept and meaning of "skills" (e.g., Soto et al., 2022). Throughout this dissertation, I use the term socioemotional characteristics.

Large-scale assessments (LSAs) and panel studies. LSAs and panel studies are two powerful study designs for measuring developmental change. They have two important design features in common: They typically collect data on a large, nationally representative sample of individuals (high N), with relatively low sampling rates (few timepoints T; e.g., individuals are observed once a year, or once every two years). However, there are differences in their designs: LSAs such as the Program for International Student Assessment (PISA), which takes place in over 160 countries of the world, aim at evaluating educational systems and therefore compare historical trends in the same age group over time, for example, skill levels of 15-year-olds in 2022 vs. 2025 (OECD, 2023). To do so, each individual is measured only once. Typical panel studies are interested in trends as well, but their focus lies in surveying processes of developmental change on the individual level over time (Blossfeld et al., 2009; Cooksey, 2018; Ehmke et al., 2020). This is only possible by observing the same individual repeatedly, resulting in a multitude of individual time series. Examples of panel studies are the National Longitudinal Surveys of Youth (NLSY-79 and NLSY-97), initiated in the 1970s and 1990s, respectively. Other examples include the German National Educational Panel Study (NEPS), which provides longitudinal data on educational processes and competence development, and the German Socioeconomic Panel Study (GSOEP), that, like the NLSY studies, provides longitudinal information on household composition, employment, occupation, income, and health indicators.

In the following, I will introduce the HIDECO framework of developmental psychology by Drewelies et al. (2019) as the thesis's guiding framework. The HIDECO framework integrates the concepts described in this chapter both conceptually and methodologically, and makes it possible to combine them into concise, empirically testable research questions. These research questions can then also be easily related to each other within the framework. For example, the HIDECO framework allows us to examine intra- and interindividual differences in lifespan psychology and lifespan development, how individuals' skills change across the lifespan, and how such changes can be depicted using large-scale assessments and panel data. Importantly, one major advantage of the framework is that it understands individual lifespan development as located in a greater historical context, making it also possible to examine the influence of historical changes on individual developmental changes.

1.2 The HIDECO framework of developmental psychology

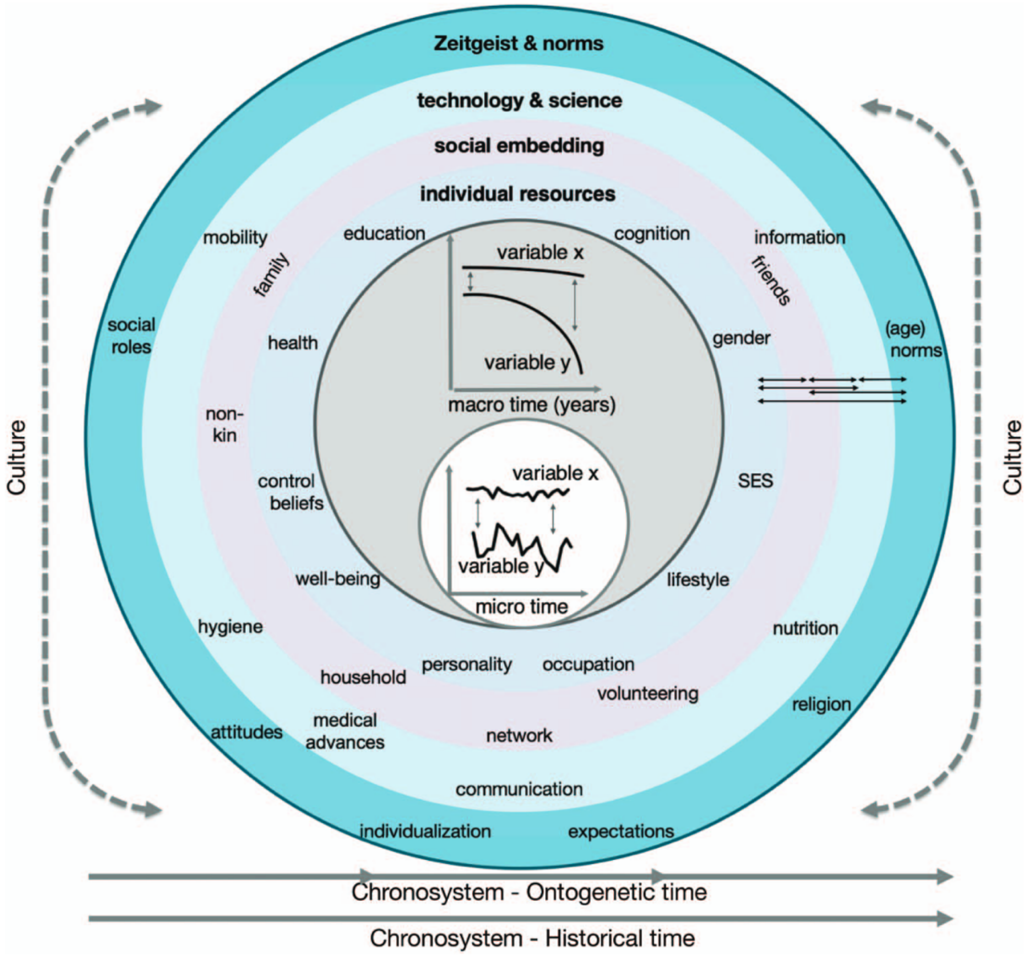
Lifespan psychology has long emphasized the significance of environments and historical changes for individual development. Less is known, however, about the mechanisms underlying the effect of historical context change on how people function and develop over time. Recognizing that lifespan development is a complex multidimensional, multidirectional, and multifunctional phenomenon (Baltes, 1987; Baltes et al., 2006), it is critical to use a multidimensional approach when investigating when, how, and by what mechanisms environmental and historical changes influence people's lives (Baltes et al., 2006; Drewelies et al., 2019). The HIDECO framework, first suggested by Drewelies et al. (2019), provides a concise framework to investigate such questions in a broader time-based context. Although Drewelies et al. (2019) place an emphasis on adult development and aging when presenting their framework, their model yields the potential for a variety of lifespan psychological developmental research questions. It is also one of the first psychological frameworks to explicitly take into account the idea that historical contexts may shape lifespan development on an institutional, organizational, and individual level. To structure and integrate potential pathways of historical change for (adult) development over the lifespan, Drewelies et al. (2019) identify five interrelated layers of contextual embedding: The outer layer is (a) Zeitgeist and norms, followed by (b) technology and science, (c) social embedding, (d) individual resources, and (e) time dimension of measurement (micro vs. macro time). Following lifespan psychology scholars Baltes et al. (2006), the framework also distinguishes between ontogenetic time, that is, developmental changes that evolve across a given individual's lifespan, and historical time, that is, developmental changes that occur throughout time within a broader (cultural) context, or when such conditions change.

Crucially, the HIDECO framework assumes that developmental contexts are not static but dynamic in nature, in that they can and do change constantly. In accordance with earlier approaches by Bronfenbrenner (1986), who differentiated between microlevel, mesolevel, and macrolevel processes, the HIDECO framework is structured in concentric layers. Thereby, developmental contexts may change for multifold reasons and may affect each level differently. This indicates that individual development across time is constantly shaped and affected by contexts and environments that change continuously themselves. The HIDECO framework also aims to allow the formulation of a priori hypotheses that can then be empirically tested (Drewelies et al., 2019). The framework can be used to quantify the distinct, shared, and interactive contributions of factors present at various contextual layers. As a result, it is for example possible to identify those aspects of the given contexts that have played a major role in translating historical changes into changes in a given outcome. As Drewelies et al. (2019) point out, this organizational structure of the framework might also help us to learn about the mechanisms underlying development, and the mediating and moderating ways in which contextual factors work and interact.

In the following, I will shortly elaborate on each of the contextual layers of the framework. Within each layer, I will provide empirical examples and methodological approaches that are pertinent to the research questions of this doctoral thesis. Importantly, even though Drewelies et al. (2019) identified distinct contextual layers within the HIDECO framework, they emphasize that contextual change operating on individuals' development works across layers and is highly integrated in nature. Figure 1 depicts the HIDECO framework graphically.

Figure 1

Drewelies and colleagues' HIDECO theoretical framework



Note. Drewelies, J., Huxhold, O., & Gerstorf, D. (2019). The role of historical change for adult development and aging: Towards a theoretical framework about the how and the why. *Psychology and Ageing, 34*(8), p. 1024 (http://dx.doi.org/10.1037/pag0000423). Copyright 2019 by American Psychological Association. Reprinted with permission.

Zeitgeist and norms. Zeitgeist and norms, which refer to the defining spirit or mood and the general set of beliefs, ideas, and feelings that are characteristic of a particular epoch in history, have undergone significant changes throughout historical time. These changes include adjustments in societal definitions of attitudes, social roles, and age norms. Examples relevant to the present thesis include continued population growth, the tendency toward individualization, and the rise of neoliberalist economic paradigms, which shaped social security and tax systems over time. For example, the neoliberal belief that markets regulate themselves and the associated cutback in social security systems in the 20th century can be related to growing inequality between individuals (Crystal et al., 2017; International Monetary Fund [IMF], 2015). These phenomena also affected individuals' daily lives, access to health care, well-being, and intergenerational mobility (Bailey & Dynarski, 2011; Crystal et al., 2017; Deaton, 2013; Pew Charitable Trusts, 2012). Interestingly, although social and economic realities have changed considerably, beliefs such as the possibility of the "American Dream" are still alive and present (Pew Chariable Trust, 2007), which points to the perseverance of the Zeitgeist, societal attitudes, and norms.

Technology and science. Throughout the past century, technological advances have profoundly influenced nearly every element of daily living, including communication opportunities, financial management, access to healthcare services, and educational settings. For example, computerization, digitalization, the introduction of the internet, and smartphone technology have revolutionized formal and informal teaching and learning. While on the one hand, this could potentially make information and knowledge more widely available for everyone (OECD, 2017a), on the other hand, new questions of access to such technologies and related educational inequalities have emerged (Christensen et al., 2013; Tawfik et al., 2016). Similarly, changes in technology have rapidly changed job markets and job demands. While new jobs in the IT and technology sector have been created (e.g., computer engineers), other jobs were lost over time (e.g., telephone operators; Autor et al., 2003; Feigenbaum & Gross, 2021). How new developments in technology, such as artificial intelligence, will influence individuals' daily lives, jobs, educational settings, as well as well-being and mental or physical health, will be the topic of future cohort research to come.

Social embedding. In the HIDECO model, Drewelies et al. (2019) emphasize social embedding especially with respect to family structure, household composition, and friendships. In this dissertation, I will take the additional angle that social embedding in childhood and adolescence takes place especially in educational contexts, that is, schools and classrooms (Eccles & Roeser, 2003, 2011). Educational contexts such as tracking in the German school system are known to affect students' trajectories across the lifespan (Maaz et al., 2008). Similarly, the transition from one context to another, especially the transition from primary to secondary school, has repeatedly shown detrimental effects on students' motivation, self-concept, and achievement-related variables (Evans et al., 2018; Zeedyk et al., 2003). Social embedding might also mean the affluence of school environments or the inclusion in social networks (e.g., OECD, 2012). For example, being born into an affluent family and attending a high-SES school with highly qualified teachers might influence students' individual-level outcomes such as academic achievement (Behtoui & Strömberg, 2020; Sirin, 2005).

Individual resources. Individual resources refer to key individual-level resources such as socioeconomic status, physical health, cognitive skills, and socioemotional characteristics, as well as educational and occupational attainment. Importantly, although individual resources are more broadly accessible today than in the past (Drewelies et al., 2019), there are still substantial individual differences in their distributions in the population (OECD, 2012, 2015, 2017b). These individual differences affect individuals' developmental trajectories: For example, higher adolescent cognitive skills and socioemotional characteristics predict educational attainment, wage levels, and health outcomes in early, middle, and even older adulthood (Roberts et al., 2007; Spengler et al., 2015, 2018). The theory of cumulative advantages proposes a mechanism for how small initial differences, for example in wages or cognitive skill development, magnify and result in growing inequality between individuals over time (Bask & Bask, 2015; Baumert et al., 2012; DiPrete & Eirich, 2006). Importantly, theoretical mechanisms explaining the evolution of inequality often include cross-layer interactions, and "status" variables such as gender and ethnicity are also subsumed under "individual resources" in the HIDECO model.

Micro and macro level of time. Developmental processes, affected by all contextual layers, unfold over both micro and macro time scales. Drewelies et al. (2019) shortly define macro-time scales as measuring developmental processes in years, and micro time scales as measuring developmental processes in days. Although not explicitly mentioned in the framework, this layer is closely intertwined with the design of measurement occasions in a longitudinal study, and how or if the time dimension of a developmental process is included in statistical analyses (Dormann & Griffin, 2015; Timmons & Preacher, 2015; Voelkle et al., 2018). Parameter estimates and effects sizes are usually dependent on the time scale chosen in a study design: For example, the autocorrelation between two repeated observations of academic motivation will likely differ depending on whether the time interval between measurement occasions is one day or one year (see e.g., Voelkle et al., 2012). Importantly, the "boundaries" of substantive knowledge gain imposed by time intervals have become more fluid due to recent developments such as continuous time models based on stochastic differential equations in psychology and the social sciences (Boker & Nesselroade, 2002; Collins, 2006; Kuhfeld & Soland, 2021; Voelkle et al., 2012).

In sum, the HIDECO model is the major theoretical framework for my doctoral thesis, as it helps to pin down the three presented research strands and relates them to each other, both on a substantive and methodological level. In the next chapter, I will introduce the topic of individual differences in socioeconomic resources and skills across the lifespan, the first research strand of my doctoral thesis.

1.3 Individual differences in resources, cognitive skills, and socioemotional characteristics across the lifespan

In the HIDECO framework, this chapter is located in the individual resources, social embedding, and Zeitgeist and norms layers. First, I will give an overview of the recent literature relating individual differences in cognitive skills and socioemotional characteristics to key life outcomes such as health, income, and well-being across the lifespan. Second, I will review how socioeconomic resources affect these life outcomes, and how the relationships between socioeconomic resources and life outcomes might be subject to ontogenetic and historical change. Third, I will introduce the concept of "cumulative advantages" as a mechanism to explain growing inequality between individuals over time.

1.3.1 Cognitive skills and socioemotional characteristics as predictors of key life outcomes

Why are individuals' skills important? In a 2015 report, the OECD emphasized skills and skill development in developing and developed nations as a crucial factor for social and economic thriving and well-being (OECD, 2015). As recent research suggests, one of the many potentials of cognitive skills and socioemotional characteristics is their malleability. Although they have a genetic basis, cognitive skills and socioemotional characteristics are crucially shaped by environments, such as families, educational contexts, schools, and peers (Bleidorn et al., 2022; Roberts et al., 2017). Skill development is a dynamic process, and especially in the early years of an individual's development, both cognitive skills and socioemotional characteristics can be fostered in the right environment. Although the malleability is greatest in childhood and adolescence, cognitive skills and socioemotional characteristics might also be malleable later on (Beier, 2021; Brunello & Schlotter, 2011; OECD, 2015, 2018; Uttal et al., 2013). Thus, the potential for lifelong learning allows individuals a lifelong flexibility to change and adapt to new situations and environments. In turn, a skilled workforce may enable societies to tackle major upcoming challenges such as digitalization, globalization, and climate change (OECD, 2015).

From a growing body of literature, we know that both cognitive skills and socioemotional characteristics are important predictors of vital life outcomes. Cognitive skills such as intelligence (IQ), grade point average (GPA), and achievement test scores have repeatedly been shown to be positively associated with physical and mental well-being, educational attainment, longevity, employment, and wage levels (Roberts et al., 2007; Spengler et al., 2015, 2018), and negatively associated with criminal activity (Caspi et al., 2017; Loeber et al., 2012), welfare dependence (Fergusson et al., 2005), and substance abuse (Fergusson et al., 2005; Shippee & Owens, 2011). These associations also held across long periods of time; for example, individuals with higher IQs in infancy also had higher IQs and higher levels of academic achievement in early adulthood (Fagan et al., 2007). Higher intelligence in middle childhood (8-9 years of age) also predicted higher educational achievement, rates of degree attainment, and employment rates seven, ten, and fifteen years later (Fergusson et al., 2005; Strenze, 2007). Similarly, high school grades positively predicted enrollment, academic performance, and persistence in college (Galla et al., 2019; Westrick et al., 2015), lifetime educational attainment (Brookhart et al., 2016; French et al., 2015), and prestige of occupation and annual income in adulthood (Borghans et al., 2016; French et al., 2015). For college GPA, Zou et al. (2022) showed that an increase of one unit in GPA was associated with an increase of 29.6 percent in starting monthly wages. Furthermore, cognitive skills such as intelligence and grade point average have not only been associated with absolute levels of vital life outcomes, but also their growth rates across the lifespan. Hall and Farkas (2011) showed that intelligence scores positively predicted initial wage levels and long-term wage growth rates. The same was true for achievement test scores and educational attainment as predictors of wage levels and their respective growth rates (Cheng, 2014; Rose, 2006; Yamauchi, 2015).

With respect to socioemotional characteristics such as self-concept, conscientiousness, and self-control, we find a similar picture. Empirical evidence suggests that social and emotional skills do not only affect important life outcomes such as subjective well-being, physical health, educational attainment, and criminal activity (Kautz et al., 2014; Moffitt et al., 2011; Spengler et al., 2016), but that they also play a role in improving educational attainment and career advancement over time (Spengler et al., 2018). Importantly, socioemotional characteristics have been found to affect a wide range of quality-of-life outcomes, such as mental health and subjective well-being, and are just as predictive as IQ and achievement tests (Almlund et al., 2011; Spengler et al., 2018). Using data from a two-wave longitudinal sample collected over a 40-year period from childhood (age 12) to middle adulthood (age 52), Spengler et al. (2015) showed that student traits and behaviors such as being a responsible and studious student predicted occupational success and income over and above IQ and parental socioeconomic background. For example, an increase of 1 *SD* in studiousness at age 12 corresponded to an increase of 0.13 *SD* in occupational status, measured by the international socioeconomic index (ISEI), at age 52.

At the same time, it is important to note that levels of cognitive skills and socioemotional characteristics are usually correlated both with each other and with socioeconomic status. For example, Duckworth et al. (2011) found that incentives influencing the motivation of test takers increased IQ scores by an average of 0.64 *SD*. Poropat (2009) reported correlations between conscientiousness and grade point averages as high as $r = .50$ (Cohen's $d = 1.14$), and for openness and GPA at $r = .43$ (Cohen's $d = .96$). Similar findings concern the relationship between SES and cognitive skills, where correlation coefficients between $r = .10$ and $r = .36$ were found from infancy to adolescence (von Stumm & Plomin, 2015). Similarly, Fergusson et al. (2005) showed that initial correlations between intelligence and substance abuse decreased significantly when controlling for socioemotional characteristics such as early behavioral and conduct problems as well as family background. Thus, it is important to distinguish between effects and compare effect sizes of socioeconomic background, socioemotional characteristics, and cognitive skills, which we will do in the next chapter. From recent literature we also know that the influence of socioeconomic status for later life outcomes might especially be sensitive to historical changes, which will be addressed in the following.

1.3.2 Socioeconomic status and inequality over ontogenetic and historical time

Among cognitive skills and socioemotional characteristics, an individual's socioeconomic background, also called socioeconomic status (SES), plays an important role in shaping key life outcomes. Parental SES is typically measured by parental educational attainment, occupational status, or income levels (Strenze, 2007), as well as by cultural assets such as the number of books in a family's home (Evans et al., 2010). Importantly, these statuses transfer into other more flexible resources such as money, time, knowledge, and social connections (Phelan et al., 2010), which in turn play a major role in shaping a person's future, because it allows parents to provide their children with certain (learning) opportunities and experiences. For example, if children's parents own many books, read with them frequently, and can help them with reading-related tasks in school assignments, they might learn to read more easily and have better language-related academic achievement in comparison to children who were not provided with this home environment (Brunner et al., 2022; Heppt et al., 2022; Sirin, 2005). Over time, such differences might persist and grow, and even translate into differential access to higher education later on (Evans et al., 2010). Accordingly, numerous studies across the years and with different cohorts showed that individuals with fewer parental socioeconomic resources are more likely to receive less favorable outcomes in physical and mental health, education, and occupation later in life (Angelini et al., 2019; Damian et al., 2015; Greenfield & Moorman, 2019; Shonkoff et al., 2009). Results like these stand in stark contrast to common assumptions such as the "American Dream" or neoliberal views, according to which an individual's life outcomes depend only on "hard work", skills, and perseverance (Pew Chariable Trust, 2007). Societies are more or less permeable when it comes to individual achievement and success. For example, in Germany and the US, wealth and income levels are very much inherited. Long-term statistics for the US have shown that about 40% of children born into families in the bottom or top income brackets (i.e., bottom or top 20%) remain in their respective groups as adults. Only 4% of those raised in the bottom brackets move to the top in adulthood (Bradbury, 2011; Pew Charitable Trusts, 2012).

These results are important not only on an individual, but also at a societal level. As the World Social Report (United Nations [UN], 2020) points out, societies with high income inequality are less successful in reducing poverty. They develop more slowly socially and economically and have a harder time maintaining economic progress over time (Cingano, 2014; UN, 2020). Due to greater disparities in health and education, it is challenging for individuals to break the cycle of poverty, oftentimes resulting in the passing of disadvantage from one generation to the next (Bradbury, 2011; UN, 2020). Based on the Dunedin cohort study, Caspi et al. (2017) identified a minority of individuals who, compared to their peers, tended to face the same four disadvantages in childhood: they were raised in socioeconomically deprived environments, had lived through child maltreatment, had low childhood IQ scores, and had low childhood self-control. These individuals constituted approximately 22% of the assessed sample but accounted for 36% of the cohort's injury insurance claims, 57% of all hospital nights, 66% of welfare benefits, 78% of prescription fills, and 81% of criminal convictions. Sustainable social and economic development thus requires early healthy and safe family environments and access to schooling, as well as long-term equal access to health services and the labor market (Caspi et al., 2017).

Importantly, the intersection between individuals' SES, cognitive skills, and socioemotional characteristics as predictors for later life outcomes might be especially prone to historical changes. As the HIDECO model proposes, individuals' development is – among other things- subject to changes in the Zeitgeist, norms, and historical realities. For example, Sng et al. (2017) and Varnum and Grossmann (2017) argue that an increasing population density may have led to a general increase in the level of individualism and competition, for example in educational settings, the job market, and in access to quality health care. This might have led to an increasing importance of cognitive skills and socioemotional characteristics over time, which for example signal excellence and employability to a future employer (Piopiunik et al., 2020). Similar arguments have been brought up for trends of globalization and migration, which may also have increased the importance of lifelong learning and individual skill levels (Brown et al., 2001; OECD, 2021). Politically, in the last decades, neoliberal "trickle-down" or "free market" policies have proposed that markets may work perfectly on their own, needing no or very little regulation by the state or government (Aghion & Bolton, 1997). By reducing taxes for wealthy citizens and businesses to stimulate business investments in the short term, wealth would "trickle down" to the rest of the society long term. As a consequence, regressive tax systems were fostered, and the US and many Western countries faced dramatic cuts in Social Security and welfare programs (Crystal et al., 2017; Crystal & Shea, 1990; Stiglitz, 2015). This led to a more unequal distribution of wealth (IMF, 2015; Stiglitz, 2015), which has been shown to consolidate and enhance the importance of parental SES over time (e.g., with respect to social mobility, Chetty et al., 2017).

Many studies have compared the predictive utilities (i.e., effect sizes) of skills and socioeconomic background with respect to later life outcomes. For example, utilizing data from the US Project Talent study with 1940s-born individuals, Spengler et al. (2018) found that IQ was a stronger predictor of later educational attainment and income than parental SES and extraversion. Spengler et al. (2015) used data from the Luxembourg MAGRIP study of individuals born in the mid-1950s. They found a similar pattern of effect sizes when comparing IQ and parental SES with respect to adult income. It differed, however, for occupational status, where being a responsible student outperformed both IQ and SES. Shanahan et al. (2014) drew on US data from individuals born in the 1980s (US National Longitudinal Study of Adolescent Health) and found that SES was a stronger predictor than conscientiousness for hourly wages and educational attainment. Importantly, although various stand-alone studies with data from different time periods exist, there is a lack of studies that systematically examine how the relationships between skills, SES, and later life outcomes have changed across historical time.

1.3.3 Cumulative advantages as a mechanism for inequality

The literature defines different approaches to describe inequality-generating mechanisms. One of the most prominent and promising approaches is the concept of so-called cumulative advantages (CA). Generally, cumulative advantages are intraindividual (i.e., within-person) processes that lead to growing heterogeneity between individuals of a population or cohort over time (Bask & Bask, 2015; Crystal et al., 2017; DiPrete & Eirich, 2006). Offering a short explanation, the concept has famously been framed as “Skills beget skills” (Cunha & Heckman, 2007; Heckman, 2008), or “The rich get richer” (also known as the “Matthew effect”; Merton, 1968, 1988). However we frame it, this implies that an individual who has an early advantage in an outcome variable – for example a higher initial wage level at labor market entry, higher cognitive skills in early childhood – will also experience greater gains in that outcome variable in subsequent time periods. Thus, the early observed advantage “accumulates” over time, shaping the developmental change trajectory of the individual, which in turn affects the population patterns of interindividual (i.e., between-person) development (Bask & Bask, 2015; Cheng, 2014). As such, cumulative advantages relate intraindividual processes on the individual level to interindividual differences on the population level (Bask & Bask, 2015; Cheng, 2014).

Originally, the concept is traceable to the work of Merton (1968, 1973, 1988), who observed the development of scientific careers. He noted that exceptional performance early in the career of a young researcher attracted new resources and rewards that facilitated continued high performance, which was not the case for young scientists who had not yet “made their mark” (Merton, 1973, p. 446; DiPrete & Eirich, 2006). In the social and educational sciences and developmental psychology, this effect is also known as the

Matthew effect. For example, Pfost et al. (2012) and Baumert et al. (2012) investigated Matthew effects with respect to reading and mathematics competence development in elementary school, drawing on time-series data across three measurement occasions. Damian et al. (2015) examined whether Matthew effects existed for parental SES and adult life outcomes by including SES as a moderator variable in their model. Bask and Bask (2015) and Cheng (2014) applied CA to intracohort patterns of inequality in individuals' wage time-series across the lifespan, making use of latent growth curve models and autoregressive models. Crystal and Shea (1990) and Crystal et al. (2017) used CA to explain evolving patterns of inequality in income and wealth among the elderly by comparing different quantiles and age groups of different cohorts with each other. Importantly, although all studies use the terms "Matthew effect" or "cumulative advantages," their definitions and subsequent empirical modeling decisions do not always imply the same theoretical mechanism that causes inequality. In this thesis, I will thus specifically draw on the definition of DiPrete and Eirich (2006) with regard to CA mechanisms.

In their extensive review on cumulative advantages as drivers of inequality, DiPrete and Eirich (2006) differentiate between "strict" CA mechanisms that conceptually correspond to compound interest effects and other inequality-generating mechanisms. They define three main characteristics of cumulative advantage processes: First, in a cumulative advantage process, the growth rate of an outcome variable depends on the outcome's present value. For example, an individual's wage level tomorrow depends on (i.e., is causally linked to) the individual's wage level today. Similarly, a student's reading skills today likely depend on his or her reading skills the day before. Second, small advantages or disadvantages at an early stage of a process magnify, or grow larger, over time. If a process akin to a compound interest effect occurs, exponential growth patterns in trajectories emerge. Thus, small initial differences between individuals' wage levels or student reading skills are magnified. Third, as a result of the CA process, between-person differences and inequality grow over time, leading to rising population inequality.

The notion of "population inequality" is an important component of CA processes, which also distinguishes strict CA processes from other approaches that explain inequality. For example, when growth rates of an outcome variable vary by some status, such as ethnicity, parental SES, or gender, and these status-unequal growth rates persist over time or across multiple stages of the lifespan, the process is often described as cumulative advantages, although it is not CA in the strict (Mertonian) sense. Here, growing inequality between groups in an outcome variable is the result of a status variable's persisting direct effects and interaction effects, where the interaction effects imply group differences in the returns to that outcome variable (see e.g., the Blau-Duncan approach; Blau & Duncan, 1967). For example, beginning with cohorts born in 1965, women increasingly outperformed men in their educational attainment (van Hek et al., 2016). This gap appears to widen for cohorts beginning in the late 1970s (OECD, 2012). Notably, however, the observed increased educational advantage of women is not due to a decline in male accomplishment. Both men's and women's educational attainment has risen over the years, although women's educational attainment has grown significantly faster than men's (van Hek et al., 2016). Thus, on a population level, levels of heterogeneity (inequality) stayed the same or even slightly decreased over time (Breen et al., 2009), even though specific group trajectories might have grown more unequal.

Importantly, even though CA mechanisms are a concept frequently used in the literature, only few studies (e.g., Bask & Bask, 2015) have ever attempted to empirically model and test assumptions of strict cumulative advantages as defined by DiPrete and Eirich (2006). This is an important motivation for the second research strand of my dissertation.

1.4 Methodological perspectives on developmental change

Because panel studies are the sources of the data for all studies of the dissertation, I will first introduce advantages and challenges of working with this data to learn about developmental change. After this, I will give an overview of different classes of longitudinal models that can be utilized to investigate developmental trajectories and underlying mechanisms of change when working with panel data. The focus here is on how the "time" variable can be incorporated in statistical analyses based on static and dynamic longitudinal models, and to highlight how the substantial interpretation of an analysis can differ significantly depending on such a decision. Lastly, I will discuss how different time scales of developmental processes and different time intervals between measurements in a longitudinal study may affect parameter estimates in dynamic models, and how continuous time modeling can be utilized to provide a solution.

1.4.1 Panel studies as a unique data environment to investigate development

Panel studies are a unique approach to learning about developmental processes across the lifespan. In particular, panel data provide opportunities to describe individuals' growth and developmental trajectories across the lifespan, and to examine patterns of causal relationships between variables over longer time periods (Blossfeld et al., 2009). Panel studies assess participants repeatedly across long periods of times, for example decades (Weston et al., 2019). Thereby, the national representativity of the observed sample is usually ensured (e.g., by statistical weights). The resulting large sample sizes (e.g., approximately 13,000 young men and women in the NLSY-79) are typically accompanied by relatively low sampling rates, such as once every one or two years (Cooksey, 2018). Importantly, panel studies are usually not only based on methodological aspects, but also have a specific conceptual focus. For example, the NEPS study is intended to investigate individuals' educational paths and competencies within the context of the German educational system, as well as how they develop through time in relation to their families, personal lives, educational institutions, and workplaces (Blossfeld et al., 2009; Blossfeld & von Maurice, 2011). The US NLSY studies focus on individuals' labor market behaviors, and seek to understand how youths' experiences relate to labor market entry, career development, participation in government programs, and family formation (Cooksey, 2018; U.S. Bureau of Labor Statistics, 2023).

Contemporary developmental psychological theories such as the HIDECO framework (Drewelies et al., 2019) emphasize the significance of institutional and historical contexts for individual development. Because panel studies are often carried out by teams from different scientific disciplines such as psychology, economics, epidemiology, sociology, and demography, the resulting data sets frequently contain unique combinations of explanatory and criterion variables that can be used to characterize the context of a specific (lifespan) developmental research question (Weston et al., 2019). For example, the NEPS measures over 700 variables in its yearly cycle (Starting Cohort 2; NEPS-Netzwerk, 2017), NLSY-79 observes over 2,000 variables, and NLSY-97 measures over 3,000 educational, occupational, health- and family-related variables in a cycle (U.S. Bureau of Labor Statistics, 2012a, 2012b). Thereby, historical developmental trends can be modeled on an individual as well as a population level. Some panel studies, like the US NLSY or the British Cohort Studies (BCS), further provide panels from different historical cohorts (NLSY: born in the 1960s vs the 1980s, BCS: born in the 1970s vs the 2000s), which allow us to compare relationships between variables in the light of historical changes.

Because panel data are multivariate and multidimensional in nature, inter- and intraindividual differences as well as intraindividual change in constructs of interest can be investigated. This is particularly useful because often researchers are interested not only in individual differences in levels of a variable like well-being or wages, but also in interindividual differences in subsequent intraindividual changes, such as changes in well-being or wage growth over time. While large scale assessment and panel data's representativity allows the inference of such statistical results to the population, their resulting sample size (high *N*) also provides statistical analyses with high levels of power, making it possible to detect even small effects (Ertl et al., 2020; Groves et al., 2009). At the same time, large and representative sample sizes often allow us to reliably learn more about the developmental trajectories of minority groups (e.g., Colen et al., 2018), or about the extremes of a given distribution (e.g., 1st and 99th percentiles of income; Chetty et al., 2017, 2020).

Lastly, one widespread challenge in lifespan developmental research is that the circumstances under which causal inferences are drawn are often complex. Oftentimes, randomization is either impractical or unethical (e.g., assigning different wage growth rates across the lifespan to individuals, or assigning children to groups that do or do not receive education), and applying strict experimental controls can be challenging (Piesse et al., 2009; Rosenbaum, 2005). Primary threats to causal inferences in observational studies are unit heterogeneity and temporal instability (Halaby, 2004). Unit heterogeneity means that the study units, for example, persons, differ from each other with respect to unobserved stable characteristics (e.g., SES or intelligence) that may confound the attribution of effect to a causal variable of interest (Blossfeld & von Maurice, 2011; Halaby, 2004). Temporal instability refers to changes over time in unobserved exogenous variables (e.g., a historical event such as the financial crisis in 2007) that could be alternative explanations for change in a response variable. Panel designs, due to their longitudinal nature, are strong in dealing with both problems (Blossfeld et al., 2009; Hsiao, 2005, 2022). Because in panel studies the same persons are observed at different times, many unobserved characteristics remain stable and can be (statistically) ruled out as alternative explanations of change in a response variable (Halaby, 2004; Piesse et al., 2009). Furthermore, because individuals in a panel are observed at the same time, the effects of specific events, seasonal patterns, or trends may be statistically accounted for in subsequent analyses (Zyphur et al., 2020).

1.4.2 Time in static and dynamic longitudinal models

It is helpful to distinguish between two broad classes of longitudinal models when studying mechanisms of change in lifespan development: dynamic models and static models. Dynamic longitudinal models account for intraindividual (i.e., within-person) *changes* in a system of variables over time as a function of the past (Voelkle et al., 2018). For example, a student's current level of academic motivation likely depends on his or her past level of academic motivation. Similarly, an individual's current wage level will likely depend on past wage levels. Hence, the present level obtained in an outcome is assumed to have a direct and causal influence on the level subsequently obtained (Baumert et al., 2012; Voelkle et al., 2018; Zyphur et al., 2020). Typically, we use autoregressive terms, difference equations, or differential equations to express dynamic models (Driver & Voelkle, 2018a; Oud & Delsing, 2010). Importantly, in terms of terminology, dynamic models often conceptualize and name individuals as "dynamic systems" (e.g., Driver & Voelkle, 2018a, 2018b). Static longitudinal models, on the other hand, account for the state of a system of variables and are frequently expressed as a function of time, meaning they include time as an exogenous predictor but do not include temporal dynamics. If we are primarily interested in describing change over time, static longitudinal models provide a straightforward way to do so (Baltes & Nesselroade, 1979; Voelkle et al., 2018). The differences between the two model classes, particularly in terms of interpretation, become evident when prototypical representatives of the different model families are considered: autoregressive models are a prototypical example for dynamic longitudinal models, and the latent growth curve model (LGCM) for static longitudinal models.

Classic LGCM models estimate person-specific trends over time (e.g., McArdle & Nesselroade, 2003). However, these are static models because they do not incorporate lagged effects, even though researchers frequently refer to them indicating "dynamic" relationships among trends (Zyphur et al., 2020). According to Voelkle et al. (2018), an LGCM in its simplest linear form can be represented as a regression model:

$$y_i(t) = \eta_0 + \eta_1 \cdot t_i + \zeta_i(t) \qquad \text{(Eq. 1)}$$

where $y_i(t)$ is the value of the continuous dependent variable y for individual $i = 1, ..., N$ at a time point $t \in R$. The term η_0 denotes the intercept, η_1 the linear slope, and the error term at time point t is denoted by $\zeta_i(t)$. Because the intercept and slope are often assumed to be random variables, an additional subscript i may be added to these two terms. As seen in Equation 1, time acts as an exogenous predictor in this model, which accounts for the time-dependent state of the system (i.e., the dependent variable $y_i(t)$). If the time point is known, it is possible to predict the state of the system (i.e., the dependent variable).

In contrast, in a dynamic model, knowledge about time points is necessary but not sufficient to learn about the state of a system (Voelkle et al., 2018). As a typical example of a dynamic model, we can consider a change score model or autoregressive model (e.g., McArdle, 2009; McArdle & Grimm, 2010). Based on Voelkle et al. (2018), Equation 2 represents such a simple autoregressive model:

$$y_i(t) = a \cdot y_i(t - \Delta t) + \zeta_i(t) \qquad \text{(Eq. 2)}$$

Here, time interval Δt is commonly fixed to one. If $y_i(t - \Delta t)$ is subtracted from both sides of Equation 2, the autoregressive model formulation becomes a mathematically equivalent change score model (i.e., $y_i(t) - y_i(t - \Delta t) = (a - 1) \cdot y_i(t - \Delta t) + \zeta_i(t)$). In this formulation it becomes clear that the model accounts for changes (i.e., $y_i(t) - y_i(t - \Delta t)$) in the state of the system (i.e., the dependent variable $y_i(t)$), as a function of both the initial state $y_i(t - \Delta t)$ and the time Δt that has passed. In contrast to static models, knowing the time point t alone is thus not sufficient for predicting the dependent variable $y_i(t)$. We also need to know something about the past, and we must know something about the system's initial state (Voelkle et al., 2018).

Given the assumption that causality is a temporal process, the two model categories have different implications for how their effects are interpreted (Zyphur et al., 2020). Time, as indicated by the term $\eta_1 \cdot t_i$ in Equation 1, serves as an exogenous predictor of the dependent variable $y_i(t)$. However, presuming there is an "effect of time" can be deceptive. Although the temporal ordering of cause-and-effect variables is required for causality (i.e., the cause must occur before the effect), time cannot be a causal component in and of itself (Baltes et al., 1988; Zyphur et al., 2020). It is also easy to overlook potentially interesting causal processes such as socialization, institutionalization, or maturation when considering time as a cause (Zyphur et al., 2020). In the words of Baltes et al. (1988): "… although time is inextricably linked to the concept of development, in itself it cannot explain any aspect of developmental change" (p. 108). Thus, when the objective of a research question is not only to describe change, but to understand the mechanisms that lead to change, dynamic models are needed (Driver & Voelkle, 2018a; Voelkle et al., 2018; Zyphur et al., 2020).

When it comes to studying lifespan developmental research questions, each model type has relative strengths and weaknesses. Static models are not superior to dynamic models, and vice versa; they just provide alternate foci and allow us to operationalize and assess different theoretical claims. Little et al. (2021), for example, investigated reading ability development using latent growth curve models. They found that reading-related growth was marked by significant individual differences during the early elementary-school period and non-significant individual differences during the late elementary school period.

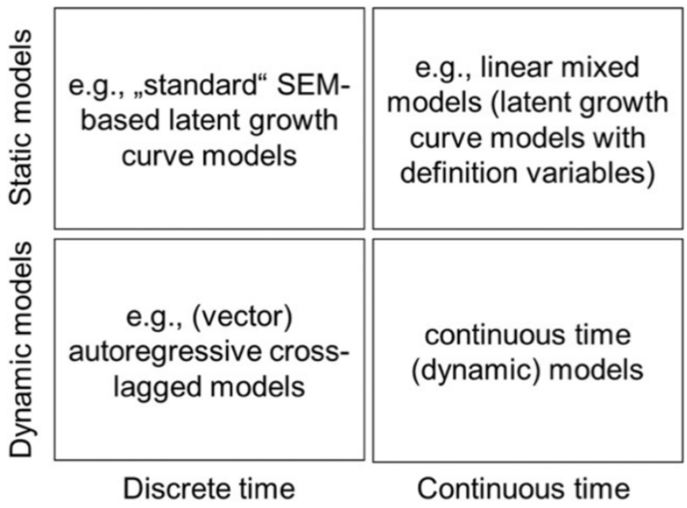
When Baumert et al. (2012) and Little et al. (2017) approached the same topic with latent change score and simplex models, which both include the temporal dynamics of a process, they focused on possible cumulative advantages in reading skill development that might have led to individual differences in reading trajectories over time. Together, these studies enriched the field with a multidimensional perspective on states and change of the complex system of reading skills. Also, the two kinds of models are not always mutually exclusive. For example, it is possible to combine dynamic and static models by adding a static component to a “dynamic” model, or a dynamic component to a “static” one (Voelkle et al., 2018). Nevertheless, the differentiation between static and dynamic modeling is helpful to distinguish what we can learn concerning substantive research questions from each model category, and what each model category’s strengths and limitations are for examining developmental change.

1.4.3 From discrete to continuous time modeling

When distinguishing between static and dynamic models, we can also distinguish between discrete and continuous time models. Figure 2 depicts the corresponding two by two classification table of longitudinal models from Voelkle et al. (2018) with prototypical examples of statistical methods for each resulting combination of static/dynamic and continuous/discrete time. Although continuous time models have a long history in disciplines such as economics or physics, they have just recently been discovered in the field of psychology. Van Montfort et al. (2018) provide a comprehensive overview of continuous time models in the behavioral and social sciences. The relationship between discrete and continuous time models has been widely discussed, for example by Oud and Delsing (2010), Voelkle and Oud (2015), and more recently van Montfort et al. (2018). In general, we can differentiate between processes that only occur at discrete points in time and those that exist continuously but are only observed at discrete intervals. Most processes in psychology and the social sciences (e.g., academic motivation, cognitive skills, well-being) likely fall into the latter category, but although they are assumed to be continuous in nature, their measurement is necessarily discrete (Hecht & Voelkle, 2021; Voelkle et al., 2018).

Figure 2

.A two-by-two classification table of longitudinal models: static versus dynamic models (vertical) and discrete versus continuous time models (horizontal).



Note. Voelkle et al. (2018). The role of time in the quest for understanding psychological mechanisms. *Multivariate Behavioral Research, 53*(6), p. 785 (https://doi.org/10.1080/00273171.2018.1496813). Copyright 2018 by Routledge. Reprinted with permission.

It is straightforward to distinguish between discrete time and continuous time models: On the one hand, in discrete time models, time is treated as a discrete variable and can only take on values from a countable set. In continuous time models, on the other hand, time is treated as a continuous variable that can take on an infinite number of values (Voelkle et al., 2018). If the true data-generating model for a process is a discrete time model, then only values at specific points or moments in time, that is, discrete occasions, exist. Autoregressive and cross-lagged effects describe the serial dependencies between these discrete occasions (Hecht & Voelkle, 2021). Such discrete time models are for example interesting when it is the goal to compare and model academic achievement from one specific reference date to another. A continuous time model, in contrast, assumes that the process is ongoing (Oud & Delsing, 2010; Ryan et al., 2018; Voelkle et al., 2012). Although we could theoretically measure the process at any arbitrary point in time, in reality there often are only a few discrete time measurement occasions. The continuous time model then tries to identify the continuous time process that has led to these discrete measures (Hecht & Voelkle, 2021). An example of such a process would be academic motivation, which is usually expected to exist continuously within an individual, but is only measured once a year.

A major concern when answering developmental research questions is the role of time in statistical analyses, or how time is incorporated in statistical analyses (Collins, 2006; Voelkle et al., 2018). From Figure 2, it becomes apparent that the treatment of time in static longitudinal models is relatively straightforward. In static longitudinal models, time is considered an exogenous predictor (see e.g. the LGCM, Eq. 1), so it therefore makes little difference whether it is treated as a continuous or discrete variable. This is significantly different for dynamic models. When time is handled as a discrete variable in dynamic models, we can calculate a change score over a discrete time interval (i.e., $(y_i(t) - y_i(t - \Delta t))/\Delta t$) and apply discrete time dynamic models such as autoregressive (see Equation 2) or change score models (Voelkle et al., 2018). In such scenarios, however, time is only considered implicitly (Voelkle et al., 2012), and autoregressive and cross-lagged effects depend on the length of the chosen time interval between discrete measurement occasions (Hecht & Voelkle, 2021; Voelkle et al., 2012). This leads to several problems: First, intervals between measurements need to be evenly spaced to allow for an unambiguous interpretation of the statistical parameters across time points. However, especially in the context of intensive longitudinal data, but also when considering panel data (e.g., Tim's fluctuating response times), equal spacing of intervals is sometimes not attainable, limiting data analysis flexibility (Hecht & Voelkle, 2021; Voelkle & Oud, 2013). Second, cross-study comparisons of effects are difficult because effects based on different time intervals can appear dissimilar when they are not (but only differ due to different time intervals), or appear similar when they are in fact dissimilar. This is also a concern in meta-analyses that combine coefficients across multiple studies with varying time intervals (Dormann et al., 2020; Kuiper & Ryan, 2020). Third, when designing equally spaced time intervals, the "correct" interval length for an effect of interest must be determined, which is not a trivial task (Hecht & Voelkle, 2021). To tackle these problems, we can treat time as a continuous variable in dynamic models by applying so called continuous time (CT) dynamic models (van Montfort et al., 2018; Voelkle et al., 2012).

To treat time as a continuous variable in dynamic models requires stochastic differential calculus. Very broadly, stochastic differential equations let $\Delta t \to 0$ between discrete measurement occasions (e.g., in Equation 2), that is, taking the derivative with respect to time. By doing so, we depict the rate of change of a process over infinitesimally small increments of time. This puts the generating mechanism on a continuous time scale and allows us to distinguish the underlying dynamics clearly from the discrete time measurement occasions (Oud & Delsing, 2010). We are no longer bound to any discrete time interval when estimating an effect of interest in our analyses, and can compute effects as a function of any arbitrary time interval Δt (Voelkle et al., 2018). An in-depth mathematical presentation and deduction of CT dynamic models can be found in Oud and Delsing (2010) and in Driver and Voelkle (2018a). Recent developments in the field of psychology presented CT models and their estimation via structural equation models (Oud & Delsing, 2010; Voelkle et al., 2012). Driver and Voelkle (2018a, 2018b) expanded the field of research to include intervention effects in CT and to modeling effects with a hierarchical structure (i.e., random effects).

An important advantage of CT models is their ability to account for unequally spaced measurement intervals in longitudinal studies. For example, in panel studies, time intervals vary between individuals or measurement waves, as well as within individuals, as a result of pragmatic restrictions (e.g., the available number of test administrators or testing instruments) during the data collection process. In discrete time dynamic models, these so-called individually varying time intervals (IVTs) typically induce bias in parameter estimates if they are not taken into consideration (Voelkle et al., 2012; Voelkle & Oud, 2013). One common cause is that parameter estimates represent the average of parameters over different time intervals Δt, rendering them uninterpretable. CT models, on the other hand, are capable of dealing with (individually) varying time intervals between observations. A study by Voelkle and Oud (2013) even found that when using CT models to learn about a process, IVTs can be advantageous for the estimation and recovery of model parameters, especially when the sampling rate is low, that is, when there are only few observations per individual in a specific time period (as is the case in typical panel studies). Interestingly, although IVTs are a widespread phenomenon, only few studies (e.g., Sterba, 2014; Voelkle & Oud, 2013) have explicitly and systematically investigated how they might contribute to parameter estimation. Similarly, panel data make it possible to track societal developments and individuals' reactions to naturally occurring events or planned interventions (Allison, 1994; Bruederl et al., 2019). Examples of such events could be the 2007 financial crisis, a Covid lockdown, or educational transition processes, such as the transition from primary to secondary school. Without panel data, it would be difficult to determine how these events affected individuals' well-being (Hübener et al., 2020; Thompson, 2021), health behaviors (Thompson, 2021), or academic motivation (Evans et al., 2018; Zeedyk et al., 2003), because no other data would have allowed for such an assessment in terms of both quality and availability. Still, applications of CT dynamic modeling in lifespan developmental research with panel data are still rare, and literature on the relationship between CT modeling, intervention effects, and individual variation in time intervals is essentially nonexistent. This lack of knowledge on the possible contribution of IVTs when estimating intervention effects from panel data is one important motivation for Study III of this dissertation.

1.5 Objectives of the present doctoral thesis

In this doctoral thesis, I aim to investigate how adolescent skills contribute to the development of vital life outcomes across the lifespan, and how statistical models can help us to represent and understand different time scales of developmental change in psycho-social processes. To address this topic, I have chosen three important strands of research that provide different angles on the influence of skills and how to model change processes within the framework of the HIDECO model. The presented research questions were examined by capitalizing on data from representative international panel studies as well as simulated data based on the typical characteristics of panel studies.

First research strand on individual differences in adolescent skills and adult life outcomes

The first strand of research, which I covered in Study I, was the extent to which individual differences in vital adult life outcomes such as mental and physical health, education, income, and occupation can be attributed to individual differences in adolescent skills and socioeconomic background. Most importantly, there is a lack of studies that have explicitly investigated how the historical context of a population at the time of measurement may have influenced these relationships. Furthermore, prior studies have often focused on the predictive validity of either skills or socioeconomic background, but have not considered them simultaneously. To this end, I aimed to tackle the following research question in Study I:

Research question 1: How have historical changes in the socioeconomic environment in the 20th century affected the extent to which adolescents' intelligence, grade point average, and socioeconomic background could predict key life outcomes in adulthood?

In a first step, I defined my target population as US citizens. By utilizing two representative US birth cohorts of 15- and 16-year-olds, one of them born in the early 1960s (National Longitudinal Survey of Youth, 1979), the other in the early 1980s (National Longitudinal Survey of Youth, 1997), the main goal was to examine how historical changes such as rising competition due to population growth, neoliberal politics and growing inequality, and the introduction of the internet, affected the relationships between adolescent skills and adult life outcomes 20 years later.

One of the biggest socioeconomic changes in the 20th century is that inequality between individuals with respect to educational, occupational, and health outcomes has grown continuously. Assuming cumulative advantages at work, I was not only interested in average relationships between adolescent skills for later life outcomes, but also whether individuals with different relative statuses (e.g., high vs low) in the examined life outcomes were affected differently by historical changes. To this end, I addressed a second research question in Study I:

Research question 2: Did historical changes affect relationships between adolescent characteristics and adult life outcomes differently depending on the individual's location on the outcome distribution?

Using the same data as for Research Question 1, the goal was to provide an overview of how relationships between adolescent intelligence, GPA, and socioeconomic background and adult educational, occupational, and health outcomes varied across the outcome distributions of adult outcomes. I suspected that especially with respect to the upper and lower ends of the distributions, the relationships between adolescent characteristics and adult life outcomes should have changed due to changes in the historical context. I examined these questions by utilizing quantile regression analyses, and chose to compare the 5^{th}, 25^{th}, 50^{th}, 75^{th}, and 95^{th} quantile of the outcome distributions across birth cohorts.

Second research strand on cumulative advantages and mechanisms of lifespan inequality

The second research strand, which I examined in Study II, refers to the question how the large inequalities in life outcomes that were observed in Study I actually come about. A prominent theory on the generating mechanisms behind growing inequality are so-called cumulative advantages or disadvantages. Cumulative advantages are often framed as intraindividual processes that result in growing interindividual differences over time. Despite their prominence in the literature, few studies have ever attempted to operationalize and investigate cumulative advantages empirically. One reason for this fact might be the former lack of statistical methods and frameworks that allowed researchers to do so. In Study II, I thus aimed to tackle the following research question:

Research question 3: How can the theoretical mechanism of cumulative advantages be operationalized and translated into a statistical framework in order to make it testable?

To test the assumptions of cumulative advantages empirically, I chose individuals' wage time series across 38 years as the time series of interest. Data stemmed from the representative US National Longitudinal Survey of Youth 1979. On the basis of substantive literature on cumulative advantage processes, three key features of a modeling framework were identified: It needed to be able to depict individuals' autoregressive (wage) dynamics, and second, to model between-person heterogeneity in these dynamics. Third, it was important that a conditional model could be estimated, allowing one to model how between-person heterogeneity in these dynamics could be predicted by individual differences in third variables (such as IQ or GPA). All of these characteristics are combined in multilevel dynamic structural equation models (DSEM), which I proposed as a promising new way to empirically investigate mechanisms that drive growing inequality over time.

Once it was possible to model cumulative advantage processes, I was interested in learning more about possible reasons for heterogeneity in cumulative advantages and wage development across the lifespan. Why is it that some individuals experience higher or lower wages and wage growth over time? Thus, the second research question in Study II was:

Research question 4: To what extent do individual differences in individuals' adolescent intelligence, grade point average, socioeconomic status, and adult highest levels of education predict differential initial wage levels and wage growth rates across the lifespan?

The goal was to examine predictors of differences in wage levels, wage growth rates, and cumulative advantages. Not all individuals in the NLSY-79 experienced "strict" cumulative advantage processes. Still, the average population pattern of wage trajectories shows that small initial wage differences between individuals magnified over time. In line with Study I, I thus examined whether adolescent intelligence, grade point average, socioeconomic status, and adult educational levels might contribute to initial wage differences as well as wage growth rates and subsequent variance spread over time.

Third research strand on intervention effects and individually varying time intervals

The third strand of research, which I covered in Study III, addressed how we can model intervention effects affecting ongoing developmental processes when time intervals between measurement occasions vary between participants. Panel studies usually feature many participants (high *N*), but have low sampling rates (low *T*, e.g., once every year). A characteristic challenge when collecting such data is that not all individuals can be measured at the same point in time. As a result, the exact time points of individuals' observations often differ both within and between measurement waves, which results in differing time intervals between individuals' observations over time. This variation is often called "individually varying time intervals" (IVTs). Previous research suggests that ignoring IVTs when modeling developmental processes likely produces biased parameter estimates. At the same time, when applying continuous time dynamic models, IVTs have even been shown to yield beneficial effects for parameter recovery in comparison to equally distributed time intervals (e.g., Voelkle & Oud, 2013). Although IVTs are a widespread phenomenon, and one goal of panel studies is to examine the effect of real-life events on developmental processes, there is a lack of research on IVTs and intervention effects. Thus, the research question tackled in Study III is as follows:

Research question 5: Can individually varying time intervals (IVTs) between measurement occasions in panel studies help us learn about the evolution of intervention effects over time?

To address the fifth research question, I conducted a simulation study based on empirical parameters estimated from the German NEPS sample, Starting Cohort 2. All parameters were estimated with continuous time dynamic models. I chose the effect of transition from primary to secondary school on students' academic motivation as a non-experimental intervention effect (i.e., a natural experiment, sensu Campbell). The corresponding empirical parameters served as true parameters for the subsequent simulation study with seven different conditions of IVTs. While the main sampling characteristics in each condition were the same as in empirical NEPS data (sample size, number of measurement occasions per student), the time intervals between observations were assumed to follow different distributions, with varying degrees of individual variation. Thus, Study III aims to investigate whether time intervals need to be equally distributed in order to derive valid substantial results, and aims to understand whether individual variation in time intervals can actually benefit the estimation precision of intervention effects in panel data.

Taken together, by combining the three research strands, answering the above-mentioned research questions, and taking advantage of state-of-the-art research methods with representative high-quality data from the US and Germany, this doctoral thesis makes important substantive and methodological contributions. From a substantive perspective, it fosters the understanding of how adolescent skills contribute to the development of vital life outcomes across the lifespan. Second, from a methodological perspective, it shows how different classes of statistical models can help us represent developmental change and the evolution of inequality, and how individual variation in time intervals between repeated measurements can help us learn more about intervention effects from panel data. In combination, the three studies cover multiple aspects of the HIDECO framework, and investigate research questions with respect to both historical and ontogenetic time.

1.6 References

Aghion, P., & Bolton, P. (1997). A theory of trickle-down growth and development. *The Review of Economic Studies*, *64*(2), 151–172. https://doi.org/10.2307/2971707

Allison, P. (1994). Using panel data to estimate the effects of events. *Sociological Methods & Research*, *23*(2), 174–199. https://doi.org/10.1177/0049124194023002002

Almlund, M., Duckworth, A. L., Heckman, J. J., & Kautz, T. D. (2011). *Personality psychology and economics (Working paper 16822)*. https://www.nber.org/papers/w16822.pdf

Angelini, V., Howdon, D. D. H., & Mierau, J. O. (2019). Childhood socioeconomic status and late-adulthood mental health: Results from the survey on health, ageing and retirement in Europe. *The Journals of Gerontology: Psychological Sciences and Social Sciences*, *74*(1), 95–104. https://doi.org/10.1093/geronb/gby028

APA Dictionary of Psychology. (2023). *Individual differences*. https://dictionary.apa.org/

Autor, D. H., Dorn, D., & Hanson, G. H. (2015). Untangling trade and technology: Evidence from local labour markets. *The Economic Journal*, *125*(584), 621–646. https://doi.org/10.1111/ecoj.12245

Bailey, M. J., & Dynarski, S. M. (2011). Inequality in postsecondary attainment. In G. J. Duncan & R. J. Murnane (Eds.), *Whither opportunity?* (pp. 117–132). Russell Sage Foundation.

Baltes, P. B. (1987). Theoretical propositions of life-span developmental psychology: On the dynamics between growth and decline. *Developmental Psychology*, *23*(5), 611–626. https://doi.org/10.1037/0012-1649.23.5.611

Baltes, P. B., Lindenberger, U., & Staudinger, U. M. (2006). Life span theory in developmental psychology. In W. Damon & R. Lerner (Eds.), *Handbook of child psychology: Theoretical models of human development* (pp. 569–664). John Wiley & Sons Inc.

Baltes, P. B., & Nesselroade, J. R. (1979). History and rationale of longitudinal research. In J. R. Nesselroade & P. B. Baltes (Eds.), *Longitudinal research in the study of behavior and development* (S. 1–39). Academic press.

Baltes, P. B., Reese, H. W., & Nesselroade, J. R. (1988). *Life-span developmental psychology: Introduction to research methods*. Lawrence Erlbaum Associates.

Bask, M., & Bask, M. (2015). Cumulative (dis)advantage and the Matthew effect in life-course analysis. *PLOS ONE*, *10*(11), e0142447. https://doi.org/10.1371/journal.pone.0142447

Baumert, J., Nagy, G., & Lehmann, R. (2012). Cumulative advantages and the emergence of social and ethnic inequality: Matthew effects in reading and mathematics development within elementary schools? *Child Development*, *83*(4), 1347–1367. https://doi.org/10.1111/j.1467-8624.2012.01779.x

Behtoui, A., & Strömberg, I. (2020). Compensatory school effects and social capital. *Social Sciences*, *9*(11), Art. 11. https://doi.org/10.3390/socsci9110193

Beier, M. (2021). Life-Span Learning and Development and Its Implications for Workplace Training. *Current Directions in Psychological Science*, *31*, 096372142110038. https://doi.org/10.1177/09637214211003891

Blau, P. M., & Duncan, O. D. (1967). *The American occupational structure* (4th edition). New York, Wiley.

Bleidorn, W., Schwaba, T., Zheng, A., Hopwood, C. J., Sosa, S. S., Roberts, B. W., & Briley, D. A. (2022). Personality stability and change: A meta-analysis of longitudinal studies. *Psychological Bulletin*, *148*, 588–619. https://doi.org/10.1037/bul0000365

Blossfeld, H.-P., Schneider, T., & Doll, J. (2009). Methodological advantages of panel studies. Designing the new National Educational Panel Study (NEPS) in Germany. *Journal for Educational Research Online*, *1*, 10–32. https://doi.org/10.25656/01:4554

Blossfeld, H.-P., & von Maurice, J. (2011). Education as a lifelong process. *Zeitschrift Für Erziehungswissenschaft*, *14*(2), 19–34. https://doi.org/10.1007/s11618-011-0179-2

Boker, S. M., & Nesselroade, J. R. (2002). A method for modeling the intrinsic dynamics of intraindividual variability: Recovering the parameters of simulated oscillators in multi-wave panel data. *Multivariate Behavioral Research*, *37*(1), 127–160. https://doi.org/10.1207/S15327906MBR3701_06

Borghans, L., Golsteyn, B. H. H., Heckman, J. J., & Humphries, J. E. (2016). What grades and achievement tests measure. *Proceedings of the National Academy of Sciences*, *113*(47), 13354–13359. https://doi.org/10.1073/pnas.1601135113

Bradbury, K. (2011). *Trends in U.S. family income mobility, 1969-2006 (Working Paper 11-10)*. https://www.bostonfed.org/publications/research-department-working-paper/2011/trends-in-us-family-income-mobility-1969-2006.aspx

Breen, R., Luijkx, R., Müller, W., & Pollak, R. (2009). Nonpersistent inequality in educational attainment: Evidence from eight European countries. *American Journal of Sociology*, *114*(5), 1475–1521. https://doi.org/10.1086/595951

Brookhart, S. M., Guskey, T. R., Bowers, A. J., McMillan, J. H., Smith, J. K., Smith, L. F., Stevens, M. T., & Welsh, M. E. (2016). A century of grading research: Meaning and value in the most common educational measure. *Review of Educational Research*, *86*(4), 803–848. https://doi.org/10.3102/0034654316672069

Brown, P., Green, A., & Lauder, H. (2001). *High skills: Globalization, competitiveness, and skill formation*. OUP Oxford.

Bruederl, J., Kratz, F., & Bauer, G. (2019). Life course research with panel data: An analysis of the reproduction of social inequality. *Advances in Life Course Research*, *41*, 100247. https://doi.org/10.1016/j.alcr.2018.09.003

Brunello, G., & Schlotter, M. (2011). *Non-cognitive skills and personality traits: Labour market relevance and their development in education & training systems*. https://doi.org/10.2139/ssrn.1858066

Brunner, M., Keller, L., Stallasch, S., Kretschmann, J., Hasl, A., Preckel, F., Lüdtke, O., & Hedges, L. (2022). Meta-analyzing individual participant data from studies with complex survey designs: A tutorial on using the two-stage approach for data from educational large-scale assessments. *Research Synthesis Methods*, *14*, 1–31. https://doi.org/10.1002/jrsm.1584

Buss, A. R. (1974). A general developmental model for interindividual differences, intraindividual differences, and intraindividual changes. *Developmental Psychology*, *10*(1), 70–78. https://doi.org/10.1037/h0035540

Caspi, A., Houts, R. M., Belsky, D. W., Harrington, H., Hogan, S., Ramrakha, S., Poulton, R., & Moffitt, T. E. (2017). Childhood forecasting of a small segment of the population with large economic burden. *Nature Human Behaviour*, *1*, 1–25. https://doi.org/10.1038/s41562-016-0005

Cattell, R. B. (1952). The three basic factor-analytic research designs—Their interrelations and derivatives. *Psychological Bulletin*, *49*, 499–520. https://doi.org/10.1037/h0054245

Cheng, S. (2014). A life course trajectory framework for understanding the intracohort pattern of wage inequality. *American Journal of Sociology*, *120*(3), 633–700. https://doi.org/10.1086/679103

Chetty, R., Grusky, D., Hell, M., Hendren, N., Manduca, R., & Narang, J. (2017). The fading American dream: Trends in absolute income mobility since 1940. *Science*, *356*(6336), 398–406. https://doi.org/10.1126/science.aal4617

Chetty, R., Hendren, N., Jones, M. R., & Porter, S. R. (2020). Race and economic opportunity in the United States: An intergenerational perspective. *The Quarterly Journal of Economics*, *135*(2), 711–783. https://doi.org/10.1093/qje/qjz042

Christensen, G., Steinmetz, A., Alcorn, B., Bennett, A., Woods, D., & Emanuel, E. (2013). *The MOOC phenomenon: Who takes massive open online courses and why?* (SSRN Scholarly Paper Nr. 2350964). https://doi.org/10.2139/ssrn.2350964

Cingano, F. (2014). *Trends in Income Inequality and its Impact on Economic Growth* (Nr. 163; OECD Social, Employment and Migration Working Papers, Bd. 163). https://doi.org/10.1787/5jxrjncwxv6j-en

Colen, C. G., Ramey, D. M., Cooksey, E. C., & Williams, D. R. (2018). Racial disparities in health among nonpoor African Americans and Hispanics: The role of acute and chronic discrimination. *Social Science & Medicine*, *199*, 167–180. https://doi.org/10.1016/j.socscimed.2017.04.051

Collins, L. M. (2006). Analysis of longitudinal data: The integration of theoretical model, temporal design, and statistical model. *Annual Review of Psychology*, *57*(1), 505–

528. https://doi.org/10.1146/annurev.psych.57.102904.190146

Cooksey, E. C. (2018). Using the National Longitudinal Surveys of Youth (NLSY) to conduct life course analyses. In N. Halfon, C. B. Forrest, R. M. Lerner, & E. M. Faustman (Eds.), *Handbook of Life Course Health Development* (S. 561–577). Springer International Publishing. https://doi.org/10.1007/978-3-319-47143-3_23

Crystal, S., & Shea, D. (1990). Cumulative advantage, cumulative disadvantage, and inequality among elderly people. *The Gerontologist*, *30*(4), 437–443. https://doi.org/10.1093/geront/30.4.437

Crystal, S., Shea, D. G., & Reyes, A. M. (2017). Cumulative advantage, cumulative disadvantage, and evolving patterns of late-life inequality. *The Gerontologist*, *57*(5), 910–920. https://doi.org/10.1093/geront/gnw056

Cunha, F., & Heckman, J. (2007). The technology of skill formation. *American Economic Review*, *97*(2), 31–47. https://doi.org/10.1257/aer.97.2.31

Damian, R. I., Su, R., Shanahan, M., Trautwein, U., & Roberts, B. W. (2015). Can personality traits and intelligence compensate for background disadvantage? Predicting status attainment in adulthood. *Journal of Personality and Social Psychology*, *109*(3), 473–489. https://doi.org/10.1037/pspp0000024

Deaton, A. (2013). *The great escape: Health, wealth, and the origins of inequality*. Princeton University Press.

DiPrete, T. A., & Eirich, G. M. (2006). Cumulative advantage as a mechanism for inequality: A review of theoretical and empirical developments. *Annual Review of Sociology*, *32*(1), 271–297. https://doi.org/10.1146/annurev.soc.32.061604.123127

Dormann, C., & Griffin, M. A. (2015). Optimal time lags in panel studies. *Psychological Methods*, *20*(4), 489–505. https://doi.org/10.1037/met0000041

Dormann, C., Guthier, C., & Cortina, J. M. (2020). Introducing continuous time meta-analysis (CoTiMA). *Organizational Research Methods*, *23*(4), 620–650.

https://doi.org/10.1177/1094428119847277

Drewelies, J., Huxhold, O., & Gerstorf, D. (2019). The role of historical change for adult development and aging: Towards a theoretical framework about the how and the why. *Psychology and Aging*, *34*(8), 1021–1039. https://doi.org/10.1037/pag0000423

Driver, C. C., & Voelkle, M. C. (2018a). Hierarchical Bayesian continuous time dynamic modeling. *Psychological Methods*, *23*(4), 774–799. https://doi.org/10.1037/met0000168

Driver, C. C., & Voelkle, M. C. (2018b). Understanding the time course of interventions with continuous time dynamic models. In K. van Montfort, J. H. L. Oud, & M. C. Voelkle (Eds.), *Continuous time modeling in the behavioral and related sciences* (S. 79–109). Springer International Publishing. https://doi.org/10.1007/978-3-319-77219-6_4

Duckworth, A. L., Quinn, P. D., Lynam, D. R., Loeber, R., & Stouthamer-Loeber, M. (2011). Role of test motivation in intelligence testing. *Proceedings of the National Academy of Sciences*, *108*(19), 7716–7720. https://doi.org/10.1073/pnas.1018601108

Duckworth, A. L., & Yeager, D. S. (2015). Measurement matters: Assessing personal qualities other than cognitive ability for educational purposes. *Educational Researcher*, *44*(4), 237–251. https://doi.org/10.3102/0013189X15584327

Eccles, J. S., & Roeser, R. W. (2003). Schools as developmental contexts. In G. R. Adams & M. D. Berzonsky (Eds.), *Blackwell handbook of adolescence* (S. 129–148). Blackwell Publishing.

Eccles, J. S., & Roeser, R. W. (2011). Schools as Developmental Contexts During Adolescence. *Journal of Research on Adolescence*, *21*(1), 225–241. https://doi.org/10.1111/j.1532-7795.2010.00725.x

Ehmke, T., van den Ham, A.-K., Sälzer, C., Heine, J., & Prenzel, M. (2020). Measuring mathematics competence in international and national large scale assessments:

Linking PISA and the national educational panel study in Germany. *Studies in Educational Evaluation*, *65*, 1–10. https://doi.org/10.1016/j.stueduc.2020.100847

Ertl, B., Hartmann, F. G., & Heine, J.-H. (2020). Analyzing large-scale studies: Benefits and challenges. *Frontiers in Psychology*, *11*, 577410. https://doi.org/10.3389/fpsyg.2020.577410

Evans, D., Borriello, G. A., & Field, A. P. (2018). A review of the academic and psychological impact of the transition to secondary education. *Frontiers in Psychology*, *9*, 1–18. https://doi.org/doi: 10.3389/fpsyg.2018.01482

Evans, M. D. R., Kelley, J., Sikora, J., & Treiman, D. J. (2010). Family scholarly culture and educational success: Books and schooling in 27 nations. *Research in Social Stratification and Mobility*, *28*(2), 171–197. https://doi.org/10.1016/j.rssm.2010.01.002

Fagan, J. F., Holland, C. R., & Wheeler, K. (2007). The prediction, from infancy, of adult IQ and achievement. *Intelligence*, *35*, 225–231.

Feigenbaum, J., & Gross, D. (2021). Automation and the fate of young workers: Evidence from telephone operation in the early 20th century (Report No. 249). Cato Institute. https://www.cato.org/article/automation-fate-young-workers-evidence-telephone-operation-early-20th-century#

Fergusson, D. M., John Horwood, L., & Ridder, E. M. (2005). Show me the child at seven II: Childhood intelligence and later outcomes in adolescence and young adulthood. *Journal of Child Psychology and Psychiatry*, *46*(8), 850–858. https://doi.org/10.1111/j.1469-7610.2005.01472.x

Firpo, S., Fortin, N. M., & Lemieux, T. (2009). Unconditional Quantile Regressions. *Econometrica*, *77*(3), 953–973. https://doi.org/10.3982/ECTA6822

French, M. T., Homer, J. F., Popovici, I., & Robins, P. K. (2015). What you do in high school matters: High school GPA, educational attainment, and labor market earnings as a young adult. *Eastern Economic Journal*, *41*(3), 370–386. https://doi.org/10.1057/eej.2014.22

Galla, B. M., Shulman, E. P., Plummer, B. D., Gardner, M., Hutt, S. J., Goyer, J. P., D'Mello, S. K., Finn, A. S., & Duckworth, A. L. (2019). Why high school grades are better predictors of on-time college graduation than are admissions test scores: The roles of self-regulation and cognitive ability. *American Educational Research Journal*, *56*(6), 2077–2115. https://doi.org/10.3102/0002831219843292

Goebel, J., Grabka, M. M., Liebig, S., Kroh, M., Richter, D., Schröder, C., & Schupp, J. (2019). The German Socio-Economic Panel (SOEP). *Jahrbücher für Nationalökonomie und Statistik*, *239*(2), 345–360. https://doi.org/10.1515/jbnst-2018-0022

Greenfield, E. A., & Moorman, S. M. (2019). Childhood socioeconomic status and later life cognition: Evidence from the Wisconsin longitudinal study. *Journal of Aging and Health*, *31*(9), 1589–1615. https://doi.org/10.1177/0898264318783489

Groves, R. M., Jr, F. J. F., Couper, M. P., Lepkowski, J. M., Singer, E., & Tourangeau, R. (2009). *Survey methodology*. John Wiley & Sons.

Halaby, C. N. (2004). Panel Models in Sociological Research: Theory into Practice. *Annual Review of Sociology*, *30*(1), 507–544. https://doi.org/10.1146/annurev.soc.30.012703.110629

Hall, M., & Farkas, G. (2011). Adolescent cognitive skills, attitudinal/behavioral traits and career wages. *Social Forces*, *89*(4), 1261–1285. https://doi.org/10.1093/sf/89.4.1261

Hamaker, E. L., Asparouhov, T., Brose, A., Schmiedek, F., & Muthén, B. (2018). At the frontiers of modeling intensive longitudinal data: Dynamic structural equation models for the affective measurements from the COGITO study. *Multivariate Behavioral Research*, *53*(6), 820–841. https://doi.org/10.1080/00273171.2018.1446819

Hecht, M., & Voelkle, M. C. (2021). Continuous-time modeling in prevention research: An illustration. *International Journal of Behavioral Development*, *45*(1), 19–27. https://doi.org/10.1177/0165025419885026

Heckman, J. J. (2008). Schools, skills, and synapses. *Economic inquiry*, *46*(3), 1–63.

Heppt, B., Olczyk, M., & Volodina, A. (2022). Number of books at home as an indicator of socioeconomic status: Examining its extensions and their incremental validity for academic achievement. *Social Psychology of Education*, *25*(4), 903–928. https://doi.org/10.1007/s11218-022-09704-8

Hsiao, C. (2005). Why panel data? *The Singapore Economic Review*, *50*(2), 143–154.

Hsiao, C. (2022). *Analysis of panel data*. Cambridge University Press.

Hübener, M., Waights, S., Spiess, C. K., Siegel, N. A., & Wagner, G. G. (2020). Parental Well-Being in Times of Covid-19 in Germany. *SOEPpapers*, 42.

International Monetary Fund. (2015). *Uneven growth: Short- and long-term factors*. International Monetary Fund. https://www.imf.org/en/Publications/WEO/Issues/2016/12/31/Uneven-Growth-Short-and-Long-Term-Factors

Kautz, T., Heckman, J. J., Diris, R., Ter Weel, B., & Borghans, L. (2014). *Fostering and measuring skills: Improving cognitive and non-cognitive skills to promote lifetime success*. OECD Publishing. http://www.oecd.org/education/ceri/Fostering-and-Measuring-Skills-Improving-Cognitive-and-Non-Cognitive-Skills-to-Promote-Lifetime-Success.pdf

Koenker, R., & Hallock, K. F. (2001). Quantile regression. *The Journal of Economic Perspectives*, *15*(4), 143–156.

Kuhfeld, M., & Soland, J. (2021). The learning curve: Revisiting the assumption of linear growth during the school year. *Journal of Research on Educational Effectiveness*, *14*(1), 143–171. https://doi.org/10.1080/19345747.2020.1839990

Kuiper, R. M., & Ryan, O. (2020). Meta-analysis of lagged regression models: A continuous-time approach. *Structural Equation Modeling: A Multidisciplinary Journal*, *27*(3), 396–413. https://doi.org/10.1080/10705511.2019.1652613

Lindenberger, U. (2001). Lifespan theories of cognitive development. In N. J. Smelser & B. Baltes (Eds.), *International Encyclopedia of the Social and Behavioral Sciences* (S. 8848–8854). Elsevier Science.

Little, C. W., Hart, S. A., Quinn, J. M., Tucker-Drob, E. M., Taylor, J., & Schatschneider, C. (2017). Exploring the co-development of reading fluency and reading comprehension: A twin study. *Child development*, *88*(3), 934–945. https://doi.org/10.1111/cdev.12670

Little, C. W., Lonigan, C. J., & Phillips, B. M. (2021). Differential patterns of growth in reading and math skills during elementary school. *Journal of educational psychology*, *113*(3), 462–476. https://doi.org/10.1037/edu0000635

Loeber, R., Menting, B., Lynam, D. R., Moffitt, T. E., Stouthamer-Loeber, M., Stallings, R., Farrington, D. P., & Pardini, D. (2012). Findings from the Pittsburgh Youth study: Cognitive impulsivity and intelligence as predictors of the age–crime curve. *Journal of the American Academy of Child & Adolescent Psychiatry*, *51*(11), 1136–1149. https://doi.org/10.1016/j.jaac.2012.08.019

Lövdén, M., Bäckman, L., Lindenberger, U., Schaefer, S., & Schmiedek, F. (2010). A theoretical framework for the study of adult cognitive plasticity. *Psychological Bulletin*, *136*, 659–676. https://doi.org/10.1037/a0020080

Maaz, K., Trautwein, U., Lüdtke, O., & Baumert, J. (2008). Educational transitions and differential learning environments: How explicit between-school tracking contributes to social inequality in educational outcomes. *Child Development Perspectives*, *2*, 99–106. https://doi.org/10.1111/j.1750-8606.2008.00048.x

Magnusson, D., & Stattin, H. (2006). The person in context: A holistic-interactionistic approach. In *Handbook of child psychology: Theoretical models of human development* (6th Aufl., Bd. 1, S. 400–464). John Wiley & Sons Inc.

McArdle, J. J. (2007). Dynamic structural equation modeling in longitudinal experimental studies. In K. v. Montfort, J. H. Oud, & A. Satorra (Eds.), *Longitudinal models in the behavioral and related sciences* (S. 159–188). Lawrence Erlbaum Associates Publishers.

McArdle, J. J. (2009). Latent variable modeling of differences and changes with longitudinal data. *Annual Review of Psychology*, *60*(1), 577–605. https://doi.org/10.1146/annurev.psych.60.110707.163612

McArdle, J. J., & Grimm, K. J. (2010). Five steps in latent curve and latent change score modeling with longitudinal data. In K. van Montfort, J. H. L. Oud, & A. Satorra (Eds.), *Longitudinal research with latent variables* (S. 245–273). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-11760-2_8

McArdle, J. J., & Nesselroade, J. R. (2003). Growth curve analysis in contemporary psychological research. In *Handbook of psychology: Research methods in psychology, Vol. 2.* (S. 447–480). John Wiley & Sons Inc.

Merton, R. K. (1968). The Matthew Effect in science. *Science*, *159*(3810), 56–63.

Merton, R. K. (1973). The Matthew effect in science. In R. K. Merton (Eds.), *The Sociology of Science* (S. 439–459). University Chicago Press.

Merton, R. K. (1988). The Matthew Effect in science, II: Cumulative advantage and the symbolism of intellectual property. *Isis*, *79*(4), 606–623.

Moffitt, T. E., Arseneault, L., Belsky, D., Dickson, N., Hancox, R. J., Harrington, H., Houts, R., Poulton, R., Roberts, B. W., Ross, S., Sears, M. R., Thomson, W. M., & Caspi, A. (2011). A gradient of childhood self-control predicts health, wealth, and public safety. *Proceedings of the National Academy of Sciences*, *108*(7), 2693–2698. https://doi.org/10.1073/pnas.1010076108

NEPS-Netzwerk. (2017). *NEPS Starting Cohort 2: Kindergarten (SC2 6.0.0)* (6.0.0) [Data set]. NEPS National Education Panel Study. https://doi.org/10.5157/NEPS:SC2:6.0.0

Nesselroade, J. R., & Ghisletta, P. (2003). Structuring and measuring change over the life span. In U. M. Staudinger & U. Lindenberger (Eds.), *Understanding human development* (S. 317–337). Springer US. https://doi.org/10.1007/978-1-4615-0357-6_14

OECD (2012). *Equity and quality in education: Supporting disadvantaged students and schools*. OECD Publishing. https://doi.org/10.1787/9789264130852-en

OECD (2015). *Skills for social progress: The power of social and emotional skills*. OECD Publishing. https://doi.org/10.1787/9789264226159-en

OECD (2017a). *Key issues for digital transformation in the G20*. https://www.oecd.org › G20 › key-issues-for-digital-transformation-in-the-G20.pdf

OECD (2017b). *Preventing ageing unequally*. OECD Publishing. https://doi.org/10.1787/9789264279087-en

OECD (2018). *Social and emotional Skills. Well-being, connectedness and success.* OECD Publishing.

OECD (2019). *Skills for 2030*. OECD Publishing. https://www.oecd.org/education/2030-project/teaching-and-learning/learning/skills/Skills_for_2030_concept_note.pdf

OECD (2021). *OECD Skills outlook 2021: Learning for life*. https://www.oecd.org/education/oecd-skills-outlook-e11c1c2d-en.htm

OECD (2023). *PISA*. https://www.oecd.org/pisa/

Oud, J. H. L., & Delsing, M. J. M. H. (2010). Continuous time modeling of panel data by means of SEM. In K. van Montfort, J. H. L. Oud, & A. Satorra (Eds.), *Longitudinal Research with Latent Variables* (S. 201–244). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-11760-2_7

Patton, G. C., & Spry, E. A. (2021). Connecting ages and stages in human development. *The*

Lancet Child & Adolescent Health, *5*(1), 4–5. https://doi.org/10.1016/S2352-4642(20)30345-X

Pew Charitable Trust. (2007). *Economic mobility: Is the American Dream alive and well?* Pew Charitable Trust. https://www.pewtrusts.org/-/media/legacy/uploadedfiles/wwwpewtrustsorg/reports/economic_mobility/empamericandreamreportpdf.pdf

Pew Charitable Trusts. (2012). *Pursuing the American dream: Economic mobility across generations*. Pew Charitable Trusts.

Pfost, M., Dörfler, T., & Artelt, C. (2012). Reading competence development of poor readers in a German elementary school sample: An empirical examination of the Matthew effect model. *Journal of Research in Reading*, *35*(4), 411–426. https://doi.org/10.1111/j.1467-9817.2010.01478.x

Phelan, J. C., Link, B. G., & Tehranifar, P. (2010). Social conditions as fundamental causes of health inequalities: Theory, evidence, and policy implications. *Journal of Health and Social Behavior*, *51*, 28–40. https://doi.org/10.1177/0022146510383498

Piesse, A., Judkins, D., & Graham, K. (2009). Using longitudinal surveys to evaluate interventions. In P. Lynn (Eds.), *Methodology of longitudinal surveys* (S. 303–316). John Wiley & Sons.

Piopiunik, M., Schwerdt, G., Simon, L., & Woessmann, L. (2020). Skills, signals, and employability: An experimental investigation. *European Economic Review*, *123*. https://doi.org/10.1016/j.euroecorev.2020.103374

Poropat, A. E. (2009). A meta-analysis of the five-factor model of personality and academic performance. *Psychological Bulletin*, *135*(2), 322–338. https://doi.org/10.1037/a0014996

Ram, N., & Gerstorf, D. (2009). Time-structured and net intraindividual variability: Tools for examining the development of dynamic characteristics and processes. *Psychology* *and aging*, *24*(4), 778–791. https://doi.org/10.1037/a0017915

Roberts, B., Luo, J., Briley, D. A., Chow, P. I., Su, R., & Hill, P. L. (2017). A systematic review of personality trait change through intervention. *Psychological Bulletin*, *143*, 117–141. https://doi.org/10.1037/bul0000088

Roberts, B., Robins, R., Trzesniewski, K., & Caspi, A. (2003). Personality Trait Development in Adulthood. In *Handbook of the Life Course* (S. 579–595). https://doi.org/10.1007/978-0-306-48247-2_26

Roberts, B. W., Kuncel, N. R., Shiner, R., Caspi, A., & Goldberg, L. R. (2007). The power of personality: The comparative validity of personality traits, socioeconomic status, and cognitive ability for predicting important life outcomes. *Perspectives on Psychological Science*, *2*(4), 313–345. https://doi.org/10.1111/j.1745-6916.2007.00047.x

Rose, H. (2006). Do gains in test scores explain labor market outcomes? *Economics of Education Review*, *25*(4), 430–446. https://doi.org/10.1016/j.econedurev.2005.07.005

Ryan, O., Kuiper, R. M., & Hamaker, E. L. (2018). A continuous-time approach to intensive longitudinal data: What, why, and how? In K. van Montfort, J. H. L. Oud, & M. C. Voelkle (Eds.), *Continuous time modeling in the behavioral and related sciences* (S. 27–54). Springer International Publishing. https://doi.org/10.1007/978-3-319-77219-6_2

Schaie, W. (1996). Intellectual development in adulthood. In J. E. Birren & W. Schaie (Eds.), *Handbook on the psychology of aging* (S. 266–286). Academic press.

Shanahan, M. J., Hill, P. L., Roberts, B. W., Eccles, J., & Friedman, H. S. (2014). Conscientiousness, health, and aging: The life course of personality model. *Developmental Psychology*, *50*(5), 1407–1425. https://doi.org/10.1037/a0031130

Shippee, N. D., & Owens, T. J. (2011). GPA, depression, and drinking: A longitudinal comparison of high school boys and girls. *Sociological Perspectives*, *54*(3), 351–376.

https://doi.org/10.1525/sop.2011.54.3.351

Shonkoff, J. P., Boyce, W. T., & McEwen, B. S. (2009). Neuroscience, molecular biology, and the childhood roots of health disparities: Building a new framework for health promotion and disease prevention. *JAMA*, *301*(21), 2252–2259. https://doi.org/10.1001/jama.2009.754

Sirin, S. R. (2005). Socioeconomic status and academic achievement: A meta-analytic review of research. *Review of Educational Research*, *75*(3), 417–453. https://doi.org/10.3102/00346543075003417

Sng, O., Neuberg, S. L., Varnum, M. E. W., & Kenrick, D. T. (2017). The crowded life is a slow life: Population density and life history strategy. *Journal of Personality and Social Psychology*, *112*, 736–754. https://doi.org/10.1037/pspi0000086

Soto, C. J., Napolitano, C. M., Sewell, M. N., Yoon, H. J., & Roberts, B. W. (2022). Going beyond traits: Social, emotional, and behavioral skills matter for adolescents' success. *Social Psychological and Personality Science*, 1–13. https://doi.org/10.1177/19485506221127483

Spengler, M., Brunner, M., Damian, R. I., Lüdtke, O., Martin, R., & Roberts, B. W. (2015). Student characteristics and behaviors at age 12 predict occupational success 40 years later over and above childhood IQ and parental socioeconomic status. *Developmental Psychology*, *51*(9), 1329–1340. https://doi.org/10.1037/dev0000025

Spengler, M., Damian, R. I., & Roberts, B. W. (2018). How you behave in school predicts life success above and beyond family background, broad traits, and cognitive ability. *Journal of Personality and Social Psychology*, *114*(4), 620–636. https://doi.org/10.1037/pspp0000185

Spengler, M., Roberts, B. W., Lüdtke, O., Martin, R., & Brunner, M. (2016). Student characteristics and behaviours in childhood predict self–reported health in middle adulthood. *European Journal of Personality*, *30*(5), 456–466.

https://doi.org/10.1002/per.2049

Staudinger, U. M. (2001). Lifespan development, Theory of. In N. J. Smelser & P. B. Baltes (Eds.), *International Encyclopedia of the Social & Behavioral sciences* (S. 8844–8848). Pergamon. https://doi.org/10.1016/B0-08-043076-7/01649-1

Staudinger, U. M., & Lindenberger, U. (Eds.). (2003). *Understanding human development: Dialogues with lifespan psychology*. Springer US. https://doi.org/10.1007/978-1-4615-0357-6

Sterba, S. K. (2014). Fitting nonlinear latent growth curve models with individually varying time points. *Structural Equation Modeling: A Multidisciplinary Journal*, *21*(4), 630–647. https://doi.org/10.1080/10705511.2014.919828

Stiglitz, J. E. (2015). *Rewriting the rules of the American economy: An agenda for growth and shared prosperity*. Roosevelt Institute.

Strenze, T. (2007). Intelligence and socioeconomic success: A meta-analytic review of longitudinal research. *Intelligence*, *35*(5), 401–426. https://doi.org/10.1016/j.intell.2006.09.004

Tawfik, A. A., Reeves, T. D., & Stich, A. (2016). Intended and unintended consequences of educational technology on social inequality. *TechTrends*, *60*(6), 598–605. https://doi.org/10.1007/s11528-016-0109-5

Thompson, P. (2021). *A study of the financial crisis and its effect on psychological well-being, health, satisfaction, and financial incapability* [Preprint]. In Review. https://doi.org/10.21203/rs.3.rs-393768/v1

Thorndike, E. L. (1914). Professor Cattell’s relation to the study of individual differences. In R. S. Woodworth (Eds.), *The psychological researches of James McKeen Cattell: A review by some of his pupils* (S. 92–101). The Science Press. https://doi.org/10.1037/13789-006

Timmons, A. C., & Preacher, K. J. (2015). The importance of temporal design: How do measurement intervals affect the accuracy and efficiency of parameter estimates in longitudinal research? *Multivariate Behavioral Research*, *50*(1), 41–55. https://doi.org/10.1080/00273171.2014.961056

United Nations. (2020). *World Social Report 2020: Inequality in a rapidly changing world*. UN. https://doi.org/10.18356/7f5d0efc-en

U.S. Bureau of Labor Statistics. (2012a). *Questionnaires NLSY 1979, Year 2012*. https://www.nlsinfo.org/content/cohorts/nlsy79/other-documentation/questionnaires

U.S. Bureau of Labor Statistics. (2012b). *Questionnaires NLSY 1997, Round 12*. https://www.nlsinfo.org/content/cohorts/nlsy97/other-documentation/questionnaires

U.S. Bureau of Labor Statistics. (2023). *National Longitudinal Surveys | A Program of the U.S. Bureau of Labor Statistics*. https://www.nlsinfo.org/

Uttal, D. H., Meadow, N. G., Tipton, E., Hand, L. L., Alden, A. R., Warren, C., & Newcombe, N. S. (2013). The malleability of spatial skills: A meta-analysis of training studies. *Psychological Bulletin*, *139*, 352–402. https://doi.org/10.1037/a0028446

van Hek, M., Kraaykamp, G., & Wolbers, M. H. J. (2016). Comparing the gender gap in educational attainment: The impact of emancipatory contexts in 33 cohorts across 33 countries. *Educational Research and Evaluation*, *22*(5–6), 260–282. https://doi.org/10.1080/13803611.2016.1256222

van Montfort, K., Oud, J. H. L., & Voelkle, M. C. (Eds.). (2018). *Continuous time modeling in the behavioral and related sciences*. Springer International Publishing. https://doi.org/10.1007/978-3-319-77219-6

Varnum, M. E. W., & Grossmann, I. (2017). Cultural change: The how and the why. *Perspectives on Psychological Science*, *12*(6), 956–972. https://doi.org/10.1177/1745691617699971

Voelkle, M. C., Gische, C., Driver, C. C., & Lindenberger, U. (2018). The role of time in the quest for understanding psychological mechanisms. *Multivariate Behavioral Research*, *53*(6), 782–805. https://doi.org/10.1080/00273171.2018.1496813

Voelkle, M. C., & Oud, J. H. L. (2013). Continuous time modelling with individually varying time intervals for oscillating and non-oscillating processes. *British Journal of Mathematical and Statistical Psychology*, *66*(1), 103–126. https://doi.org/10.1111/j.2044-8317.2012.02043.x

Voelkle, M. C., & Oud, J. H. L. (2015). Relating latent change score and continuous time models. *Structural Equation Modeling: A Multidisciplinary Journal*, *22*(3), 366–381. https://doi.org/10.1080/10705511.2014.935918

Voelkle, M. C., Oud, J. H. L., Davidov, E., & Schmidt, P. (2012). An SEM approach to continuous time modeling of panel data: Relating authoritarianism and anomia. *Psychological Methods*, *17*(2), 176–192. https://doi.org/10.1037/a0027543

von Stumm, S., & Plomin, R. (2015). Socioeconomic status and the growth of intelligence from infancy through adolescence. *Intelligence*, *48*, 30–36. https://doi.org/10.1016/j.intell.2014.10.002

Weston, S. J., Ritchie, S. J., Rohrer, J. M., & Przybylski, A. K. (2019). Recommendations for increasing the transparency of analysis of preexisting data sets. *Advances in Methods and Practices in Psychological Science*, *2*(3), 214–227. https://doi.org/10.1177/2515245919848684

Westrick, P. A., Huy Le, Robbins, S. B., Radunzel, J. M. R., & Schmidt, F. L. (2015). College performance and retention: A meta-analysis of the predictive validities of ACT ® scores, high school grades, and SES. *Educational Assessment*, *20*(1), 23–45. https://doi.org/10.1080/10627197.2015.997614

Yamauchi, F. (2015). *Wage dynamics, turnover, and human capital: Evidence from adolescent transition from school to work in the Philippines*. https://doi.org/10.1596/1813-9450-7184

Zeedyk, M. S., Gallacher, J., Henderson, M., Hope, G., Husband, B., & Lindsay, K. (2003). Negotiating the transition from primary to secondary school: Perceptions of pupils, parents and teachers. *School Psychology International*, *24*(1), 67–79. https://doi.org/10.1177/0143034303024001010

Zou, T., Zhang, Y., & Zhou, B. (2022). Does GPA matter for university graduates' wages? New evidence revisited. *PLOS ONE*, *17*(4), e0266981. https://doi.org/10.1371/journal.pone.0266981

Zyphur, M. J., Voelkle, M. C., Tay, L., Allison, P. D., Preacher, K. J., Zhang, Z., Hamaker, E. L., Shamsollahi, A., Pierides, D. C., Koval, P., & Diener, E. (2020). From data to causes II: Comparing approaches to panel data analysis. *Organizational Research Methods*, *23*(4), 688–716. https://doi.org/10.1177/1094428119847280

2

Study I

Investigating Core Assumptions of the "American Dream": Historical Changes in How Adolescents' Socioeconomic Status, IQ, and GPA Are Related to Key Life Outcomes in Adulthood

Hasl, A., Kretschmann, J., Richter, D., Voelkle, M., & Brunner, M. (2019). Investigating core assumptions of the "American Dream": Historical changes in how adolescents' socioeconomic status, IQ, and GPA are related to key life outcomes in adulthood. *Psychology and Aging, 34*(8), 1055 – 1076. 10.1037/pag0000392

2 Study I: Investigating Core Assumptions of the "American Dream": Historical Changes in How Adolescents' Socioeconomic Status, IQ, and GPA Are Related to Key Life Outcomes in Adulthood

Abstract

The present study examines how historical changes in the U.S. socioeconomic environment in the 20th century may have affected core assumptions of the "American Dream." Specifically, the authors examined whether such changes modulated the extent to which adolescents' intelligence (IQ), their grade point average (GPA), and their parents' SES could predict key life outcomes in adulthood about 20 years later. The data stemmed from two representative U.S. birth cohorts of 15- and 16-year-olds who were born in the early 1960s (N = 3,040) and 1980s (N = 3,524) and who participated in the National Longitudinal Surveys of Youth (NLSY). Cohort differences were analyzed with respect to differences in average relations by means of multiple and logistic regression and for specific points in each outcome distribution by means of quantile regressions. In both cohorts, IQ, GPA, and parental SES predicted important educational, occupational, and health-related life outcomes about 20 years later. Across historical time, the predictive utility of adolescent IQ and parental SES remained stable for the most part. Yet, the combined effects of social-ecological and socioeconomic changes may have increased the predictive utility (that is, the regression weights) of adolescent GPA for educational, occupational, and health outcomes over time for individuals who were born in the 1980s. Theoretical implications concerning adult development, aging, and late life inequality are discussed.

Keywords: cohort differences, intelligence, grade point average, socioeconomic status, life-span research

Investigating Core Assumptions of the "American Dream": Historical Changes in How Adolescents' Socioeconomic Status, IQ, and GPA are Related to Key Life Outcomes in Adulthood

The "American Dream" was coined by the American writer and historian James Truslow Adams in the 1930s (Adams, 1931, 2017) to describe the U.S. national ethos. This ethos proposes an opportunity for wealth, health, and well-being for each individual according to ability (e.g., intelligence [IQ]) and effort (e.g., as manifested in achieving a high grade point average [GPA]), regardless of social class (e.g., socioeconomic status [SES]) or circumstances of birth (e.g., gender or ethnicity). The idea of the "American Dream" is still alive. Representative surveys have shown that U.S. Americans still believe they can achieve prosperity, success, and upward social mobility for their children and that hard work pays off (Pew Charitable Trusts, 2009). However, because the US has undergone major social, political, and economic changes in recent decades (e.g., OECD, 2015; Pew Charitable Trusts, 2012; Stiglitz, 2015), it seems justified to ask whether these changes affected core assumptions of the "American Dream."

Studies have established that individual differences in characteristics that are central to the American Dream (e.g., IQ, GPA, SES) can significantly predict key life outcomes (e.g., educational and occupational success, health) across the lifespan (e.g., Almlund, Duckworth, Heckman, & Kautz, 2011; Deary, 2012; Roberts, Kuncel, Shiner, Caspi, & Goldberg, 2007). However, empirical findings are still limited with respect to how individual difference variables and social environmental factors might interact in achieving these outcomes (Roberts et al., 2007). The present study integrates psychological, sociological, and socioeconomic perspectives to systematically examine this question with respect to how historical changes in the social and economic environment may affect a central question of the "American Dream": To what extent can adolescents' IQ, GPA, and parental SES predict educational and occupational success and health about 20 years later when these individuals are in their 30s? To address this question, we drew on data from two nationally representative U.S. samples of 15- and 16-year-old adolescents across a broad set of commensurate measures: one cohort born in the early 1960s and one in the early 1980s.

Capitalizing on these unique data, our study overcomes several limitations of previous research: (a) Previous population-level studies on how socioeconomic changes affect health or social class (e.g., Chetty et al., 2017; Reynolds & Himes, 2007) have primarily been cross-sectional and could not address questions about individual level processes (e.g., with respect to IQ or GPA) that constitute the American Dream. (b) Previous excellent longitudinal studies (e.g., Borghans, Golsteyn, Heckman, & Humphries, 2016; Damian, Su, Shanahan, Trautwein, & Roberts, 2015) examined longitudinal relations for specific samples representing specific cohorts only. Thus, these studies could not answer questions about whether predictive relations could generalize across cohorts who grew up in different socioeconomic environments. To sum up, drawing on unique data, the present study contributes significantly to the cumulative body of knowledge on adult development by examining the extent to which predictive relations of important antecedents in adolescence for key components of individual well-being in adulthood may generalize across cohorts facing historical changes in the socioeconomic environment. Note that differences in economic and health outcomes as observed for individuals in their 30s are very likely to grow larger over the lifespan (Crystal, Shea, & Reyes, 2017; DiPrete & Eirich, 2006). In the Discussion we therefore conclude with implications of our findings for late life inequality.

Long-Term Effects of IQ, GPA, and Family Background

One important assumption of the “American Dream” is that skills play major roles in shaping a person’s future. Studies have shown that IQ (as an indicator of cognitive skills) and high school GPA (often considered a composite measure of both cognitive and socioemotional skills; Brookhart et al., 2016) substantially predict key life outcomes in adulthood, above and beyond each other and parental SES (Almlund et al., 2011; Deary, 2012; French, Homer, Popovici, & Robins, 2015; Brookhart et al., 2016; Kautz, Heckman, Diris, Weel, & Borghans, 2014).

In particular, studies on IQ have shown that adolescent IQ is a significant predictor of educational and occupational outcomes (e.g., highest degrees, income, occupational prestige; Deary, 2012; Heckman & Mosso, 2014; Roberts et al., 2007; Spengler, Damian, & Roberts, 2018). High-IQ individuals have also demonstrated better health-related behaviors and (physical and mental) health. In particular, they have been found to be more physically active (Gottfredson & Deary, 2004), to live longer (Deary, 2012), to less often suffer from depression (Newacheck et al., 2003) or obesity (Levine, 2011), and to have fewer constraints on their daily life activities (Johnson, Corley, Starr, & Deary, 2011).

Many studies have found similar results for high school GPA as a predictor of key life outcomes. For example, high school GPA has repeatedly been found to positively predict adult educational success (French et al., 2015; Brookhart et al., 2016) and income (French et al., 2015; Borghans et al., 2016), even after IQ and family SES have been accounted for (Fischbach, Baudson, Preckel, Martin, & Brunner, 2013). Higher GPA has also predicted health outcomes in adulthood, such as better general health (Herd, 2010), lower Body Mass Index (Alatupa et al., 2010; Borghans et al., 2016), lower depressive symptoms, and less alcohol consumption (Shippee & Owens, 2011).

A second important assumption of the “American Dream” is that the opportunity to achieve desirable life outcomes should not depend on social class, but it has received little empirical support. Parental SES translates into “flexible resources” (e.g., money, power, prestige, knowledge, and social connections; Phelan, Link, & Tehranifar, 2010) which in turn play a major role in shaping a person’s future over and above IQ or GPA (APA Task Force, 2009; Bradley & Corwyn, 2002; Duncan, Magnuson, & Votruba-Drzal, 2017; French et al., 2015). For example, Damian et al. (2015) showed that with an increase of 1 SD in parental SES, a person gained an additional 8.3 months of education and $4,233 US (year 2014) of yearly income 11 years later. People from wealthy families were also found to be more physically active (Gottfredson & Deary, 2004), to have fewer constraints on their daily life activities (Johnson et al., 2011), and to less often suffer from depression (Newacheck et al., 2003) or obesity (Levine, 2011).

The "American Dream" and Historical Changes in the Socioeconomic Environment

Lifespan theories predict that individual development is shaped by social and historical circumstances (Baltes, 1987). Cultures and societies are not static, but rather —as shown in studies applying ecological approaches—political and economic systems as well as culture-based sociology and psychology (e.g., social norms and attitudes) are changing over time (Greenfield, 2017; Varnum & Grossmann, 2017). More specifically, the US has undergone dramatic societal and economic changes in recent decades (see Tables 1 and 2 for an overview). In the following, we highlight several changes that may have modulated the predictive utility of IQ, GPA, and parental SES for the two cohorts of adolescents in this study born in the early 1960s and 1980s.

First, the US population has grown considerably over the last decades (see Table 1). According to ecological approaches a rising population density leads to greater levels of competition, for example in educational settings, the job market or access to quality health care (see Sng, Neuberg, Varnum, & Kenrick, 2017; Varnum & Grossmann, 2017). Moreover, competitive environments lead to an increased pressure to perform and typically promote greater individualism rather than community goals (Santos, Varnum, & Grossmann, 2017; Grossmann & Varnum, 2015). Thus, skills as represented by IQ or GPA but also resources as represented by parental SES are important assets that help to succeed in such competitive environments.

Second, since the late 1970s, dominant economic frameworks (e.g., neoliberalism and "trickle-down economics") have substantially promoted policies that (a) are guided by the idea that markets work perfectly on their own by fostering deregulation, especially in the financial sector, (b) have fostered regressive tax systems (i.e., imposing high tax rates on low incomes and low tax rates on top incomes to stimulate investment), and (c) have led to dramatic cuts in the resources invested in Social Security and welfare programs in important areas of life: education, occupation, and health (Crystal & Shea, 1990; Crystal et al., 2017; Stiglitz, 2015). “Trickle-down” (or “Free-market”) theory is an economic theory that emphasizes the importance of tax reductions for wealthy citizens and businesses to stimulate business investments in the short term so that wealth can “trickle down” to the rest of society in the long term (Aghion & Bolton, 1997). However, instead of “freeing up” the economy so that it could thrive, these policies have led to economic instability (financial crises in 1989, 2008), underinvestment in jobs and the future, low growth, an unbridled increase in inequality, and the decimation of America’s middle class (International Monetary Fund [IMF], 2015; Stiglitz, 2015). Whereas wages have stagnated for the working majority, those in the top percentiles of the income distribution have experienced dramatic economic gains (IMF, 2015; Saez & Zucman, 2016). As Stiglitz (2015) pointed out, these developments have severe implications for the “American Dream” and social mobility opportunities. Indeed, long-term statistics have shown that about 40% of children born into families in the bottom or top income brackets (bottom/top 20%) remain in their respective groups as adults. Only 4% of those raised in the bottom brackets move to the top in adulthood, thus going from “rags to riches” (Bradbury, 2011; Pew Charitable Trusts, 2012). Such phenomena have gotten more extreme in the past decade (Chetty et al., 2017). Crucially, rising inequality in the US has been found to apply to growing gaps not only in income but also in health (Crystal et al., 2017; Deaton, 2013) and educational (Bailey & Dynarski, 2011) outcomes.

Third, with the US transitioning from a manufacturing economy to a service economy, job requirements have markedly changed. In 1990, the manufacturing industry was the leading employer in most U.S. states. The automation of industrial production, computerization, and the rise of offshoring and importing have led to a steady decline in employment in manufacturing from 1980 to the present (Autor, Dorn, & Hanson, 2015; U.S. Bureau of Labor Statistics [BLS], 2014). After retail jobs took over in 2003, by 2013, health care and social assistance was the dominant U.S. industry (BLS, 2014). Accordingly, the number of jobs requiring high levels of cognitive and socioemotional skills has been growing rapidly in recent decades (National Academy of Science, 2017). Correspondingly, recent studies have shown that admission to U.S. colleges has become more competitive over time, rendering (admission) criteria such as GPA and cognitive skills (which are empirically closely related to IQ; see Frey & Detterman, 2004) very important for higher education and labor market entry (Barton, 2006; Bound, Hershbein, & Long, 2009; Deming, 2015).

The "American Dream" and Cumulative Advantages across the Life Course

The social, economic, and labor-market changes in the US described above have been accompanied by dramatic increases in inequality on the population level in educational and health outcomes in recent decades. One general explanation for increasing inequality in population-level outcomes are microlevel processes where individual differences (i.e., relative advantages over other individuals) in adolescents' IQ, GPA, and parental SES have led to cumulative advantages in (a) educational, (b) occupational, and (c) health-related outcomes across the life course (Crystal & Shea, 1990; DiPrete & Eirich, 2006; Shanahan, Hill, Roberts, Eccles, & Friedman, 2014). First, these adolescent characteristics are proposed to be related to more effective learning (e.g., access to better schools, ability to learn faster and to put more effort and persistence into learning). Given that prior grades and IQ belong to the best predictors of future learning, and given that better schools may offer better learning opportunities, initial differences in adolescent characteristics may lead to growing inequalities in educational outcomes over time (e.g., knowledge and skills, grades, certificates, educational qualifications). Second, individuals with high levels in these adolescent characteristics are more likely to, for example, have access to better occupations because of social networks (e.g., wealthy parents' networks help their offspring get high-paying jobs; Corak, 2016; Stiglitz, 2015). These individuals also tend to have higher educational entrance qualifications (see above) that promote their chances of recruitment. Further, individuals with high IQs may also demonstrate better job performance because they are better able to cope with the cognitive demands of their job-related tasks. These effects may accumulate over time and thus lead to increasing inequalities in occupational outcomes. Third, these adolescent characteristics are also proposed to be related to health-related processes that may operate consistently across the life course (e.g., access to better health care, more physical activity, better diet, or less consumption of tobacco, alcohol, or drugs) and may in turn lead to increasing individual differences in health over time. Crucially, educational level, occupational success, and health are positively interrelated. As noted above, education qualifies people for better occupations (e.g., with higher income and prestige). Education also decreases the likelihood of health-related "snares" in adulthood (Shanahan et al., 2014) and promotes health-related behaviors. Further, better health promotes occupational success (e.g., healthy individuals show better job performance), and occupational success promotes better health (e.g., because higher income ensures access to better health care). In other words, rising inequalities in educational, occupational, and health outcomes may magnify inequalities in other outcome domains.

Whereas individuals born in the early 1960s faced early effects of social and economic changes, individuals born in the early 1980s grew up when these change processes (presumably) were exerting considerably stronger effects creating an environment with an even greater level of competitiveness. Specifically, given the strong belief that markets work perfectly on their own, tax cuts affecting mostly the top earners were imposed, and public resources devoted to welfare (see above) were dramatically reduced (for an overview of the most important acts of deregulation, tax, and welfare reduction, see Table 2; Crystal & Shea, 1990; Crystal et al., 2017; Danzinger & Haveman, 1981; Institute on Taxation and Economic Policy [ITEP], 2015; Stiglitz, 2009, 2010). Because welfare programs serve as a compensating measure, the relative advantage concerning individual differences in adolescents' parents' SES but also in adolescents' IQ and GPA may have become more important for adolescents born in the 1980s than for those born in the 1960s in achieving vital outcomes. This process may have been magnified by an increase in the importance of GPA and cognitive skills (which are empirically closely related to IQ; see Frey & Detterman, 2004) as college admission criteria and greater demands in the labor market for individuals with high levels of cognitive and socioemotional skills. In sum, social, economic, and labor-market changes may have led to an increased level of competitiveness in the US, and thus increased the predictive utility of individual differences in adolescents' IQ, GPA, and parental SES across time with different implications for the central ideas of the "American Dream." An increasing predictive utility of IQ and GPA would support a core assumption of the "American Dream": Ability and hard work pay off. However, the increasing importance of parental SES would not: Achieving positive life outcomes depends on social class.

The Present Study

The US has undergone dramatic societal and economic changes in recent decades, leading us to investigate how these changes were related to core assumptions of the "American Dream." In accordance with the idea of cumulative advantages, we expected to find that individual differences in adolescents' IQ, GPA, and parental SES have become more important over time in predicting life outcomes.[1] By drawing on representative U.S.

[1] Note that when we preregistered our study (osf.io/hm5pt), we formulated specific hypotheses concerning parental SES only. At that time, we did not take into account how societal and economic changes may have affected the predictive utility of IQ and GPA. Thus, although corresponding expectations seem theoretically plausible, the empirical analyses of changes in the predictive utility of IQ and GPA have an exploratory character in this manuscript.

data from two birth cohorts, this study is the first to systematically analyze how historical changes in social and economic conditions may modulate the utility of adolescents' IQ, GPA, and parental SES in predicting outcomes in the domains of education, occupation, and health. Given the large inequalities in outcomes related to education, occupation, and health in the US (Bailey & Dynarski, 2011; Crystal & Shea, 1990; Crystal et al., 2017; Deaton, 2013; Stiglitz, 2015), we were interested not only in cohort differences in the average predictive relations as estimated for the entire outcome distribution but also in the extent to which historical changes differentially affect patterns of relations between adolescent characteristics and each outcome for people located at different points in the outcome distribution.

Method

Participants and Procedure

The current data stemmed from two representative U.S. birth cohorts of 15- and 16-year-olds born in the early 1960s and 1980s and who participated in the National Longitudinal Study of Youth (NLSY; Frankel, McWilliams, & Spencer, 1983; Moore, Pedlow, Krishnamurty, & Wolter, 2000) in 1979 (NLSY-79) and 1997 (NLSY-97), respectively. NLSY-79 started with an initial sample of 12,686 young men and women born between 1957 and 1964; NLSY-97 comprises data from a sample of 8,984 young people born between 1980 and 1984. Respondents were between 14 and 22 years of age when first interviewed in NLSY-79 and between 12 and 17 in NLSY-97 (Cooksey, 2018). The NLSY samples were designed to be representative probability samples in a two-step sampling procedure (Frankel et al., 1983; Moore et al., 2000). Following the rationale of international large-scale assessments (e.g., PISA), we included participants in the present analyses only if they were 15 or 16 years old at the time of the first interview (Time 1; NLSY-79: *N* = 3,130, NLSY-97: $N = 3{,}598$). These adolescents were at the end of compulsory education—when important decisions that affect future life trajectories are made. In selecting these age groups, we also ensured that the sample sizes of both birth cohorts were large enough to reliably estimate cohort differences with high statistical power.

Both cohorts have been surveyed at least biennially since the first surveys in 1979 and 1997, respectively. To allow for comparisons across cohorts, we chose the longest prediction interval for which commensurate measures were available for both cohorts. Thus, Time 2 refers to the survey in 1998 for NLSY-79 (prediction interval: 19 years) and to the survey in 2015 for NLSY-97 (prediction interval: 18 years) when the 1960s cohort members were between 34 and 35 years of age and the 1980s cohort members were between 33 and 34 years of age. For the present analyses, we excluded all people who died before Time 2. Doing so yielded a final sample of $N = 3{,}040$ for the 1960s cohort (Age 15: $N = 1{,}524$, Age 16: $N = 1{,}516$; 50% female adolescents; 56% White, 26% Black, 18% Hispanic) and $N = 3{,}524$ for the 1980s cohort (Age 15: $N = 1{,}839$, Age 16: $N = 1{,}685$; 49% female adolescents; 52% White, 26% Black, 22% Hispanic).

Predictor Measures (Time 1)

We applied regression models in which we predicted each adult outcome with the same set of predictor variables that were all measured at Time 1. The indicators of educational, occupational, and health-related outcomes were measured at Time 2. To obtain commensurate measures for the two cohorts, we either relied on existing scores or carefully applied various harmonization or adjustment procedures that we explain next (Curran & Hussong, 2009).

IQ. NLSY applied tests measuring four vital cognitive skills (mathematical knowledge, arithmetic reasoning, word knowledge, paragraph comprehension) that were derived from the Armed Services Vocational Aptitude Battery (ASVAB), a widely used measure of intelligence (Borghans et al., 2016; Heckman, 2011; Heckman, Stixrud, &

Urzua, 2006). Percentile scores that were commensurate across cohorts were available for all four subtests. For each individual, these subtest scores were combined into a global IQ score ranging from zero to 99.

GPA. To compute adolescents' GPA, we used data from NLSY high school transcripts that were taken from the official high school records. We calculated Carnegie-credit-weighted GPAs for each individual (15-year-olds: ninth grade; 16-year-olds: 10^{th} grade) based on up to 64 courses (Appendix 11, Codebook Supplement NLSY97). GPA scores ranged from 0 to 4 points (A = 4 points, E/F = 0 points) across all courses. Higher GPA scores indicate better grades.

Parental SES. To obtain a composite SES score, we drew on two standard indicators of SES (APA Task Force, 2009; Bradley & Corwyn, 2002): the highest level of education in the family (student reports of mother's and father's years of education) and parent-reported family income. Years of education ranged from 1 (*first grade*) to 20 (*8 years of college or more*). To obtain commensurate income measures, income was adjusted for inflation, representing January 2015 values, and log-transformed afterwards. Years of Education and log-transformed income were *z*-standardized across cohorts. These scores were then entered into a Principal Component Analysis (R-package psych; Revelle, 2018) based on the data from both cohorts. An index representing parental SES was then derived as a component score for the first component (Vyas & Kumaranayake, 2006).

Covariates. We included three demographic measures as covariates in all regression analyses: gender, ethnicity, and age group. Gender was coded 0 (*male*) and 1 (*female*). Ethnicity (i.e., Black, Hispanic, and White) was represented by two dummy-coded variables with White being the reference group. Age group represented the age of the participants at the time of their first interview (0 = 15 years old, 1 = 16 years old).

Outcome Measures (Time 2)

Educational success. All participants answered questions concerning the highest grade they had ever completed, ranging from 1 (*first grade*) to 20 (*8 years of college or more*).

Occupational success. We analyzed two important outcomes representing occupational success: income and occupational prestige. Participants provided information about their total income that was based on wages and salary, including running a business or a farm, in the past year. First, each respondent's total income was adjusted for inflation to January 2015 U.S. dollars. Second, to normalize the highly skewed income distribution, we log-transformed all scores, which in turn allowed for a better approximation of income as an outcome variable in linear regression models. For analyses that involved income, we included only participants with a valid individual income > 0 U.S. dollars, therefore excluding, averaged over 10 imputed data sets, 392 individuals in the 1960s cohort and 871 individuals in the 1980s cohort. Thus, these analyses were based on a sample size of an average of N = 2,648/2,653 for the 1960s/1980s cohorts (see Table A1 for sample details).

Occupational prestige refers to the social status of a specific occupation in the eyes of the members of a society (Hauser & Warren, 1997). In NLSY, information on participants' occupation at Time 2 is given in terms of U.S. Census Occupational classifications (1960s cohort: 1980 U.S. census; 1980s cohort: 2002 U.S. census). We assigned prestige scores as provided by the National Opinion Research Center (NORC, 2018) to these census codes. Of note, no prestige scores were available for the 2002 census codes. We therefore applied the prestige scores corresponding to the 2010 census because the assignment of occupations to the overarching categories was the same for the 2002 and 2010 census codes (Crosswalk tables, U.S. Census Bureau, 2017). Prestige scores range from zero to 100. We assigned mean prestige scores that corresponded to an individual's occupational category (see Table 3).

Health. We included several health-related outcomes as indicators of individuals' physical, mental, and functional health and their health-protective behavior.

Body Mass Index (BMI) is the most widely used marker of obesity (< 18.50 = underweight, 18.50-24.99 = normal, 25-30 = overweight, > 30 = obese; WHO, 2014). For each individual, BMI was calculated with the formula: weight (lb) / [height (in)]2 * 703.

Two different measures of depressive symptoms were administered in NLSY-79 and NLSY-97. Members of the 1960s cohort answered seven items from the Center for Epidemiologic Studies Depression (CES-D) Scale, whereas members of the 1980s cohort answered a five-item short version of the Mental Health Inventory (MHI-5). Previous studies reported satisfactory internal consistencies for the CES-D ($\alpha = .81$; Mossakowski, 2009) and MHI-5 ($\alpha = .84$; Wilkinson, Glover, Probst, Cai, & Wigfall, 2015). To obtain commensurate scores, we first computed a sum score across items within each cohort with higher scores representing higher levels of depressive symptoms. To capture an individual's level of depressive symptoms, we z-standardized these sum scores within cohorts.

We studied two indicators of functional (job-related) health. Specifically, participants in both cohorts were asked whether their health caused them to experience limitations in the (a) kind or (b) amount of work they could do. Answers on both indicators were coded 0 (no limitations) or 1 (limitations).

Finally, participants in both cohorts provided information about one important aspect of health-protective behavior. All participants were asked whether they had undergone a routine check-up by a physician in the past year. NLSY-97 participants answered yes/no. NLSY-79 participants stated how long it had been since their last routine check-up, coded 1 for the answer "A year or less," otherwise 0. Therefore, for both cohorts, 0 indicated no checkup, and 1 indicated a routine check-up in the past year.

Data Analysis

As expected in any large-scale assessment, several variables were affected by attrition and missing values.

NLSY statistics reported that the attrition between T1 and T2 was 15.7% for NLSY-79 and 21% for NLSY-97 (BLS, 2019a, 2019b). Several studies have shown that attrition in NLSY samples is unlikely to introduce biases in the estimation of labor-market and health variables, especially when individual characteristics that may predict attrition (e.g., gender, SES, ethnicity) are included in the analyses of interest (Aughinbaugh & Gardecki, 2007; Quesnel-Vallée & Taylor, 2012).

In addition to missing data due to attrition we also observed missing data within T1 and/or T2 (e.g., due to non-response of participants to certain questions). The percentage of missing values ranged from 0% to 36% (see Table A1 in the Appendix).

To deal with missing values (due to attrition and nonresponse), we applied multiple imputation with MPlus 8 (Muthén & Muthén, 1998-2017) where we used cohort membership as a grouping variable. We imputed a total of 10 data sets. The results provided in this study are pooled estimates.

To achieve an unbiased estimator of the population total, we ran all regression models using the sample weights provided for Time 1 (Frankel et al., 1983; Moore et al., 2000). To learn about cohort differences in the average predictive utility of adolescents' IQ, GPA, and parental SES, we specified multigroup linear regression models (for all continuous outcomes, i.e., years of education, income, occupational prestige, BMI, depressive symptoms) and multigroup logistic regression models (for all dichotomous outcomes, i.e., the indicators of health-related work limitations and a routine check-up by a physician). To this end, we used cohort membership as the grouping variable and the MLR estimator implemented in Mplus 8 (Muthén & Muthén, 1998-2017) in combination with the "complex" function. In doing so, for all model parameters in each cohort, we obtained standard errors that accounted for the nonindependence of observations, resulting from about one third of the participants stemming from the same families. To put the results obtained from these regression analyses (see Table 4) into perspective, we provide effect size estimates translated into natural metrics in Table 5.

Linear regression analysis is aimed at representing the best overall (i.e., average) estimate for all individuals in a given sample ("What is the average relation between X and Y?"). To learn about the predictive utility of adolescents' IQ, GPA, and parental SES for key life outcomes at specific points in the outcome distribution, we ran quantile regressions (see Petscher & Logan, 2014, for a gentle introduction) in which we included the same set of predictors as in the linear (and logistic) regression models. A particular benefit of quantile regression is that it estimates the relation between predictors and outcomes at specific quantiles of the outcome distribution (e.g., "What is the relation between X and Y for those individuals belonging to the top 5% of the outcome distribution?"). The results are displayed in Figures 2 to 6 and Tables A2 to A6 in the Appendix. We specified our models for the .05, .25, .50, .75, and .95 quantiles of the distribution of each life outcome using the QR function (Koenker, 2018) in R. To estimate standard errors for the regression parameters, we used the bootstrap method proposed by Hagenmann (2017) as implemented in the QR function. Thus, we could account for the nonindependence of observations (see above). The number of bootstrapped replications was set to 1,000.

Finally, to estimate the extent of cohort differences in the predictive utility of adolescent characteristics, we computed the difference between corresponding unstandardized regression coefficients as obtained for each cohort. The major results are summarized in Figure 1 (numeric results underlying Figure 1 are shown in Tables 4 and A2 to A6): A positive difference value indicates that the unstandardized regression coefficient was larger in the 1980s cohort than in the 1960s cohort. We estimated the 95% confidence intervals for these difference values using (a) Cheung's (2009) method for all linear and logistic regression analyses and (b) Cohen, Cohen, West, and Aiken's (2003, p.46) formula for the quantile regression analyses.

Results

Educational Success

In both cohorts, we found the same pattern of results concerning the average predictive relations (Table 4): IQ (B = 0.039/0.037 for the 1960s/1980s cohort) and GPA (B = 0.708/1.264) significantly and positively predicted individuals' educational success about 20 years later. Parental SES (B = 0.473/0.485) also positively predicted educational success even when IQ and GPA were controlled for. Table 5 shows that an increase of 1 SD in IQ/GPA/SES (with 1 SD being obtained for the 1980s cohort [NLSY-97] as the reference) was associated with about 14/7/5 additional months of education in the 1960s cohort and 13/11/6 additional months of education in the 1980s cohort, respectively.

The average relations between IQ (ΔB = -0.002) and parental SES (ΔB = 0.011) on the one side and educational success on the other did not change substantially over time. However, cohort differences concerning the predictive utility of IQ were not consistent across the outcome distribution (Figures 1 and 2 and Table A2): IQ gained importance in the 1980s cohort in predicting years of education up to the 50th quantile (median) and then lost importance in predicting educational outcomes at higher quantiles. Moreover, we found a significant increase in the predictive utility of adolescents' GPA for years of education for the 1980s cohort that was manifested in the average relations (ΔB = 0.556) and consistent across the entire outcome distribution.

Occupational Success

Income. We found a consistent pattern of results in both cohorts showing that IQ, GPA, and parental SES substantially predicted income (Tables 4 and 5). The predictive utility of adolescent characteristics did not differ significantly between cohorts with respect to the average relations (Table 4). There were also no substantial cohort differences found at specific points in the income distribution (Figures 1 and 3 and Table A3).

Occupational prestige. We also found a consistent pattern of results in both cohorts showing that IQ, GPA, and parental SES substantially predicted occupational prestige (Tables 4 and 5). The predictive utility of parental SES did not differ significantly between cohorts with respect to average relations (Table 4) or at specific points in the distribution of occupational prestige (Table A4). The average predictive utility of GPA was somewhat larger in the 1980s cohort with respect to average relations (Table 4). Yet, this increase was not homogenous across the outcome distribution: The largest (significant) difference was found at the 50th quantile (Figures 1 and 4 and Table A4), whereas smaller differences were found at the lower and upper ends of the outcome distribution. Finally, the average predictive utility of IQ was significantly larger in the 1960s than in the 1980s cohort (Table 4). However, the difference in predictive utility was not consistent across the outcome distribution (Figures 1 and 4 and Table A4): The predictive utility of IQ was significantly larger for the 1960s cohort at the 25th and 75th quantiles, respectively. At other points in the outcome distribution, the cohort differences were negligible.

Health

BMI. We found a consistent pattern of results in both cohorts showing that IQ, GPA, and parental SES were associated with a lower BMI score in adulthood (however, only the average relation found for parental SES was statistically significant; see Table 4). We found no substantial cohort differences with respect to average relations (Table 4) or with respect to specific points in the BMI distribution (Figures 1 and 5, Table A5).

Depressive symptoms. We found a consistent pattern of results in both cohorts showing that higher GPA and higher parental SES were associated with a lower level of depressive symptoms in adulthood (however, only the average relation found for GPA was statistically significant in both cohorts; see Table 4). The predictive relations found for GPA and parental SES did not differ substantially between cohorts with respect to the average relations (Table 4) and with respect to different points in the outcome distribution (Figures 1 and 6, Table A6). However, the predictive relation for IQ changed over time: Whereas higher IQ was related to a lower level of depressive symptoms in the 1960s cohort, the predictive utility was negligible in the 1980s cohort (Table 4). This average trend was observable across the entire outcome distribution. Notably, differences in corresponding regression weights were statistically different from each other on average and at the 50th quantile of the outcome distribution (Figures 1 and 6, Table A6).

Health-related limitations regarding work. In the 1980s cohort, but not the 1960s cohort, we found that higher GPA was associated with a significantly lower risk that health issues would limit the (a) kind or (b) amount of work. We found no substantial differences between cohorts in these predictive relations (Table 4). In the 1980s cohort, IQ predicted a significantly lower risk of both kinds of health limitations, whereas this predictive relation was negligible in the 1960s cohort. However, the difference in corresponding regression weights was not statistically significant (Table 4). Finally, in both cohorts, parental SES was not significantly associated with health-related limitations regarding work, and differences in regression weights were not statistically significant (Table 4).

Check-up by a physician. In both cohorts, IQ, GPA, and parental SES did not significantly predict an individual’s likelihood of having had a check-up by a physician in the last year (Table 4). Yet, it seems that the predictive relation found for GPA changed over time: Whereas higher GPA was associated with a lower likelihood of a check-up in the 1960s cohort, a positive association was found in the 1980s cohort. Most part of the 95% confidence interval supported this conclusion, yet, the difference in these predictive associations was not statistically significant.

Discussion

Capitalizing on representative data from two U.S. cohorts of 15- and 16-year-olds born in the early 1960s and 1980s, the present study systematically examined for the first time the extent to which historical changes in the socioeconomic environment may modulate core assumptions of the "American Dream": the predictive utility of adolescents' IQ, GPA, and parental SES in achieving educational, occupational and health-related outcomes in adulthood.

Investigating Core Assumptions of the American Dream

Lifespan theories hypothesize that individual development is shaped by social and historical circumstances (Baltes, 1987). Thus, changes in the socioeconomic environment and corresponding socioecological pressures may modulate the importance of individual differences in achieving key life outcomes (Roberts et al., 2007). Indeed, the US has undergone dramatic social, political, economic, and labor-market changes. Individuals born in the early 1960s faced early effects of (a) an increasing population density in the US that may have led to a general increase of the level of individualism and competition, for example in educational settings, the job market or access to quality health care (see Sng, Neuberg, Varnum, & Kenrick, 2017; Varnum & Grossmann, 2017). Moreover, the 1960s cohort also experienced early effects of (b) "trickle-down-economic" policies that fostered regressive tax systems and dramatic cuts in the resources invested in Social Security and welfare programs, and (c) college admission processes and a changing labor market where skills (as represented by IQ and GPA) increasingly served as entrance qualifications and success factors. However, individuals born in the early 1980s were presumably at the core of these processes while growing up and thus faced even larger demands for the skillsets represented by IQ and GPA in our study.

Inequalities in educational outcomes, income, and health were increasing for the 1980s cohort relative to the 1960s cohort. A general explanation for rising inequalities on the population level are microlevel processes related to individuals' relative advantage in important individual difference characteristics. Importantly, because Social Security and welfare programs serve as compensating measures and because of the increasing importance of high levels of GPA and high levels of cognitive skills such as IQ, the relative advantages offered by parental SES but also by adolescents' IQ and GPA may have become more important for the 1980s cohort compared with the 1960s cohort in achieving key life outcomes. Thus, we expected an increased predictive utility of parental SES and of adolescents' IQ and GPA for key life outcomes for the 1980s cohort relative to the 1960s cohort.

We systematically examined this set of expectations with respect to outcomes in the domains of education, occupation, and health. The pattern of results can be summarized as follows: First, consistent with previous research, we found higher IQ and higher GPA to be associated with the completion of more years of education, higher income, and higher occupational prestige in both cohorts. Moreover, higher GPA was predictive of lower levels of depressive symptoms in both cohorts and a reduced risk that health would limit the amount and kind of work in the 1980s cohort. Most of these relations were also consistently found across the entire outcome distribution.

Second, consistent with previous research, we also found that adolescents from families with higher parental SES completed more years of education, received somewhat higher incomes, had jobs with higher occupational prestige, and had lower BMI scores. Again, most of these relations were also consistently found across the entire outcome distribution.

Third, contrary to our expectations, the predictive utility of parental SES did not differ significantly between cohorts for any of the outcomes under investigation with respect to average relations or with respect to specific points in the outcome distribution.

Fourth, we found mixed results concerning cohort differences in the predictive utility of IQ. Contrary to our expectations, the average predictive utility of IQ for occupational prestige was significantly larger in the 1960s cohort than in the 1980s cohort with the largest differences found at the 25th and 75th quantiles. Further, higher IQ was (on average) related to a lower level of depressive symptoms in the 1960s cohort, yet the same relation was negligible in the 1980s cohort. Finally, in line with our expectations, IQ gained importance in the 1980s cohort in predicting years of education up to the 50th quantile (median) but then lost (relative to the 1960s cohort) importance for predicting this outcome at higher quantiles.

Fifth, in line with our expectations, the predictive utility of adolescents' GPA for several outcomes increased in the 1980s cohort relative to the 1960s cohort. (a) We found a significant increase in the predictive utility of adolescents' GPA for years of education in the 1980s cohort that was manifested in average relations and consistent across the entire outcome distribution. (b) The average predictive utility of GPA for occupational prestige was somewhat larger in the 1980s cohort with respect to average relations. Yet, this increase was not homogenous across the outcome distribution: The largest (significant) difference was found at the 50th quantile, whereas smaller differences were found at the lower and upper ends of the outcome distribution. (c) Higher GPA was associated with a lower likelihood of having a check-up by a physician in the 1960s cohort, whereas a positive association was found in the 1980s cohort.

Taken together, this pattern of findings empirically underscores that one core assumption of the "American Dream " holds in both cohorts: High levels of IQ (as an indicator of ability) and GPA (presumably a composite indicator of ability, effort, and further socioemotional skills; see below) predicted key life outcomes irrespective of parental SES and circumstances of birth (i.e., gender or ethnicity) in both cohorts. For several outcomes, the predictive utility of individual differences in GPA was even higher in the 1980s cohort than the 1960s cohort. Yet, the present findings also indicate that a second core assumption of the American Dream has not been fulfilled, because parental SES also predicted life outcomes with similar strength in both cohorts.

GPA as a Composite Measure of a Broad Set of Cognitive and Socioemotional Skills?

Our results showed that GPA substantially predicted educational, occupational, and health-related outcomes (after controlling for IQ and parental SES) in both cohorts. In light of these findings, it is intriguing to ask: What does GPA measure? In their *task-based assessment framework*, Heckman and Kautz (2014) argued that performance on any (observable) task (e.g., an IQ test, a self-report measure, or a behavioral task such as achieving a high GPA) depends on (latent) cognitive and socioemotional skills and effort (that is driven by the incentives associated with achieving the task; Kautz et al., 2014). This framework suggests that GPA should be conceived as a multidimensional composite comprising cognitive and socioemotional components (see also Brookhart et al., 2016). This idea has received empirical support. For example, Roth et al.'s (2015) meta-analysis suggested that about 25% of the variance in GPA is shared with IQ. At the same time, personality traits (e.g., conscientiousness, openness) have been found to predict school grades, even when IQ was controlled for (Noftle & Robins, 2007; Poropat, 2009).

Drawing on the "task-based assessment" framework, the present results obtained for GPA can also be thought of in a new way: When controlling for IQ (and other covariates), does the incremental predictive utility of GPA represent the predictive utility of a broad set of adolescents' socioemotional skills? This interpretation is well-aligned with recent work in econometrics where Borghans et al. (2016) concluded that GPA may have even "greater predictive power than IQ or personality alone because [it] embod[ies] extra dimensions of personality not captured by our [i.e., IQ and self-report personality] measures" (Borghans et al., 2016, p. 13358). Adopting this interpretation of GPA opens a promising window for future research: Socioemotional skills can be assessed not only with the predominant method of self-reports (Duckworth & Yeager, 2015) but also (when controlling for cognitive skills such as IQ) by means of GPA as a behavioral measure.

The Predictive Utility of IQ Over Time

Unexpectedly, we observed changes in the predictive utility of IQ over time. First, although IQ was the strongest predictor of educational achievement in both cohorts, there was a trend of diminishing predictive utility in higher quantiles of educational outcomes. One possible reason is that U.S. colleges have become more competitive over time, and thus, high school GPA may have become more important. Hence, individuals in the highest quantiles of educational outcomes in the 1980s cohort might not have only needed to have high cognitive skills but might also have needed a high enough GPA and related socioemotional skills (e.g., conscientiousness and discipline) to succeed. This shift in assessment criteria could have led to IQ losing (some) predictive value to GPA for the highest educational quantiles over time.

Second, we observed changes in how IQ was related to depressive symptoms over time (i.e., the negative association got closer to zero). We can only speculate about possible reasons. First, in times of rising inequality, even high-IQ individuals might not be able to afford treatment for depressive symptoms. Second, mental illnesses has undergone a process of destigmatization in recent decades, enabling (high-IQ) individuals to report depressive symptoms more openly. Third, socioeconomic changes toward neoliberalism and capitalism and the concomitant higher pressure to perform in educational and occupational settings may have led to a generally higher incidence of depressive symptoms, regardless of individuals' IQs. In statistical terms, these scenarios could have led to diminishing effects of IQ on the population level.

Strengths, Limitations, and Outlook

Strengths. Presently, empirical research is still limited with respect to the question of how individual difference variables and social environmental factors may interact in helping a person achieve key life outcomes (Roberts et al., 2007). Therefore, we systematically examined this question with respect to how historical changes in social and economic conditions and the labor market may have modulated the utility of adolescents' IQ and GPA and their parents' SES in predicting vital outcomes in the domains of education, occupation, and health. To this end, we capitalized on the large representative NLSY database, which ensured the broad generalizability of our findings and offered the opportunity to detect potential cohort differences with high statistical power. Using these unique data, we carefully analyzed cohort differences in average predictive utility across the entire outcome distribution and determined whether these differences generalized to specific points in each distribution.

Tentative explanations for cohort differences. Theoretical explanations concerning how historical changes in the socioeconomic environment may modulate the predictive utility of adolescents' characteristics are in an early stage of development. In particular, drawing on the idea of cumulative advantages over the life course, we highlighted several historical developments (e.g., increasing population density, trickle-down economics, changes in the labor-market) which may have increased the predictive utility of individual differences in adolescent characteristics. However, we did not directly address the precise mechanism (DiPrete & Eirich, 2006) by which individual differences in IQ, GPA, or parental SES led to cumulative advantages in various life outcomes. Moreover, we argued that policies based on the idea of "trickle-down economics" led to strong cuts in Social Security and welfare programs, which in turn may have magnified the processes of cumulative advantages in relation to individual differences in IQ, GPA, or parental SES. Yet, at the same time, U.S. politics established *affirmative action*, a set of laws, policies, and administrative practices intended to grant special consideration to excluded groups, such as racial minorities (Anderson, 2004). Given that such policies may even work in opposite directions to those imposed by "trickle-down economics," the cohort differences observed in this study represent the net effect on predictive utility and may have resulted in a lack of cohort differences or in cohort differences that even went in the opposite direction of what we expected.

The need for commensurate measures. Any cohort comparison study needs commensurate measures, and this often requires the application of one of several harmonization procedures (Hussong, Curran, & Bauer, 2013). Importantly, when interpreting observed cohort differences in regression coefficients, it is important to keep the nature or metric of the (harmonized) measures in mind. First, different measures of depressive symptoms were applied in NLSY-79 and NLSY-97. We harmonized these measures by computing z-standardized scores for each cohort. If two individuals belonging to different cohorts have the same z-score, they have the same level of depressive symptoms in relation to the other members of their cohort. Yet, it is not possible to say that these two individuals have the same overall level of depressive symptoms. Thus, the cohort difference in regression coefficients that we observed for IQ might also be explained by the interaction between IQ and the specific measure of depressive symptoms used in NLSY-79 and NLSY-97 rather than cohort differences in predictive relations.

Second, occupational prestige is based on the social status of a specific occupation in the eyes of the members of a society (Hauser & Warren, 1997). Specifically, for the 1960s cohort, we used 1989 prestige scores, and for the 1980s cohort, we applied the 2012 ratings (NORC, 2018). Yet, the interpretation of the occupational prestige metric may have changed (somewhat) over time. As shown by recent polls (Harris Poll, 2007), the prestige ratings for the 1980s cohort might reflect to a larger extent an occupation’s perceived impact on welfare rather than salary or the cognitive complexity of a job. This is why, for example, firefighters or teachers may have been ranked at the top, whereas lower ranking jobs also included cognitively demanding and well-paid occupations such as brokers or bankers. These changes in the occupational prestige metric might also provide one explanation for cohort differences concerning IQ and for some of the nonlinear relations found for IQ and GPA with occupational prestige at specific points in the outcome distribution.

Generalizability of the present findings. Over the last decades, many Western countries faced social, economic, and labor-market changes similar to the changes seen in the US (Lee & Mason, 2014; Miller, 2001). For example, neoliberal politics have grown increasingly dominant in global discourse and practice and reshaped health, education and welfare, global flows of finance, trade, and labor in many Western countries (Sewpaul, 2015). Thus, the present findings might constitute rather global trends that are not limited to the US. In cross-cultural psychology, however, many scholars are very cautious about broad generalizations (e.g., Henrich, Heine & Norenzayan, 2010; Segall, Lonner, & Berry, 1998). For example, Segall et al. (1998, p. 1103) highlight that "The universality of psychological mechanisms cannot be assumed in advance". Specifically, the present results are based on data from longitudinal probability samples that are representative of U.S. populations of 15- and 16-year-old adolescents born in the early 1960s and in the early 1980s. These individuals not only experienced socioeconomic changes that were similar in many other Western countries, but, for example, also politics that were specific to the US (e.g., affirmative action). Moreover, public beliefs in social mobility seem to be less pronounced in other Western countries than in the US (Lumpe, 2017). Thus, in line with the recommendations by Simons, Shoda, and Lindsay (2017) we deliberately constrained our inferences to the US target populations. An important empirical question for future research is therefore to examine the extent to which the present findings on (changes in) the predictive utility of adolescent IQ, GPA and SES for educational, occupational and health-related life outcomes are tied to the US context or generalizable to other (Western) countries.

Restrictions due to the use of the NLSY archive data. As with the use of any archival data, we experienced some limitations that were inherent to the NLSY data.

First, we included individuals in the analyses involving income as an outcome only when they actually had an income larger than $0. Moreover, to ensure the anonymity of participants, NLSY data truncated the income values (of parents and respondents) that were above a certain level. Hence, the income distributions were truncated for parental SES but also when income was used as an outcome variable, and this may have distorted the present results at the highest and lowest ends of parental SES (as a predictor) and income (as an outcome).

Second, we were restricted to the temporal design of NLSY (i.e., timing, spacing, frequency of observations) to examine how socioeconomic change processes may have affected the predictive utility of adolescent characteristics (Collins, 2003). For example, the timing of survey waves could have been "too late" to detect a presumed increase in the importance of IQ for occupational outcomes because globalization processes and changes in occupations due to the development of computers and the Internet had already occurred before 1998 (Time 2 of NLSY-79), and later changes up to 2015 (Time 2 of NLSY-97) might not have had a strong enough influence to modulate the predictive utility of adolescents' IQ. On the other hand, it could still be "too early," given that major technical and societal challenges such as the integration of artificial intelligence in all spheres of life (e.g., health administration, science, large-scale logistic automation) or the impact of global Blockchain-based technologies lie just ahead of us (Brockman, 2015; Tapscott & Tapscott, 2016; Wright & De Filippi, 2015). Moreover, at Time 2, the members of both cohorts were in their early to mid-30s, with many highly educated individuals still establishing their careers. Cohort differences in the cumulative advantages related to adolescents' IQ and GPA and their parents' SES might therefore have yet to fully unfold at that point in an individual's life course.

Conclusion

"Aging is a stratified process that reflects the inequalities that structure our life chances from birth onward" (Abramson, 2016, p.69 ff.). Taking this life-span perspective, and drawing on the literature on cumulative advantage, we expect that the observed relative advantages in educational, occupational and health outcomes over other individuals when individuals age 30—as predicted by adolescents' IQ, GPA, and parental SES in the present study—magnify in older and old age (Crystal, Shea, & Reyes, 2017; DiPrete & Eirich, 2006; Dannefer, 1991). It is also reasonable to expect that this stratification process is further fueled by reinforcing feedback loops where inequalities in educational, occupational, and health outcomes amplify inequalities in other outcome domains (e.g., better health leads to better educational and occupational success and vice versa). In line with this reasoning, recent empirical research shows that economic and health related inequality increased in each successive age group, and that inequality is greater among the elderly than at any other adult age (Crystal et al., 2017). Additionally, returns to education may be even greater after retirement than at working ages (Crystal et al., 2017). This causes serious hardship among the elderly: Late-life consequences of educational and socioeconomic inequality were associated with significantly higher rates of disease incidence and earlier mortality among less-educated and less wealthy persons compared to the well-educated and wealthy (Abramson, 2016; Freese & Lutfey, 2011; Mirowsky & Ross, 2005).

In a nutshell, the US has faced dramatic socioeconomic changes during the last decades. The present findings suggest that for two birth cohorts—born in the early 1960s and in the early 1980s—inequalities in educational, occupational, and health-related outcomes, which can be assumed to increase in later adulthood and old age, can be predicted by individual differences in adolescents' IQ, GPA, and parental SES. The patterns of associations between life outcomes and parental SES did not vary much, and that of IQ remained largely the same or varied inconsistently between cohorts. However, the observed increased predictive utility of GPA suggests that combined effects of social, economic, and labor-market changes may have increased stratification processes due to individual differences in GPA for adolescents belonging to the 1980s cohort.

References

Adams, J. T. (1931). *The epic of America.* Boston, MA: Little, Brown & Company.

Adams, J. T. (2017). *The epic of America*. London, UK: Routledge.

Aghion, P. & Bolton, P. (1997). A theory of trickle-down growth and development. *The Review of Economic Studies, 64*(2), 151- 172.

Alatupa, S., Pulkki-Råback, L., Hintsanen, M., Ravaja, N., Raitakari, O. T., Telama, R., …Autor, A. (2010) School performance as a predictor of adulthood obesity: a 21-year follow-up study. *European Journal of Epidemiology* 25(4), 267–274.

Almlund, M., Duckworth, A. L., Heckman, J., & Kautz, T. (2011). *Personality Psychology and Economics* (Working Paper 16822). Retrieved from: http://www.nber.org/papers/w16822.pdf

Anderson, T. H. (2004). *The pursuit of fairness: A history of affirmative action*. Oxford: Oxford University Press.

APA Task Force on Socioeconomic Status (2007). *Report of the APA Task Force on Socioeconomic Status*. Washington, DC: American Psychological Association.

Aughinbaugh, A. & Gardecki, R. M. (2007). *Attrition in the National Longitudinal Survey of Youth 1997*. Washington, DC: Bureau of Labor Statistics.

Autor, H., Dorn, D., & Hanson, G. (2015). Untangling trade and technology: Evidence from local labour markets. *The Economic Journal, 125*, 621–646. doi: 10.1111/ecoj.12245

Bailey, M., & Dynarski, S. M. (2011). Inequality in postsecondary attainment. In J. Duncan & J. Murnane (Eds.), *Whither Opportunity* (pp. 117-132). New York: Russell Sage.

Baltes, P. B. (1987). Theoretical proposition of the lifespan developmental psychology: On the dynamics between growth and decline. *Developmental Psychology*, *23*(5), 611–696. http://doi.org/10.1037/0012-1649.23.5.611

Barton, P. (2006). *High school reform and work: Facing labor market realities.* Princeton: Educational Testing Service. Retrieved from https://files.eric.ed.gov/fulltext/ED492034.pdf

Bhide, A. (2009). An accident waiting to happen. *Critical Review, 21*(2-3), 211-247.

Borghans, L., Golsteyn, B. H. H., Heckman, J., & Humphries, J. E. (2016). What grades and achievement tests measure. *Proceedings of the National Academy of Sciences*, *113*(47), 13354–13359. http://doi.org/10.1073/pnas.1601135113

Bound, J., Hershbein, B., & Long, B. T. (2009). Playing the admissions game: Student reactions to increasing college competition. *Journal of Economic Perspectives*, *23*(4), 119-146.

Bradbury, K. (2011). *Trends in U.S. family income mobility, 1969-2006* (Working Paper 11-10). Retrieved from https://www.bostonfed.org/publications/research-department-working-paper/2011/trends-in-us-family-income-mobility-1969-2006.aspx

Bradley, R. H. & Corwyn, R. F. (2002). Socioeconomic status and child development. *Annual Review of Psychology*, *53*(1), 371–399. http://doi.org/10.1146/annurev.psych.53.100901.135233

Brookhart, S. M., Guskey, T. R., Bowers, A. J., McMillan, J. H., Smith, J. K., Smith, L. F., ..., Welsh, M. E. (2016). A century of grading research: Meaning and value in the most common educational measure. *Review of Educational Research, 86*(4), 803-848. http://doi.org/10.3102/0034654316672069

Brockman, J. (2015). *What to think about machines that think*. New York City: Harper Perennial.

Bureau of Labor Statistics (2014). *Largest industries by state, 1990-2013*. Retrieved from https://www.bls.gov/opub/ted/2014/ted_20140728.htm

Bureau of Labor Statistics (2019a). *Retention & Reasons for Noninterview in the NLSY79.* Retrieved from https://www.nlsinfo.org/content/cohorts/nlsy79/intro-to-the-sample/retention-reasons-noninterview

Bureau of Labor Statistics (2019b). *Retention & Reasons for Noninterview in the NLSY97.*

Retrieved from https://www.nlsinfo.org/content/cohorts/nlsy97/intro-to-the-sample/retention-reasons-non-interview

Chetty, R., Grusky, D., Hell, M., Hendren, N., Manduca, R., & Narang, J. (2017). The fading American dream: Trends in absolute income mobility since 1940. *Science*, *406*, 398–406.

Cheung, M. W. L. (2009). Comparison of methods for constructing confidence intervals of standardized indirect effects. *Behavior Research Methods*, *41*(2), 425–438. http://doi.org/10.3758/BRM.41.2.425

Cohen, J., Cohen, P., West, S. G., & Aiken, L. S. (2003). *Applied multiple regression/correlation analysis for the behavioral sciences*. London, UK: Psychology Press.

Collins, H. (2003). Discrimination, equality and social inclusion. *Modern Law Review*, *66*(1), 16–43. http://doi.org/10.1111/1468-2230.6601002

Cooksey, E. (2018). Using the National Longitudinal Surveys of Youth (NLSY) to conduct life course analyses. In: N. Halfon, C. Forrest, R. Lerner, and E. Faustmann (Eds.), *Handbook of Life Course Health Development* (561-577). Berlin: Springer.

Corak, M. (2016). "Inequality is the root of social evil," or maybe not? Two stories about inequality and public policy. *Canadian Public Policy*, *42*(4), 367–414. http://doi.org/10.3138/cpp.2016-056

Crystal, S., & Shea, D. (1990). Cumulative advantage, cumulative disadvantage, and inequality among elderly people. *The Gerontologist*, *30*(4), 437–443. http://dx.doi.org/10.1093/geront/30.4.437

Crystal, S., Shea, D. G., & Reyes, A. M. (2017). Cumulative advantage, cumulative disadvantage, and evolving patterns of late-life inequality. The *Gerontologist*, *57*(5), 910–920. http://doi.org/10.1093/geront/gnw056

Curran, P. J., & Hussong, A. M. (2009). Integrative Data Analysis: The simultaneous analysis of multiple data sets. *Psychological Methods*, *14*(2), 81–100. http://doi.org/10.1037/a0015914.Integrative

Damian, R. I., Su, R., Shanahan, M., Trautwein, U., & Roberts, B. W. (2015). Can personality traits and intelligence compensate for background disadvantage? Predicting status attainment in adulthood. *Journal of Personality and Social Psychology*, *109*(3), 473.

Danzinger, S., & Haveman, R. (1981). The Reagan administration's budget cuts: Their impact on the poor. *Challenge*, *24*, 5–13.

Deary, I. J. (2012). Intelligence. *Annual Review of Psychology*, *63*(1), 453–482. http://doi.org/https://doi.org/10.1146/annurev-psych-120710-100353

Deaton, A. (2013). *The great escape: Health, wealth, and the origins of inequality*. Princeton: Princeton University Press.

Deming, J. (2015). *The growing importance of social skills in the labor market* (Working Paper 21473). Retrieved from https://www.nber.org/papers/w21473.pdf

DiPrete, T. A., & Eirich, G. M. (2006). Cumulative advantage as a mechanism for inequality: A review of theoretical and empirical developments. *Annual Review of Sociology*, *32*(1), 271–297. http://doi.org/10.1146/annurev.soc.32.061604.123127

Duckworth, A. L., & Yeager, D. S. (2015). Measurement matters: Assessing personal qualities other than cognitive ability for educational purposes. *Educational Researcher*, *44*(4), 237–251. http://doi.org/10.3102/0013189X15584327

Duncan, G. J., Magnuson, K., & Votruba-Drzal, E. (2017). Moving beyond correlations in assessing the consequences of poverty. *Annual Review of Psychology*, *68*, 413–434.

Fischbach, A., Baudson, T. G., Preckel, F., Martin, R., & Brunner, M. (2013). Do teacher judgments of student intelligence predict life outcomes? *Learning and Individual Differences, 27,* 109–119.

Frankel, M. R., McWilliams, H. A., & Spencer, B. D. (1983). *National Longitudinal Survey* *of Labor Force Behavior, Youth Survey (NLS) Technical Sampling Report.* Retrieved from https://www.nlsinfo.org/sites/nlsinfo.org/files/attachments/130212/NLSY79%20Tech%20Samp%20Rpt.pdf

French, M., Homer, J. F., Popovici, I., & Robins, P. (2015). What you do in high school matters: High School GPA, educational attainment, and labor market earnings as a young adult. *Eastern Economic Journal*, *41*(3), 370-386. https://doi.org/10.1057/eej.2014.22

Frey, M. C., & Detterman, D. K. (2004). Scholastic assessment or g? The relationship between the scholastic assessment test and general cognitive ability. *Psychological Science*, *5*, 373–378.

Gottfredson, L. S., & Deary, I. J. (2004). Intelligence predicts health and longevity, but why? *Current Directions in Psychological Science*, *13*(1), 1–4. http://doi.org/10.1111/j.0963-7214.2004.01301001.x

Greenfield, P. M. (2017). Cultural change over time: Why replicability should not be the gold standard in psychological science. Perspectives in Psychological Science, 12, 762-771.

Grossmann, I. & Varnum, M. (2015). Social structure, infectious diseases, disasters, secularism, and cultural change in America. *Psychological Science, 26*(3), 311-324. https://doi.org/10.1177/0956797614563765

Harris Poll. (2007). *Firefighters, scientists And teachers top list as " Most prestigious occupations" according to latest Harris Poll.* Retrieved from https://theharrispoll.com/wp-content/uploads/2017/12/Harris-Interactive-Poll-Research-Pres-Occupations-2007-08.pdf

Hauser, R. M., & Warren, J. R. (1997). Socioeconomic indexes for occupations: A review, update, and critique. *Sociological Methodology*, *27*(1), 177–298.

http://doi.org/10.1111/1467-9531.271028

Heckman, J. (2011). The economics of inequality: The value of early childhood education. *American Educator, 35*(1), 31–36. Retrieved from http://files.eric.ed.gov/fulltext/EJ920516.pdf

Heckman, J., & Kautz, T. (2014). Fostering and measuring skills: Interventions that improve character and cognition. In J. Heckman, J. Humphries, & T. Kautz (Eds.), *The myth of achievement tests: The GED and the role of character in American life* (pp. 341–430). Chicago, IL: University of Chicago Press. http://doi.org/10.3386/w19656

Heckman, J., & Mosso, S. (2014). The economics of human development and social mobility. *Annual Review of Econonomics*, *6*, 689–733. http://doi.org/10.1146/annurev-economics-080213-040753.

Heckman, J., Stixrud, J., & Urzua, S. (2006). *The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior* (Working Paper 12006). Retrieved from http://www.nber.org/papers/w12006.pdf

Henrich, J., Heine, S., & Norenzayan, A. (2010). The weirdest people in the world? *Behavioral and Brain Sciences, 33*(2/3), 1-75. https://doi:10.1017/S0140525X0999152X

Herd, P. (2010). Education and health in late-life among high school graduates: Cognitive versus psychological aspects of human capital. *Journal of Health and Social Behavior, 51*(4), 478-496. https://doi: 10.1177/0022146510386796.

Hussong, A. M., Curran, P. J., & Bauer, D. J. (2013). Integrative data analysis in clinical psychology research. *Annual Review of Clinical Psychology*, *9*, 61–89.

International Monetary Fund. (2015). *World Economic Outlook: Uneven Growth—Short- and Long-Term Factors*. *World Economic and Financial Surveys*. Washington, DC: International Monetary Fund. http://doi.org/10.1163/187502311797543854

Institute on Taxation & Economic Policy (ITEP). (2015). Who pays ? *A distributional* *analysis of the tax systems in all 50 states* (5th edition). Retrieved from https://itep.org/wp-content/uploads/whopaysreport.pdf

Johnson, W., Corley, J., Starr, J. M., & Deary, I. J. (2011). Psychological and physical health at age 70 in the Lothian birth cohort 1936: Links with early life IQ, SES, and current cognitive function and neighborhood environment. *Health Psychology*, *30*(1), 1–11. http://doi.org/10.1037/a0021834

Kautz, T., Heckman, J., Diris, R., Weel, B. T., & Borghans, L. (2014). *Fostering and measuring skills : Improving cognitive and non-cognitive skills to promote lifetime success.* Retrieved from http://www.oecd.org/education/ceri/Fostering-and-Measuring-Skills-Improving-Cognitive-and-Non-Cognitive-Skills-to-Promote-Lifetime-Success.pdf

Koenker, R. (2018). *Package 'quantreg'.* Retrieved from https://cran.r-project.org/web/packages/quantreg/quantreg.pdf

Levine, J. A. (2011). Poverty and obesity in the U.S. *Diabetes*, *60*(11), 2667–2668. http://doi.org/10.2337/db11-1118

Lewit, E., Terman, D., & Behrman, E. (1997). Children and poverty: Analysis and recommendations. *The Future of Children, 7*(2), 4-24.

Lumpe, C. (2017). *Public beliefs in social mobility and high-skilled migration* (Ruhr Economic Papers 691). Retrieved from https://www.econstor.eu/bitstream/10419/158023/1/888009178.pdf

Moore, W., Pedlow, S., Krishnamurty, P., & Wolter, K. (2000). *National Longitudinal Survey of Youth 1997 (NLSY97). Technical sampling report.* Retrieved from https://www.bls.gov/nls/nlsy97techsamp.pdf

Mossakowski K. N. (2009). The influence of past unemployment duration on symptoms of depression among young women and men in the United States. *American Journal of Public Health, 99*(10), 1826–1832. doi:10.2105/AJPH.2008.152561

Muthén, B.O. (1998-2004). *Mplus technical appendices*. Los Angeles, CA: Muthén & Muthén

Muthén, L. K., & Muthén, B. (1998- 2017). *Mplus user's guide (8th ed.).* Los Angeles, CA: Muthén & Muthén.

National Opinion Research Center (NORC) (2018). Retrieved from http://gss.norc.org/documents/codebook/gss_codebook.pdf

Newacheck, P. W., Hung, Y. Y., Park, M. J., Brindis, C. D., Irwin, C. E., Jane Park, M., … Irwin, C. E. (2003). Access and quality disparities in adolescent health and health care: Does socioeconomic status matter? *Health Services Research*, *38*(5), 1235–1252. http://doi.org/10.1111/1475-6773.00174

Noftle, E. E., & Robins, R. W. (2007). Personality predictors of academic outcomes: Big Five correlates of GPA and SAT scores. *Journal of Personality and Social Psychology*, *93*(1), 116–130. http://doi.org/10.1037/0022-3514.93.1.116

Organisation for Economic Cooperation and Development (OECD) (2015). *Skills for social progress*. Retrieved from http://doi.org/10.1787/9789264226159-en

Petscher, Y. & Logan, J. A. R. (2014). Quantile regression in the study of developmental sciences. *Child Development*, *85*(3), 861–881. http://doi.org/10.1111/cdev.12190

Pew Charitable Trusts (2012). *Pursuing the American Dream: Economic mobility across generations.* Washington, DC: Pew Charitable Trusts.

Pew Charitable Trusts. (2009). *Economic Mobility Project. Key findings from a 2009 national survey and focus groups.* Retrieved from https://www.pewtrusts.org/-/media/assets/2009/emppollmainfindings31209final11.pdf

Phelan, J. C., Link, B. G., & Tehranifar, P. (2010). Social Conditions as Fundamental Causes of Health Inequalities: Theory, Evidence, and Policy Implications. *Journal of Health and Social Behavior*, *51*(1_suppl), S28–S40. https://doi.org/10.1177/0022146510383498

Poropat, A. E. (2009). A meta-analysis of the five-factor model of personality and academic performance. *Psychological Bulletin*, *135*(2), 322–338. http://doi.org/10.1037/a0014996

Quesnel-Vallée, A. & Taylor, M. (2012). Socioeconomic pathways to depressive symptoms in adulthood: evidence from the National Longitudinal Survey of Youth 1979. *Social Science & Medicine, 74*(5), 734–743. doi:10.1016/j.socscimed.2011.10.038

Revelle, W. (2018). *Package 'psych'*. Retrieved from https://cran.r-project.org/web/packages/psych/psych.pdf

Reynolds, S. & Himes, C. (2007). Cohort differences in adult obesity in the United States: 1982 – 2002. *Journal of Aging and Health, 19*(5), 831-850. DOI: 10.1177/0898264307305182

Roberts, B., Kuncel, N. R., Shiner, R., Caspi, A., & Goldberg, L. R. (2007). The power of personality: The comparative validity of personality traits, socioeconomic status, and cognitive ability for predicting important life outcomes. *Perspectives on Psychological Science*, *2*(4), 313–345. http://doi.org/10.1111/j.1745-6916.2007.00047.x

Roth, B., Becker, N., Romeyke, S., Schäfer, S., Domnick, F., & Spinath, F. M. (2015). Intelligence and school grades: A meta-analysis. *Intelligence*, *53*, 118–137. http://doi.org/10.1016/j.intell.2015.09.002

Saez, E., & Zucman, G. (2016). Wealth inequality in the United States since 1913: Evidence from capitalized income tax data. *Quarterly Journal of Economics*, *131*, 519–578. http://doi.org/10.1093/qje/qjw004.Advance

Santos, H., Varnum, M., & Grossmann, I. (2017). Global increases in individualism. *Psychological Science, 28*(9), 1228-1239. https://doi.org/10.1177/0956797617700622

Shanahan, M. J., Hill, P. L., Roberts, B. W., Eccles, J., & Friedman, H. S. (2014). Conscientiousness, health, and aging: The life course of personality model. *Developmental Psychology*, *50*(5), 1407–1425. http://doi.org/10.1037/a0031130

Shippee, N. D., & Owens, T. J. (2011). GPA, depression, and drinking: A longitudinal comparison of high school boys and girls. *Sociological Perspectives*, *54*(3), 351-376. https://doi.org/10.1525/sop.2011.54.3.351

Simons, D. J., Shoda, Y.,& Lindsay. D.S. (2017). Constraints on Generality (COG): A proposed addition to all empirical papers. *Perspectives on Psychological Science, 12*(6), 1123-1128.

Sng, O., Neuberg, S. L., Varnum, M. E. W., & Kenrick, D. T. (2017). The crowded life is a slow life: Population density and life history strategy. Journal of Personality and Social Psychology, 112(5), 736-754. http://dx.doi.org/10.1037/pspi0000086

Spengler, M., Damian, R. I., & Roberts, B. W. (2018). How you behave in school predicts life success above and beyond family background, broad traits, and cognitive ability. *Journal of Personality and Social Psychology*, *114*(4), 620–636. http://doi.org/10.1037/pspp0000185

Stiglitz, J. (2009). The anatomy of a murder: Who killed America's economy? *Critical Review*, *21*(2–3), 329–339. http://doi.org/10.1080/08913810902934133

Stiglitz, J. (2010). *Freefall: America, free markets, and the sinking of the world economy.* New York, NY: W.W. Norton & Company.

Stiglitz, J. (2015). *Rewriting the rules of the American economy. An agenda for growth and shared prosperity.* New York: Roosevelt Institute.

Tapscott, D., & Tapscott, A. (2016). *Blockchain revolution: How the technology behind bitcoin is changing money, business, and the world*. London, UK: Penguin.

The National Academy of Science. (2017). *2017 report to congress*. Retrieved from http://www.nationalacademies.org/annualreport/Report_to_Congress_2017.pdf

U.S. Census Bureau (2017). 2010 Census occupation codes with crosswalk. Retrieved from https://www.census.gov/topics/employment/industry-occupation/guidance/code-lists.html

Varnum, M. & Grossmann, I. (2017). Cultural Change: The How and the Why. *Perspectives on Psychological Science, 12*(6), 956–972. https://doi.org/10.1177/1745691617699971

Vyas, S., & Kumaranayake, L. (2006). Constructing socio-economic status indices: How to use principal components analysis. *Health Policy and Planning*, *21*(6), 459–468. http://doi.org/10.1093/heapol/czl029

Wilkinson, L. L., Glover, S. H., Probst, J. C., Cai, B., & Wigfall, L. T. (2015). Psychological distress and health insurance coverage among formerly incarcerated young adults in the United States. *AIMS Public Health, 2*(3), 227–246. doi:10.3934/publichealth.2015.3.227

Wright, A., & De Filippi, P. (2015). Decentralized Blockchain technology and the rise of Lex Cryptographia. *SSRN Electronic Journal,* 1-58. http://doi.org/10.2139/ssrn.2580664

Tables

Table 1

Political, Historical, and Economic Indicators of the 1960s and 1980s Cohorts

Indicators	1960s cohort	
	Time 1 (1979)	Time 2 (1998)
GDP (USD)	2,441 trillion	8,429 trillion
GNI/ capita (USD)	11,342	29,816
Population total	225 million	276 million
Inflation (%)	11.27	1.55
Unemployment (%)	5.85	4.51
Presidencies (Birth to T2)	Johnson (1963-69), Nixon (1969- 74), Ford (1974-77), Carter (1977-81), Reagan (1981 -89), Bush (1989 -1993), Clinton (1993-2001)	
Historical events (Birth to T2)	Vietnam War (1955-75), Civil Rights Act (1964), Counter Culture (1969), Watergate Scandal (1972), Oil Crisis (1973), Cold War (1947-91), Reagonomics (1981-89), Republican Revolution (1994)	
	1980s cohort	
	Time 1 (1997)	Time 2 (2015)
GDP (USD)	7,984 trillion	16,804 trillion
GNI/ capita (USD)	29,111	52,212
Population total	273 million	321 million
Inflation (%)	2.34	0.12
Unemployment (%)	4.94	5.28
Presidencies (Birth to T2)	Reagan (1981-89), Bush (1989-93), Clinton (1993-2001), Bush (2001-09), Obama (2009 –17)	
Historical events (Birth to T2)	1980 to 1997 see above; World Trade Center Bombing (2001), Iraq Invasion (2003), Global Financial Crisis (2008), WikiLeaks (2010), NSA Global surveillance disclosures (2013)	

Note. GDP = Gross Domestic Product, GNI = Gross National Income. Information on political and economic indicators was gathered from the World Bank and the U.S. Bureau of Labor Statistics. All values are in 2015 U.S. Dollars.

Table 2

Milestones of U.S. Legislation Fostering Trickle-Down Economics 1980-2010: Budget and Welfare Retrenchment, Finance Deregulation, and Tax Cut Policies

Act	Significance
Omnibus Budget Reconciliation Act of 1981; Economic Recovery Tax Act of 1981 (Kemp-Roth Tax-Cuts)	Budgetary retrenchment and reallocations led to a reduction of 6% in public spending in 1982, with a reduction in all categories except national defense. Over half of the budget reduction came from two areas, mainly impacting the poor: income security; and education, training, employment, and social services. Welfare programs that grew most rapidly from 1965 to 1981 (e.g., Food Stamps, federal guaranteed loan programs for higher education, Legal Assistance) faced the largest cuts, up to 20% (Danzinger & Haveman, 1981).
Personal Responsibility and Work Opportunity Reconciliation Act of 1996	“Welfare-to-Work”: U.S. welfare programs “Aid to Families with Dependent Children” (AFDC), Job Opportunities and Basic Skills Training (JOBS) program, and the Emergency Assistance (EA) program were replaced with a cash welfare block grant called “Temporary Assistance to Needy Families” (TANF). Contrary to ADFC, JOBS, and EA, TANF required work participation in exchange for providing funds and imposed a lifetime limit of 5 years on welfare assistance paid by federal money. Funds available for unmarried parents under 18 were limited, and any funding to immigrants (i.e., health care) was restricted. States were granted broad flexibility in program design (Lewit, Terman, & Behrmanm, 1997).
Depository Institutions Deregulation and Monetary Control Act of 1980; Gramm-Leach-Bliley Act (GLBA) of 1999	Deregulation of the financial sector. Both acts repealed parts of the Glass-Steagall Act of 1933, which prohibited institutions from acting as any combination of an investment bank, a commercial bank, and an insurance company. GLBA failed to give any financial regulatory agency the authority to regulate large investment bank holding companies. The act is often considered to have helped in creating the 2007-2008 financial crisis, its passage clearing the way for companies to be “too big to fail” (Bhide, 2009; Stiglitz, 2009, 2010).
Tax Reform Act of 1986; Economic Growth and Tax Relief Reconciliation of 2001; Tax Relief, Unemployment Insurance Reauthorization, and Job Creation Act of 2010	The U.S. tax system takes a much greater share of income from low- and middle-income families than from wealthy ones. By 2015, putting together all state and local income, property, sales and excise taxes, the average effective state and local tax rates by income group are 10.9% for the poorest 20% of individuals and families, 9.4 % for the middle 20%, and 5.4% for the top 1% (ITEP, 2015). From a long-term perspective, these developments are problematic because they prevent states from investing in the priorities that can bolster the prospects of low- and middle-income residents: education, workforce, infrastructure improvements, and adequate healthcare (ITEP, 2015)

Table 3

Sample of Prestige Scores matched with Job Titles, following the NORC Occupational Prestige Coding Systems 1989 (1960s Cohort) and 2012 (1980s Cohort)

Prestige scores	Job title
	NLSY-79
33.38 Points	Operators, Fabricators, and Laborers
34.95 Points	Service Occupations
35.57 Points	Farming, Forest, and Fishing Occupations
38.51 Points	Precision Production, Craft, and Repair Occupations
40.43 Points	Technical, Sales, and Administrative Support Occupations
62.24 Points	Managerial and Professional Specialty Occupations
	NLSY-97
36.22 Points	Production, Transportation, and Material Moving Occupations
37.23 Points	Sales and Office Occupations
37.37 Points	Natural Resources, Construction, and Maintenance Occupations
38.96 Points	Service Occupations
55.63 Points	Management, Professional, and Related Occupations

Note. Mean values for broad job classification categories based on 1980/2000 U.S. census job titles. 1989 prestige scores are representative of 1980 census job titles for the 1960s cohort, 2012 prestige scores are representative of 2010 census job titles for the 1980s cohort (NORC, 2018).

Table 4

Results from Multiple and Logistic Regression Analyses Predicting Educational Attainment, Income, Occupational Prestige, and Health (as Outcomes) from Students' IQ, GPA, and SES (as Predictors) across an 18/19-Year Time Interval in the 1960s and 1980s Cohorts

Predictors	1960s cohort		1980s cohort		Cohort comparison	
	B	95% CI	*B*	95% CI	Δ*B*	95% CI
Outcome: Education (years)						
IQ	**.039**	**[.035, .043]**	**.037**	**[.033, .041]**	-.002	[-.008, .003]
GPA	**.708**	**[.591, .825]**	**1.264**	**[1.108, 1.420]**	**.556**	**[.356, .757]**
SES	**.473**	**[.335, .612]**	**.485**	**[.315, .655]**	.011	[-.208, .231]
R^2		.444		.407		
Outcome: Income in US $ (log-transformed)						
IQ	**.012**	**[.008, .016]**	**.013**	**[.004, .020]**	.001	[-.008, .010]
GPA	**.198**	**[.028, .369]**	.317	[-.033, .430]	.119	[-.168, .406]
SES	.102	[-.034, .238]	.092	[-.123, .327]	-.010	[-.273, .253]
R^2		.070		.120		
Outcome: Occupational prestige						
IQ	**.139**	**[.118, .159]**	**.068**	**[.052, .083]**	**-.071**	**[-.047, -.095]**
GPA	**1.474**	**[.803, 2.146]**	**1.913**	**[1.208, 2.619]**	.439	[-.475, 1.353]
SES	**1.245**	**[.579, 1.910]**	**1.106**	**[.647, 1.564]**	-.139	[-1.003, .725]
R^2		.201		.166		
Outcome: Body Mass Index (BMI)						
IQ	-.007	[-.022, .008]	-.011	[-.023, .001]	-.004	[-.022, .015]
GPA	-.238	[-.782, .306]	**-.556**	**[-.977, -.135]**	-.318	[-1.007, .371]
SES	**-.455**	**[-.736, -.174]**	-.349	[-.713, .015]	.106	[-.401, .612]
R^2		.025		.018		
Outcome: Depressive symptoms						
IQ	**-.003**	**[-.005, -.001]**	.001	[-.001, .002]	**.004**	**[.001, .007]**
GPA	**-.088**	**[-.161, -.015]**	**-.152**	**[-.227, -.076]**	-.063	[-.179, .052]
SES	-.027	[-.085, .031]	-.006	[-.049, .037]	.021	[-.040, .081]
R^2		.057		.036		
Outcome: Physical examination in past year[a]						
IQ	-.002	[-.005, .001]	.001	[-.002, .003]	.002	[-.001, .006]
GPA	-.047	[-.149, .056]	.064	[-.027, .154]	.110	[-.023, .244]
SES	.053	[-.020, .126]	.033	[-.032, .097]	-.021	[-.128, .087]
R^2		. 071		.119		
Outcome: Limitations in kind of work[a]						
IQ	-.001	[-.007, .005]	**-.005**	**[-.009, -.002]**	-.004	[-.011, .002]
GPA	-.143	[-.362, .076]	**-.240**	**[-.387, -.093]**	-.097	[-.340, .147]
SES	.070	[-.097, .238]	**-.082**	**[-.160, -.005]**	-.152	[-.351, .046]
R^2		.027		.095		
Outcome: Limitations in amount of work[a]						
IQ	-.002	[-.008, .004]	**-.006**	**[-.010, -.003]**	-.004	[-.011, .002]
GPA	-.173	[-.438, .092]	**-.252**	**[-.391, -.113]**	-.079	[-.354, .196]
SES	.010	[-.166, .186]	-.063	[-.155, .029]	-.073	[-.278, .132]
R^2		.039		.107		

Note. *B* = Unstandardized regression coefficients. CI = Confidence Interval. Δ*B* = Cohort differences in unstandardized regression coefficients (1980s cohort vs. 1960s cohort). Higher GPA scores represent better grades. Parameters for Physical Examination as well as Work Limitations represent log odds (0 = no physical examination in past year/no work limitations, 1 = physical examination/work limitations) for White men. All regression parameters shown in this table were adjusted for ethnicity, gender, and age group, which were included as additional independent variables in the regression models. A complete report of all regression parameters is provided in the Online Supplemental Material. Significant results are printed in bold font, indicating that the 95% CI does not contain zero. If it contains zero in the table, it is due to rounding.

[a]The R^2 values represent pseudo R^2 values for logistic regression models (see Muthén, 1998-2004, Equation 15).

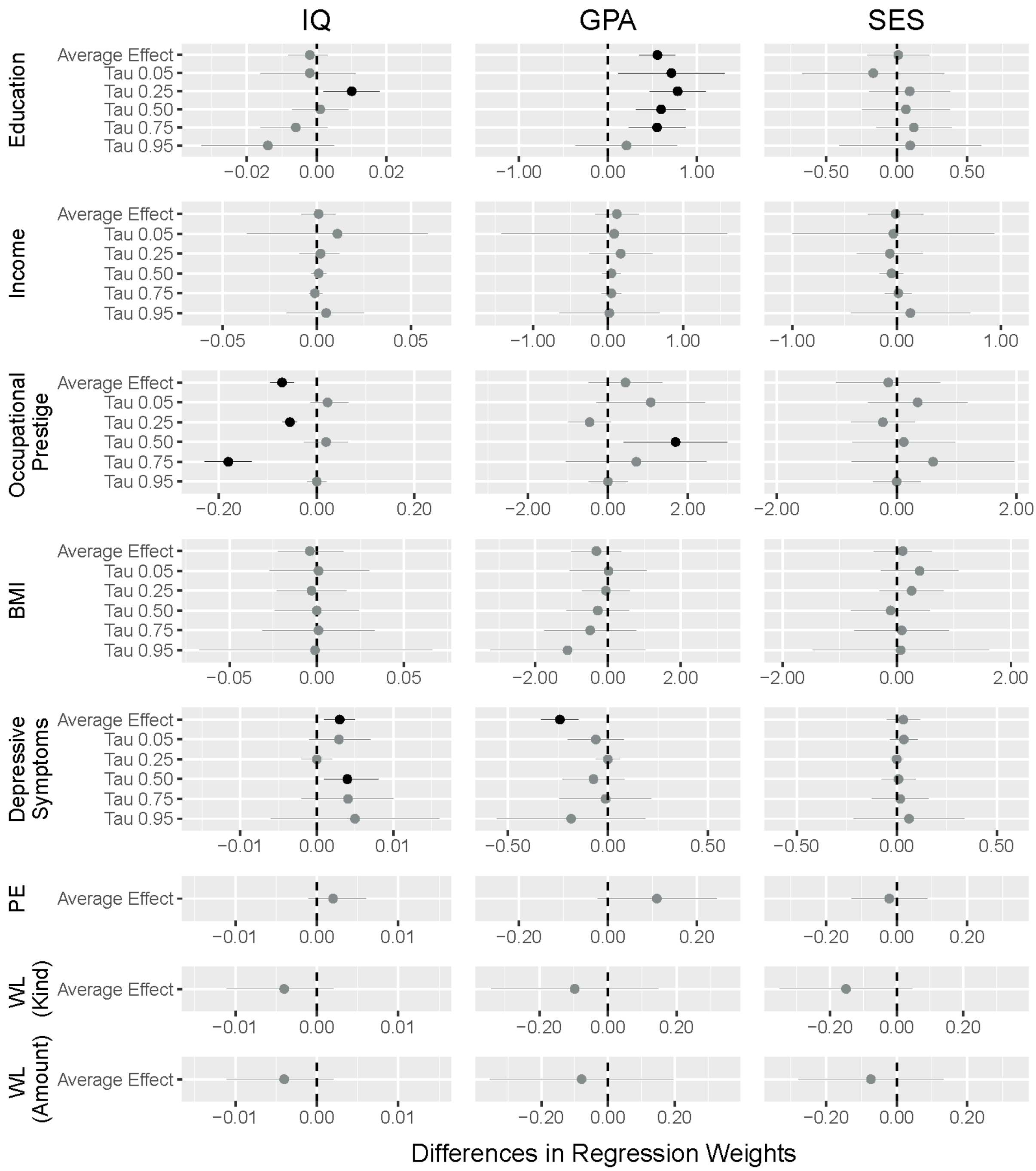
Table 5

Effect Size Estimates in Natural Metrics: Relation of an increase of 1 SD in Students' IQ, GPA, and SES (as Predictors) to Key Life Outcomes across an 18/19-Year Time Interval in the 1960s and 1980s Cohorts

Predictors	1960s cohort	1980s cohort
	Outcome: Education (years)	
IQ	13.5 Months	12.9 Months
GPA	6.8 Months	10.5 Months
SES	5.1 Months	5.6 Months
	Outcome: Income in US $ (log-transformed)	
IQ	$ 12,572	$ 13,869
GPA	$ 5,205	$ 7,382
SES	$ 2,825	$ 2,825
	Outcome: Occupational prestige	
IQ	"Service Occupations" (4.02 Points)	"Service Occupations" (1.98 Points)
GPA	"Construction/Maintenance" (1.18 Points)	"Construction/Maintenance" (1.32 Points)
SES	"Construction/Maintenance" (1.12 Points)	"Sales/ Office" (1.06 Points)
	Outcome: Body Mass Index (BMI)	
IQ	-.20 Points	-.32 Points
GPA	-.19 Points	-.38 Points
SES	-.41 Points	-.33 Points
	Outcome: Depressive symptoms	
IQ	-.09 Points	.03 Points
GPA	-.07 Points	-.10 Points
SES	-.02 Points	-.01 Points
	Outcome: Physical examination in past year	
IQ	- 6 % Probability	+ 3 % Probability
GPA	- 4 % Probability	+ 4 % Probability
SES	+ 5 % Probability	+ 3 % Probability
	Outcome: Limitations in kind of work	
IQ	- 3 % Probability	- 14 % Probability
GPA	- 10 % Probability	- 16 % Probability
SES	+ 6 % Probability	- 8 % Probability
	Outcome: Limitations in amount of work	
IQ	- 6 % Probability	- 16 % Probability
GPA	- 13 % Probability	- 16 % Probability
SES	+ 1 % Probability	- 6 % Probability

Note. All transformations into natural metrics are based on the results shown in Tables 4 and A1. Higher GPA scores represent better grades. The units of IQ, GPA, and SES refer to 1 SD as obtained for the 1960s and 1980s cohorts, respectively. Thus, the effect size entries in this table refer to an estimate in the extent to which an increase of 1 SD in IQ / 1 SD in GPA/ 1 SD in SES were associated with x units of outcome y. To ease interpretation of results, we computed all effects on income in 2015 dollars; dollar amount differences were computed at an average yearly income of $30,000 by applying exp(b x SD). As for occupational prestige, prestige scores for both cohorts are given in 2010 U.S. Census occupational codes. Percentage changes for the odds of having had a physical examination or experiencing work limitations were computed by applying exp(bxSD) for White men. The reference category for Occupational Prestige is "Production, Transportation, and Material Occupations." Depressive symptom scores represent z-standardized values (M = 0, SD = 1).

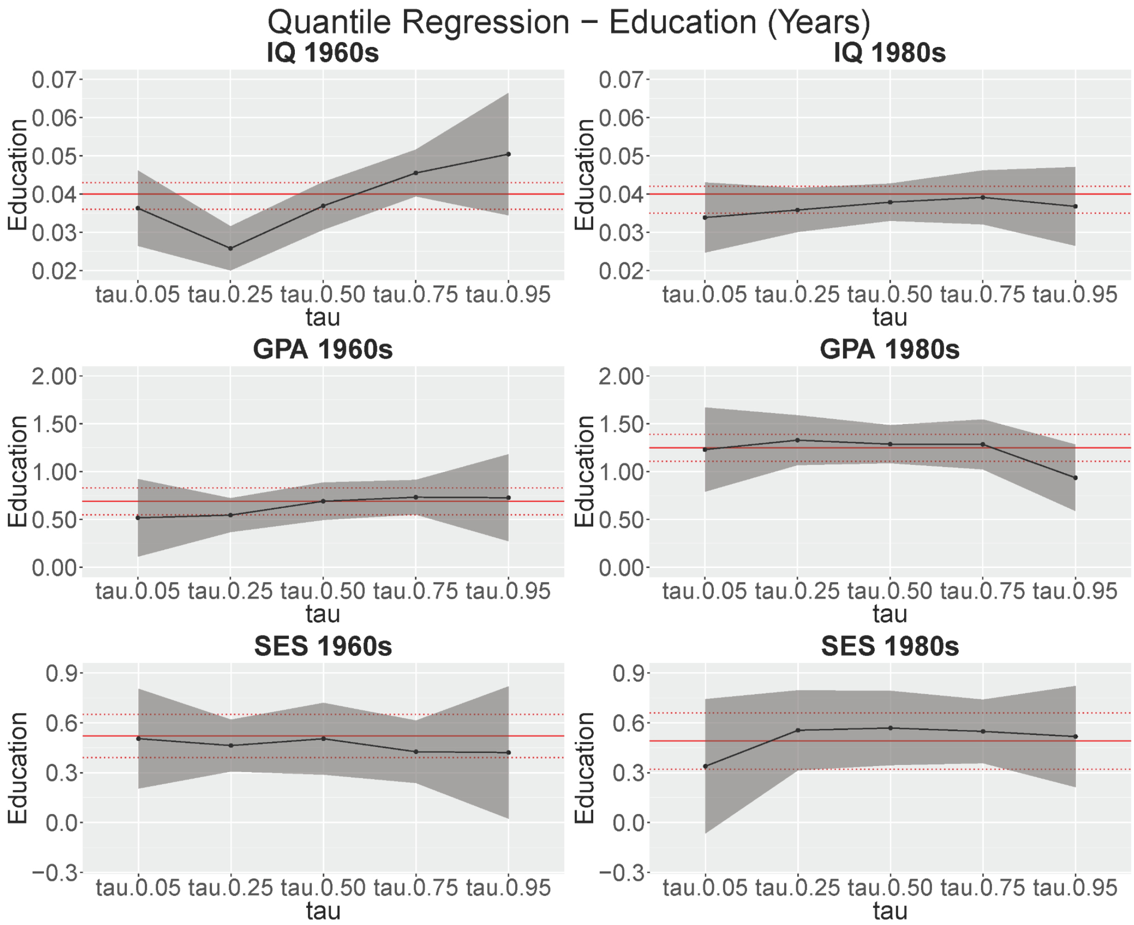
Figure 1



Note. Cohort differences for the 1960s versus 1980s cohorts in unstandardized regression coefficients for students' intelligence (IQ), grade point average (GPA), and socioeconomic status (SES) in predicting key life outcomes 18/19 years later. Error bars show the 95% confidence intervals. Confidence intervals including 0 are marked in grey; confidence intervals not including 0 are marked in black. PE = Physical examination, WL = Work limitations. Tau values represent quantiles of the outcome distributions (i.e., tau 0.05

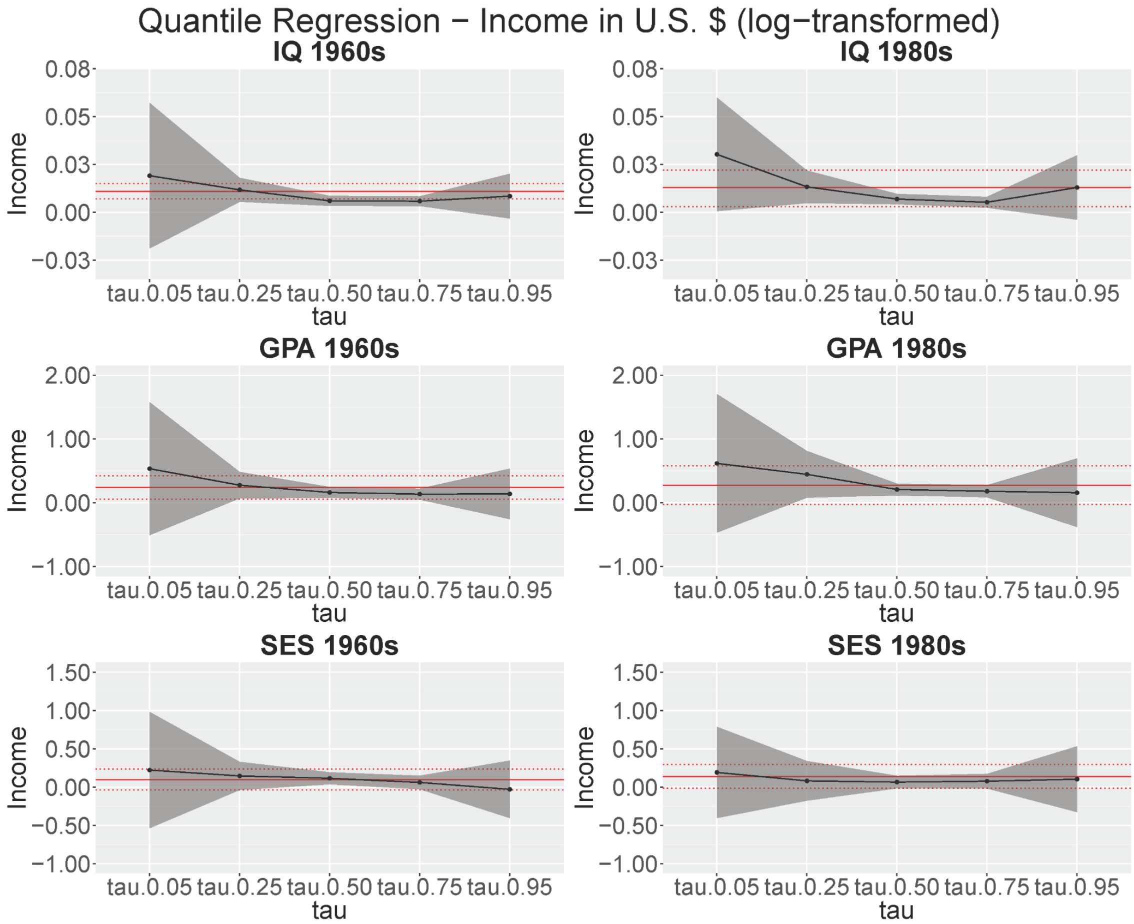
represents the 5^{th} quantile, tau 0.25 the 25^{th} quantile, and so on). Positive differences indicate that regression coefficients were larger for the 1980s than for the 1960s cohort; negative differences indicate that regression coefficients were larger for the 1960s than for 1980s cohort. The results show that (a) the predictive utility of parental SES did not vary much, (b) the predictive utility of IQ remained largely the same or varied inconsistently between cohorts, and (c) the predictive utility of GPA for achieving educational, occupational, and some health-related outcomes increased for individuals who were born in the 1980s.

Figure 2



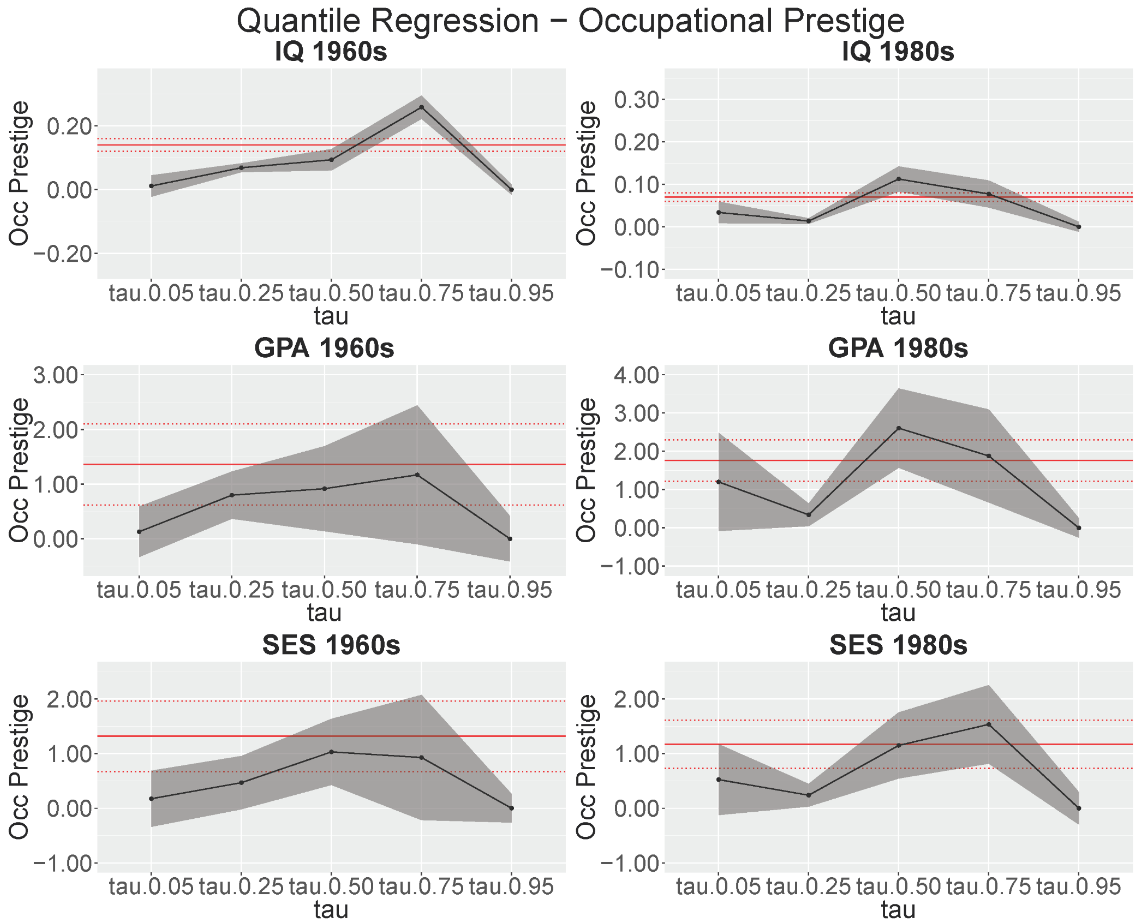
Note. Quantile multiple regression for years of education for the 1960s and 1980s cohorts. Plots represent unstandardized coefficients for students' IQ, GPA, and SES in estimating educational attainment (in years of education) 18/19 years later for different quantiles of the outcome distribution with 95% confidence intervals. The horizontal lines represent the results of multiple linear regression estimates with 95% confidence intervals (dotted lines).

Figure 3



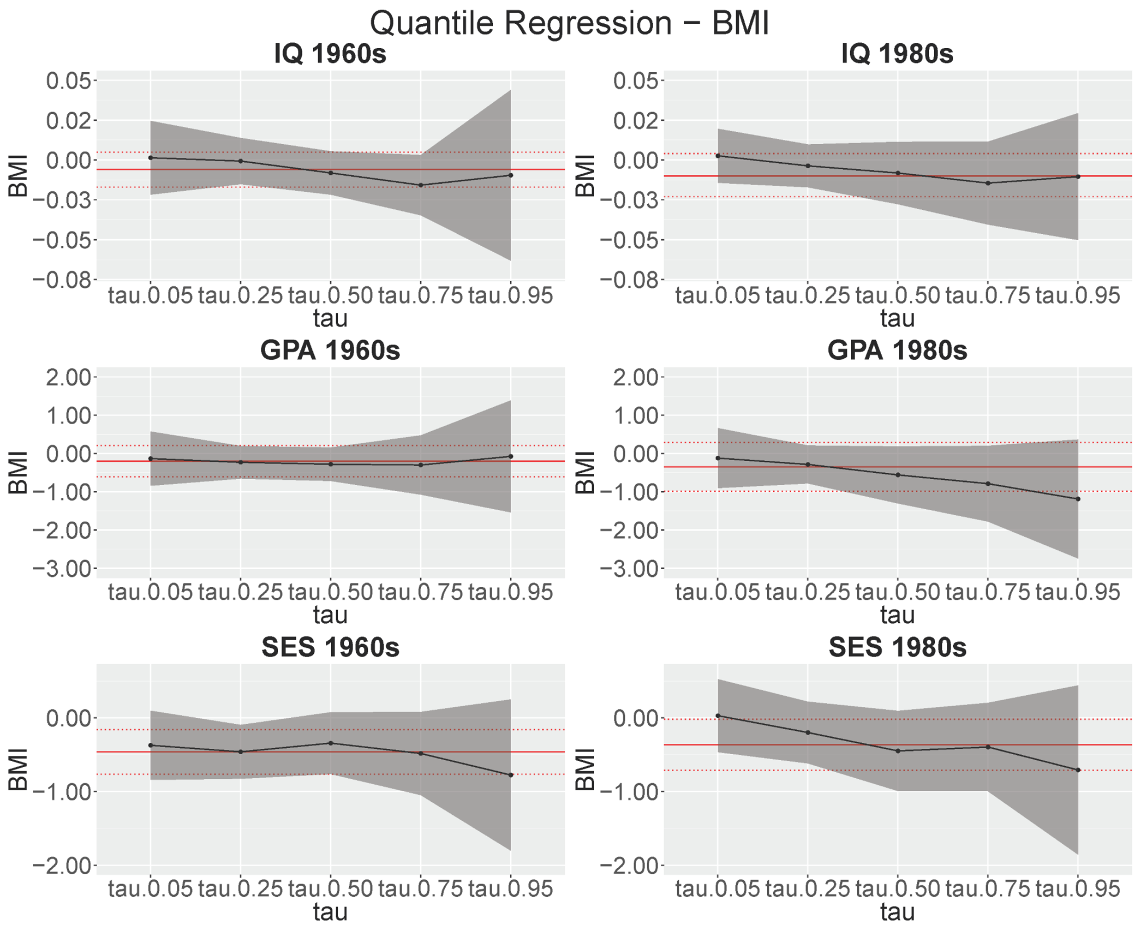
Note. Quantile multiple regressions for income for the 1960s and 1980s cohorts. Plots represent unstandardized coefficients for sudents' IQ, GPA, and SES in estimating income 18/19 years later for different quantiles of the outcome distribution with 95% confidence intervals. The horizontal lines represent the results of linear multiple regression estimates with 95% confidence intervals for the parameters represented by dotted lines.

Figure 4



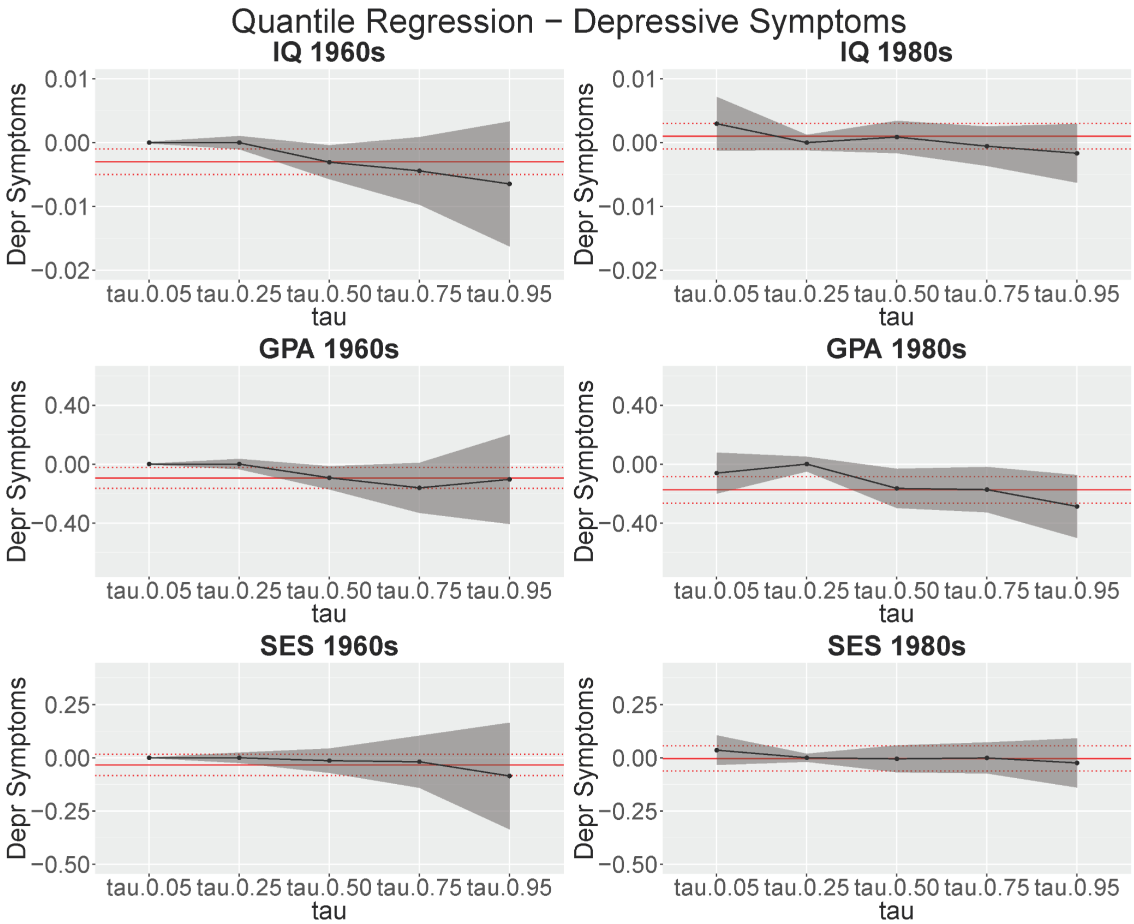
Note. Quantile multiple regressions for occupational prestige for the 1960s and 1980s cohorts. Plots represent unstandardized coefficients for students' IQ, GPA, and SES in estimating occupational prestige 18/19 years later for different quantiles of the outcome distribution with 95% confidence intervals. The horizontal lines represent the results of linear multiple regression estimates with 95% confidence intervals for the parameters represented by dotted lines. Note that we did not use cluster-adjusted standard errors (SEs) in this specific case because the SE estimates for the 1960s cohort were not reliable.

Figure 5



Note. Quantile multiple regressions for BMI for the 1960s and 1980s cohorts. Plots represent unstandardized coefficients for students' IQ, GPA, and SES in estimating BMI 18/19 years later for different quantiles of the outcome distribution with 95% confidence intervals. The horizontal lines represent the results of linear multiple regression estimates with 95% confidence intervals for the parameters represented by dotted lines.

Figure 6



Note. Quantile multiple regressions for depressive symptoms for the 1960s and 1980s cohorts. Plots represent unstandardized coefficients for students' IQ, GPA, and SES in estimating depressive symptoms 18/19 years later for different quantiles of the outcome distribution with 95% confidence intervals. The horizontal lines represent the results of linear multiple regression estimates with 95% confidence intervals for the parameters represented by dotted lines.

3

Study II

A Dynamic Structural Equation Approach to Modeling Wage Dynamics and Cumulative Advantage across the Lifespan

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3 Study II: A Dynamic Structural Equation Approach to Modeling Wage Dynamics and Cumulative Advantage across the Lifespan

Abstract

Wages and wage dynamics directly affect individuals' and families' daily lives. In this article, we show how major theoretical branches of research on wages and inequality—that is, cumulative advantage (CA), human capital theory, and the lifespan perspective—can be integrated into a coherent statistical framework and analyzed with multilevel dynamic structural equation modeling (DSEM). This opens up a new way to empirically investigate the mechanisms that drive growing inequality over time. We demonstrate the new approach by making use of longitudinal, representative U.S. data (NLSY-79). Analyses revealed fundamental between-person differences in both initial wages and autoregressive wage growth rates across the lifespan. Only 0.5% of the sample experienced a "strict" CA and unbounded wage growth, whereas most individuals revealed logarithmic wage growth over time. Adolescent intelligence and adult educational levels explained substantial heterogeneity in both parameters. We discuss how DSEM may help researchers study CA processes and related developmental dynamics, and we highlight the extensions and limitations of the DSEM framework.

Keywords: Dynamic Structural Equation Modeling (DSEM), wage dynamics, cumulative advantage (CA), autoregressive wage growth, human capital theory

A Dynamic Structural Equation Approach to Modeling Wage Dynamics and Cumulative Advantage Across the Lifespan

The overarching goal of the present paper is to show how dynamic structural equation models can be used to study the nature, causes, and development of inequality in personal income and wages. Wages are a cornerstone of economic organizations and constitute an important dimension of individuals' and families' daily lives. Higher wages grant people access to education and healthcare services and ensure long-term socioeconomic opportunities, well-being (Diener, Ng, Harter, & Arora, 2010), and personal autonomy (Di Domenico & Fournier, 2014). Thus, inequality in wages affects individuals and society as a whole. Particularly in highly developed economies, high rates of wage inequality (i.e., wider gaps between the rich and the poor) have been found to be associated with lower long-term development and productivity (Cingano, 2014).

To this day, researchers have not had a clear way to "translate" key theoretical ideas about wage dynamics (e.g., cumulative advantage; DiPrete & Eirich, 2006) into empirically testable models, despite the importance of doing so. The major objective of the present paper is therefore to bridge the gap between theoretical assumptions on the one side and empirical research on wage dynamics and the mechanisms underlying wage inequality on the other. To this end, we propose the use of dynamic structural equation models as a versatile statistical framework. Dynamic structural equation modeling (DSEM) is a general structural equation modeling approach that can be applied to analyze change in the sense of a differential or difference equation (e.g., McArdle, 1988, 2007, 2009). The approach is not new to the literature, but recent advances in software development offer new opportunities to exploit the full potential of these models for applied research. There are already several tutorials and illustrations on DSEM in the literature (e.g., Multilevel AR(1) modeling using R or WinBugs: Jongerling et al., 2015; Liu, 2017; DSEM in discrete time via Mplus; Hamaker, Asparouhov, Brose, Schmiedek, & Muthén, 2018; McNeish & Hamaker, 2020).

What has been missing so far, however, is information about and recommendations on how to take advantage of dynamic structural equation models to conduct applied research on wage dynamics. Specifically, one important advancement of DSEM we present throughout this article involves the use of conditional models in which interindividual differences in parameters that characterize wage dynamics are "conditional" on one or more explanatory (i.e., predictor) variable(s), such as IQ or level of education.

The article is structured as follows. First, we address theoretical perspectives on wage dynamics. Second, we discuss how these theoretical assumptions can be translated into statistical parameters of dynamic structural equation models that allow these theoretical ideas to be empirically tested. Here, we place special emphasis on conditional models, namely, random effects models with covariates. Third, in the Method section, we elaborate on the DSEM estimation procedure, decisions that must be made by the researcher, and how to evaluate the fitted models. To this end, we provide an empirical example using data from the U.S. National Longitudinal Survey of Youth 1979 (NLSY-79). Finally, in the Discussion section, we elaborate on substantive knowledge gained by using DSEM to study wage dynamics for the NLSY-79 cohort as well as extended applications and limitations of DSEM for this field of research in general.

Theoretical Perspectives on Wage Dynamics

Early theories on wage inequality focused on the question of how the distribution of wages is related to the distribution of individual abilities. Individual abilities, measured with the intelligence quotient (IQ), have been found to follow a normal distribution in the population. However, in the light of empirical data, the hypothesis of normally distributed wages has been refuted going back at least as far as Pareto (1896). Given the belief that wages should (at least to some extent) reflect abilities, how can this paradox possibly be reconciled?

One proposed solution, and until today one of the most widely used approaches in research on wages in general, is the well-known “Mincer Equation.” Mincer (1958) was among the first scholars to assume that interindividual differences in formal schooling affect wages and that individuals’ wages change as a function of time (i.e., work experience). Drawing on U.S. data from the National Longitudinal Survey of Youth 1979 (NLSY-79), Figure 1 illustrates this idea by depicting the empirically observed wages of a cohort of individuals across a period of 38 years. In line with Mincer’s assumption, we see that mean and median wages rose with growing labor market experience. However, Figure 1 also shows that wage inequality between individuals increased over time (i.e., the population variance increased) despite the fact that the years of labor market experience were the same for all people at a given time point.

What are the factors that can explain the growing variance in wages in a population? One answer to the question of heterogeneity in wages was formulated by Becker and Chiswick (1966). These scholars refined Mincer’s theory when they developed their Human Capital Theory, which is still prominent in contemporary economics (e.g., Heckman & Carneiro, 2003; Heckman, Lochner, & Todd, 2008). Individuals’ human capital involves their educational achievement, cognitive and socioemotional skills, and work experience, among other things. Because individuals demonstrate considerable between-person heterogeneity in their human capital, and because the market yields positive returns on human capital, this theory predicts that individuals will differ in their entry levels wages and wage growth over time. Indeed, years of education (OECD, 2019), IQ, high school grade point average (GPA), and socioemotional skills (e.g., conscientiousness) have repeatedly been shown to positively affect (initial) wage levels and long-term wage growth (Hasl, Kretschmann, Richter, Voelkle, & Brunner, 2019; Heckman et al., 2008; Spengler, Damian, & Roberts, 2018). Importantly, this is also true for parental socioeconomic status (pSES), yielding advantages both via children's early skill development and individuals' networks and nepotism (Duncan, Magnuson, & Votruba-Drzal, 2017; Spengler et al., 2015).

More recent empirical studies have adopted a lifespan perspective to study wage dynamics and inequality (e.g., Cheng, 2014; OECD, 2017). These studies drew on the idea that wage trajectories are shaped by mechanisms that link their outcomes at earlier life stages to those at later life stages. Thereby, trajectories may display large heterogeneity in growth patterns across the lifespan. Figure 2 illustrates such wage dynamics by showing several possible wage trajectories, including exponential, linear, and logarithmic growth. In examining patterns in these intracohort wage trajectories, studies recurrently observed a so-called fan-spread effect, indicating that between-person differences tended to grow over time (as in Figure 1 and in Panels A.1, A.2, B.2, and C.2 in Figure 2), that is, intracohort inequality in wages rose.

To explain such growth phenomena in the context of scientific productivity, Merton, (1968) introduced the notion of cumulative advantage (CA), which states that the advantage of one individual or group over another grows (i.e., accumulates), thereby magnifying small initial differences and leading to patterns of growing inequality over time. From there, the concept of CA found its way into numerous other disciplines, such as the social sciences, psychology, sociology, and economics. In their extensive review, DiPrete and Eirich (2006) elaborated on the concept and addressed the question of how macrolevel patterns of wage inequality are linked to individual microlevel processes. CA provided them with a theoretical framework that could explain how the convergence or divergence of individual trajectories on the microlevel translates into the macrolevel distribution of wage inequality within a given cohort on the population level (Cheng, 2014). In its original so-called "strict" form, CA follows a Yule process of exponential ("explosive") growth, analogous to the process of wealth accumulation through the mechanism of compound interest. In its simplest form, it can be formalized as

$$Y_{it} = \left(1 + \gamma_i\right) Y_{i,t\text{-}1}, \tag{1}$$

where the current levels of individuals' wages Y_{it} are predicted by previous levels of wages $Y_{i,t\text{-}1}$. Thereby, Y_{it} evolves over time as a function of an individual's previous wage and the fraction of the increment depicted by γ_i. Importantly, the strict CA parameter γ may differ across individuals. In Figure 2, strict CA processes are shown in Panel A.2 where $\gamma_i > 0$.

Notably, empirical studies that have examined individual differences in wage dynamics and mechanisms of intracohort wage inequality are scarce. The studies that come closest are those by Cheng (2014), who depicted CA from different group characteristics, such as gender and ethnicity; Bagger, Fontaine, Postel-Vinay, and Robin (2014), who investigated cumulative wage-experience profiles; and Crystal, Shea, and Reyes (2017), who cross-sectionally compared income inequality across age groups in different cohorts. Likewise, Tomaskovic-Devey, Thomas, and Johnson (2005) conceptualized wage development across individuals' working lives as a result of the accumulation of human capital that is embedded in the interactions between individual workers, colleagues, employers, and the workplace environment; they used this conceptualization to explain growing inequality between ethnic groups. However, none of the statistical frameworks of these studies could test for strict CA processes. Hence, although theoretically plausible, there is a dearth of empirical knowledge about the prevalence of CA processes. DiPrete and Eirich (2006, p. 272) concluded: "Ironically, despite the obvious theoretical and policy importance of CA models, and despite widespread references to their existence in the literature, the sustained development and testing of CA models has been more the exception than the rule." (p. 272). One explanation for this paradox is that researchers need versatile statistical models that allow them to capture CA processes.

Translating Theoretical Perspectives on Wage Dynamics into Empirical Models

Ideally, statistical models integrate key theoretical perspectives on wage dynamics and equality by incorporating (a) human capital theory, (b) the lifespan perspective, and (c) (strict) CA processes into one coherent statistical framework. To this end, it is helpful to differentiate between two broad classes of models that can be used to investigate longitudinal data: static models and dynamic models. Static models account for the state of a system of variables, with this state often being expressed as a function of time. Dynamic models, on the other hand, account for within-person changes in a system of variables over time as a function of the past (Voelkle, Gische, Driver, & Lindenberger, 2018). A common example of a static model that has been used to investigate wage trajectories and that was also applied by Cheng (2014) and Bagger, Fontaine, Postel-Vinay, and Robin (2014), is the linear or polynomial latent growth curve model (LGCM). In its simplest form, the LGCM can be denoted by

$$Y_{it} = \eta_{0_i} + \eta_{1_i} t + \zeta_{it}. \qquad (2)$$

Current levels of individuals' wages Y_{it} are a function of the initial wage level η_{0_i} of individual i, a person-specific linear slope η_{1_i} over time (t), and a person-specific error term at time point t. The LGCM allows researchers to describe interindividual differences in wage development on the basis of the time that has passed, or how between-person characteristics, such as group membership (e.g., gender, ethnicity), are related to growth rates. However, the LGCM is inherently limited because it cannot depict CA in its "strict" form given in Equation 1. As apparent from the term $\eta_{1_i} t$ in Equation 2, time itself serves as an exogenous predictor of wages. However, assuming an "effect of time" for the development of wages can be misleading. The temporal ordering of cause and effect variables is part of the definition of causality (i.e., the cause must happen before the effect), but time itself cannot be a causal factor (Baltes et al., 1988; Zyphur et al., 2020). Thus, a causal interpretation of such models is not possible (Voelkle et al., 2018). When researchers not only want to describe individual differences in wage trajectories in a population but also to understand the mechanisms (e.g., CA) that bring about these differences, dynamic models are needed.

In the present paper, we therefore discuss how DSEM can be used to capture wage dynamics and processes that may result in wage inequality. To this end, we show how major theoretical branches in research on wages and inequality (i.e., human capital theory, the lifespan perspective, and CA mechanisms) can be integrated into DSEM. Specifically, in the present paper, we applied DSEM to account for these ideas by decomposing the data into a within-person (Equation 3) and a between-person part (Equations 4 and 5; see Hamaker et al., 2018):

$$Y_{it} = \alpha_i + \phi_i Y_{i,\, t\text{-}1} + \zeta_{it} \tag{3}$$

$$\alpha_i = \beta_{00} + \varepsilon_{0i} \tag{4}$$

$$\phi_i = \beta_{10} + \varepsilon_{1i} \tag{5}$$

$$\mathrm{Var}(\alpha_i) = \sigma^2_\alpha \tag{6}$$

$$\mathrm{Var}(\phi_i) = \sigma^2_\phi \tag{7}$$

$$\mathrm{Var}(\zeta_{it}) = \sigma^2_\zeta \tag{8}$$

Equation 3 represents the within-person level model, which is similar to statistical models used in time-series analyses. This model part can be used to account for individuals' wage dynamics, that is, individuals' autoregressive relations between wages at time t and time t -1, across many points in time (see Equation 1). Specifically, Equation 3 depicts a first-order autoregressive AR(1) model that specifies the wage Y for person i at time point t as a function of the person's wage at the preceding time point, t-1. Thus, current levels of wages are modeled as a function of previous levels of wages, and, in contrast to static models, time is not considered as an explanatory factor in itself but rather as a dimension within which causal processes unfold. In Equation 3, ϕ_i is the lagged parameter that links wages from one time point to the next. In our context, we interpret this coefficient as the individual's mean wage growth rate from one time point to the next, depicting the functional form of an autoregressive trajectory that links current wages to previous ones. Specifically, if $\phi_i < 1$, wage dynamics follow a logarithmic growth process[2] (see Panel C in Figure 2); if $\phi_i = 1$, wage growth is linear (see Panel B in Figure 2). If strict CA processes are present as discussed by DiPrete and Eirich (2006), individual ϕ_i parameters are greater than 1 ($\phi_i > 1$), indicating that a person's wage grows exponentially over time (see Panel A in Figure 2). Importantly, because we were interested in CA and "explosive" wage growth ($\phi_i > 1$), we cannot make the "standard" assumption of stationarity. A stationary process has the property that its mean, variance, and autocorrelation structure do not change over time. However, (strict) CA processes are inherently nonstationary because they result in growing inequality between individuals over time (see Figure 1 in the text and Figure A1 in the Online Supplemental Material). Further, the intercept parameter α_i in Equation 3 represents an individual's initial wage at t_0 (i.e., labor market entry). Finally, ζ_{it} represents the residual of person i at time point t, depicting a random shock to an individual's wage dynamics. Examples of such shocks could be events (e.g., a financial crisis or a global pandemic) that lead to job losses or unexpected changes in employment structures and payments. As ζ_{it} may vary across individuals (variance denoted by σ^2_ζ), these shocks may differ between people.

Equations 4 and 5 represent the between-person-level model, which is similar to a multilevel model. DSEM extends the application of time-series analyses (as represented by Equation 3) to the modeling of the longitudinal data of many individuals simultaneously but allowing for (random) wage-dynamic parameters that are specific to each person. Hence, the framework depicts between-person variance in the entry level wage α_i as well as growth rates ϕ_i with variances denoted as σ^2_α and σ^2_ϕ. Thus, if so-called "within-cohort CA" (Cheng, 2014) (contrary to only strict CA) is present, α_i and ϕ_i should be positively correlated (i.e.,

[2] Importantly, the notion expressed by $\phi_i < 1$ in a logarithmic trajectory holds only when the individual has not yet reached their equilibrium wage at t_0. If wage dynamics had reached the equilibrium point, that is, if the wage at time t_0 for participant i was equal to $\alpha_i/(1-\phi_i)$, we would expect a flat line with a constant wage for the wage dynamics (indicating that the wage of individual i remains the same across the person's entire working life). We thank the anonymous reviewer who kindly alerted us to this issue during the peer-review process.

wage growth will depend on the initial wage level). If this assumption holds, it indicates that even if $\phi_i < 1$, the microlevel trajectories will result in growing macrolevel inequality over time (although at a significantly lower rate than in the exponential case) because individuals with higher initial wages also tend to have larger wage growth rates. An outcome like this would express a logarithmic growth pattern over time as depicted in Panels C.1 and C.2 of Figure 1. Notably, the ζ_{it} are assumed to follow a multivariate normal distribution with a mean of zero within and between individuals. Interindividual differences in ζ_{it} are captured by the variance σ^2_ζ, which is typically assumed to be constant across time. In our specific case, the ζ_{it} are not allowed to correlate over time to ensure that possible nonstationarity in the wage time series (i.e., strict CA processes) is captured in the growth parameter ϕ_i rather than a residual autoregressive process. Further, α_i and ϕ_i are also assumed to follow a multivariate normal distribution with a mean vector of zero, and α_i and ϕ_i are also allowed to covary ($Cov(\alpha_i, \phi_i)$; see Hamaker et al., p. 827). However, no covariation is assumed between α_i and ζ_{it} or ϕ_i and ζ_{it} (i.e., $Cov(\alpha_i, \zeta_{it})$ and $Cov(\phi_i, \zeta_{it})$ are fixed to zero).

Another important feature of DSEM (akin to multilevel models) is that the between-person variance in entry level wages α_i as well as growth rates ϕ_i may be explained by additional variables. Hence, DSEM allows researchers to study the relations between key individual characteristics proposed in human capital theory (e.g., IQ, educational attainment) to explain between-person differences in parameters that characterize individuals' wage dynamics. Specifically, incorporating the human capital approach, Equations 6 and 7 depict the prediction of between-person heterogeneity in wages and growth rates, respectively, by individual differences in adolescent *IQ* (represented by the parameters β_{01} and β_{11}), *GPA* (β_{02} and β_{12}), *pSES* (β_{03} and β_{13}), and the highest level of education in adulthood (*Edu*; β_{04} and β_{14}).

$$\alpha_i = \beta_{00} + \beta_{01}IQ_i + \beta_{02}GPA_i + \beta_{03}pSES_i + \beta_{04}Edu_i + \varepsilon_{0i} \tag{9}$$

$$\phi_i = \beta_{10} + \beta_{11}IQ_i + \beta_{12}GPA_i + \beta_{13}pSES_i + \beta_{14}Edu_i + \varepsilon_{1i} \tag{10}$$

Equations 9 and 10 highlight the idea that even if individuals (on average) do not experience strict CA processes, a pattern of growing inequality can arise from individual differences in these between-person variables. If these characteristics yield positive effects on both initial wages and subsequent wage growth rates, their effects can be assumed to persist across the lifespan and contribute to growing macrolevel inequality. This can be considered a generalization of Cheng's (2014) concept of "between-group CA."

Research Objectives

The major objective of the present paper is to bridge the gap between theoretical assumptions and empirical investigations in research on wage dynamics and the mechanisms underlying wage inequality. We aim to show how DSEM can provide a versatile statistical framework that can be applied to map theoretical assumptions of strict cumulative advantages, life-span development, and human capital theory onto statistical parameters, thus putting these assumptions to an empirical test. To this end, we capitalized on representative U.S. data from NLSY-79. Doing so made it possible to demonstrate how DSEM is suited for empirically modeling (a) individuals' autoregressive wage dynamics and (b) the between-person heterogeneity in these dynamics. Another key strength of dynamic structural equation models is that we could use them to specify conditional models that allowed us to model (c) how between-person heterogeneity in these dynamics could be predicted by individual differences in key characteristics related to human capital, namely, IQ, GPA, pSES, and level of education.

Method

Sample

The data for the empirical example stemmed from a representative U.S. birth cohort, the National Longitudinal Survey of Youth 1979 (NLSY-79; Frankel, McWilliams, &

Spencer, 1983). NLSY-79 began with an initial sample of 12,686 young men and women who were between 14 and 22 years old at the time of their first interview in 1979. All participants have been surveyed at least biennially since then, yielding data for a period of up to 38 years and a maximum of 27 measurement occasions per participant. Because we focused on adolescent characteristics as predictors, we excluded 3,792 individuals who were younger than 13 or older than 19 in 1979. We further excluded 5,060 individuals who had missing data on their initial wages because they entered the labor market before 1979.[3] Finally, we excluded 274 participants from the analyses because they had missing values on all the variables used in the statistical analyses. We included all eligible participants' wage data, even extreme outliers. Doing so yielded a final sample size of N = 3,720 (53% young women; 50% White, 32% Black, 18% Hispanic). Of these individuals, two thirds (2483/3720 = 66.75%) began working in the years 1979 and 1980. By 1983, 92% of all individuals in the sample had entered the labor market (3,426/3,720 = 92.10%). The smallest number of observed data points for the wages of individuals included in the analysis was three, and the average number of observed data points for wages per individual was 16. The initial age distribution (in 1979) of the final sample used in the analyses as well as the distribution of how many individuals entered the labor market for the first time in a given historical year can be found in Figure A2 (Online Supplemental Material).

Measures

Wages

[3] Please note that the year when each individual entered the labor market for the very first time was given by a filter variable (Variable A). On the basis of this information, we excluded participants who received their first wage prior to the initial sampling round of NLSY-79 in 1979. Hence, each t_0 of a time series represents the individual's *actual* first wage rather than the first observation given in the wage variable (Variable B) itself. This procedure allowed us to rule out any left-truncation in individuals' time series. However, it left us with the potential to have missing values on wages at the first measurement occasion, namely, if a person actually received their first wage in Year x (based on Variable A) but did not report the value of the wage (given in Variable B) in that year. Because the estimation procedure does not allow data to be missing on the first occasion of a time series, we imputed missing values for t_0 prior to the analysis. The corresponding code can be found in the Open Code file at the Open Science Framework, where we also refer to Variables A and B from this footnote.

We followed Cheng (2014) and used participants' gross hourly pay rates at the time of the interview. If a participant had held more than one job during the year, we used the pay rate from the most recent job. These hourly pay rates were first adjusted for inflation to January 2019 in U.S. dollars. We then log-transformed the inflation-adjusted hourly pay rates to account for the skewed nature of the wage distribution (see Mincer, 1958). These log-transformed hourly pay rates were used to study individuals' wage trajectories.

Intelligence

NLSY participants were tested with the Armed Service Vocational Aptitude Battery (ASVAB) at the first measurement point in 1979. It measures four cognitive skills (mathematical knowledge, arithmetic reasoning, word knowledge, and paragraph comprehension), which were combined into a global IQ score. We used IQ percentile scores ranging from zero to 100 as provided in the NLSY data set.

Grade Point Average

To derive adolescents' grade point average (GPA), we used data from the NLSY high school transcripts that were taken from official high school records. We calculated a Carnegie-credit-weighted GPA for each individual (13-year-olds: seventh grade; 14-year-olds: eighth grade; 15-year-olds: ninth grade; 16-year-olds: 10th grade; 17-year-olds: 11th grade; 18- and 19-year-olds: 12th grade) based on up to 64 courses (Appendix 11, codebook Supplement NLSY-97). GPA ranged from 0 to 4 points (A = 4 points, E/F = 0 points) in each course. Higher values represent better grades.

Parental SES

Participants reported information on two standard indicators of SES (APA Task Force on Socioeconomic Status, 2007). Students reported years of education for their mothers and fathers, and participants' parents reported the yearly family income. Years of education ranged from 1 (first grade) to 20 (8 years of college or more). We used the highest level of education in a family for our analyses. We adjusted family income for inflation, representing January 2019 U.S. dollars and log-transformed the inflation-adjusted values. Both SES indicators (i.e., highest level of education in the family and log-transformed, inflation-adjusted income) were then entered into a Principal Component Analysis. The component score for the first component served as an index representing parental SES in our study (Vyas & Kumaranayake, 2006).

Education

Education was measured as the highest level of education a person achieved, irrespective of whether it happened before or after the labor market was entered for the first time. The level of education was measured as the years of education a person completed successfully, ranging from 1 (first grade) to 20 (8 years of college or more).

Please consult Table A1 (Online Supplemental Material) for descriptive statistics and intercorrelations of all described measures.

Analytic Strategy

Dynamic Structural Equation Modeling (DSEM)

We estimated DSEM as implemented in Mplus 8 (Muthén & Muthén, 2017) via R 4.0.3 (using the package *MplusAutomation*; Hallquist, Wiley, & van Lissa, 2018). Time points (i.e., interview waves in the NLSY) were considered to be nested within individuals, yielding a two-level structure of analysis. We treated time as relative to the individual (Driver et al., 2017). Specifically, the entry level wage was defined as the wage at time point t_0 when individuals entered the labor market and received wages for the first time, irrespective of their chronological age. All time-independent variables (IQ, GPA, SES, and years of education) were grand-mean centered on 0 to allow meaningful interpretations of individuals' intercept terms.

Model Hierarchy for Operationalizing CA Processes

Notably, we understand the variance of wages at t, that is, $\mathrm{Var}(Y_{it})$, as the indicator of total wage inequality for individuals with t years of labor market experience. This is also in line with common practice in the literature (Altonji, Smith, & Vidango, 2013; Cheng, 2014; OECD, 2017). If rising wage inequality is a function of (strict) cumulative advantage processes on the individual level, individuals need to differ in their wages and growth rates. To examine whether this assumption of between-person heterogeneity in wage dynamics was met, we first specified a series of three models that built on Equations 3 to 5 to examine the notion of between-person heterogeneity in wage dynamics in terms of initial wages (as depicted by α_i) and autoregressive wage growth rates (as depicted by ϕ_i). Model 1 allows no differences between individuals in initial wages and growth rates, that is, the between-person variance of α_i and ϕ_i are both fixed to zero. This is most likely an unrealistic assumption, implying that all people earn the same wage when they enter the labor market and grow equally over time. Nevertheless, it is a useful benchmark model that can be used to learn whether models that relax these restrictions provide a substantively better fit to the empirical data. Model 2 assumes that initial wages vary between persons (i.e., α_i is a random parameter) but growth rates are equal (i.e., ϕ_i is specified to be constant for all persons, as was the case in Model 1). In this scenario, individuals would differ in their initial wage levels but would experience the same growth in their wages. If this fixed growth parameter was linear or logarithmic in nature, within-cohort inequality would stay the same over time (see Panels B.1 and C.1 in Figure 2). Rising within-cohort inequality can evolve only if CA processes in their strict form are present, that is, if the fixed growth coefficient is greater than 1 (which, given different initial wage levels, leads to growing between-person differences over time, even if the rate itself does not differ across individuals; see Panel A.1 in Figure 2). In a third model, Model 3, α_i and ϕ_i are both specified as random parameters, allowing initial wage levels and growth rates to vary between persons (see Equation 2). If people differ in both their wage levels and growth rates, CA can manifest in different forms, as previously set out. Of course, combinations are also plausible.

Finally, a fourth model, Model 4, expands on Model 3 by adding the human capital variables of *IQ*, *GPA*, *SES*, and years of education (*Edu*) as predictors of individual differences in wage dynamics, that is, initial wage levels and growth rates. Model 4 represents the conditional model in which individual differences in wage dynamics are conditional on human capital variables. It is also the most complex model, with its complete setup depicted by Equations 3, 9, and 10.

Model Estimation and Model Evaluation

Estimation Procedure. Mplus uses Bayesian estimation for DSEM. This allows for the estimation of a large number of random effects, which is often not feasible in a frequentist framework (Hamaker et al., 2018). More specifically, an iterative Markov chain Monte Carlo (MCMC) procedure using the Markov Gibbs sampler is applied.

Number of Iterations and Convergence. When applying an MCMC procedure, it is important to choose the number of iterations that will be used for estimation. Commonly, the maximum number of iterations is specified in advance or the potential scale reduction criterion (PSR) is used to determine model convergence and thus the number of iterations. The PSR criterion is computed for each model parameter separately by dividing the total variability across the selected number of MCMC chains by the variance within a chain (Gelman et al., 2014; Hamaker et al., 2018). A PSR value close to 1 implies that the between-chain variance approximates zero, meaning that the total variance across the chains becomes identical to the within-chain variance. This indicates that the associated chains are likely to have converged into one target distribution (i.e., the final parameter estimates are approximately the same in all chains).[4] The number of iterations required to reach convergence and to have sufficient accuracy in estimation depends on the complexity of the

[4] Computation time may vary considerably by model complexity, available computational capacities, and the chosen convergence stopping criteria. Please consult Table A3 in the Online Supplemental Material to obtain computational time comparisons that were based on the complexity of the presented models (Models 1 to 4), different computational capacities (standard laptop with i7-8650U processor/ 4 cores vs. computer with i9-9900k processor/ 8 cores), and stopping criteria (Mplus default PSR vs. MCMC chains with 10,000 iterations).

data and model. On the basis of Schultzberg and Muthén (2018), we considered 10,000 to 50,000 iterations a large number given our data and models. Furthermore, it is highly recommended to check trace plots and autocorrelation plots of the parameters to evaluate possible irregularities in model convergence.

Starting Values. For each chain, estimation starting values have to be chosen. Usually, available software solutions (e.g., Mplus) automatically generate starting values for the iterative estimation process. This starting parameter value is then perturbed from the original ("unperturbed") values by adding uniform noise (Asparouhov & Muthén, 2003; Merkle & Rosseel, 2016). The longer each MCMC chain, the less the starting values affect the final results (Gelman et al., 2014).

Priors. In Bayesian estimation, all unknown parameters need to be given a prior distribution. In using informative prior distributions, it is possible to include prior knowledge or subjective expectations in a model. Noninformative prior distributions, on the other hand, "let the data speak for themselves" (Gelman et al., 2014, p. 51) and do not allow the results (i.e., the posterior distributions of the unknown parameters) to be affected by information external to the data. Using informative priors can help regularize the estimates; that is, by making the fitted models less sensitive to certain details in the data, they can stabilize estimates and predictions. We recommend that readers consult Gelman et al. (2014) for in-depth information on this topic. In our example, we made use of diffuse (i.e., noninformative) priors. In Mplus, they are reported as part of the TECH1 output. The default prior for means and intercepts is a univariate normal distribution with a mean of zero and infinite variance approximated by 10^{10}. For covariance matrices, an inverse Wishart with a zero matrix for scaling and degrees of freedom equal to the number of variables minus 1 is used. The prior for the variance parameter is an inverse-gamma distribution (Asparouhov & Muthén, 2010; Hamaker et al., 2018). Please find a detailed list of priors used for each parameter in the present study in Table A2 (Online Supplemental Material).

Application to the NLSY Data. In the present study, we followed Gelman et al. (2014) to set high standards for estimation. Specifically, we used four chains with 10,000 iterations per chain (i.e., a total of 40,000 iterations) and a thinning factor of 10 (i.e., only 1 in 10 iterations was saved and used to estimate the parameters' posterior distribution). The first half of the iterations within each chain was discarded as a warm-up. Hence, the parameters for Models 1 to 4 are based on 2,000 iterations each. Convergence was judged to be successful when the PSR value was less than 1.05 (McNeish, 2019). We let Mplus generate perturbed starting values (i.e., the default option; Asparouhov & Muthén, 2003) that could be derived as part of the TECH1 output. The chains in the trace plots revealed good mixing (i.e., each chain quickly reached a steady state solution from where the estimated parameter posterior distributions no longer changed much) and, as shown in the autocorrelation plots, the autocorrelations (i.e., the serial correlation with the previous estimate in the chain) between the iterations decreased over time. Hence, convergence could be assumed (see Figures A3 and A4, Online Supplemental Material). All plots and results are reproducible via the open code provided on the Open Science Framework.

Missing Values. Importantly, researchers might face challenges in estimation when data are missing. Especially wage data are prone to selective reporting, oftentimes leading to high proportions of missing data. Further, we chose time as relative to the individual, but we defined the time of labor market entry t_0 for each individual by using a second variable (see also Footnote 1) that denoted the year in which an individual reported becoming employed and receiving a wage for the first time. Thus, missing values for wages could also occur at t_0. However, the DSEM estimation procedure in Mplus needs a predetermined starting point (i.e., wage value at t_0) for each person. If we assumed stationary processes, it would be possible to derive predetermined starting points (i.e., initial wages) of an individual time series from the rest of the time series. However, because we were interested in the existence of nonstationary processes (AR > 1), this was mathematically impossible. The solution we chose was therefore to impute missing data for the first measurement occasion (t_0) of hourly wages per person via the EM algorithm.

Missing values on all other measurement occasions and variables were treated in the same way as random effects and model parameters as is characteristic for Bayesian analyses. We used the corresponding default option in Mplus 8. Thus, at each iteration of the MCMC algorithm, missing data were sampled from their conditional posterior distribution. A related concern involved unequally spaced measurement occasions in the data (Hamaker et al., 2018; Voelkle et al., 2012). These can result from missing observations (e.g., if participants did not fill out the NLSY questionnaire in a particular year). Unequal time intervals are of concern for researchers who are interested in lagged relationships because the strength of a lagged effect depends on the length of the time interval between measurements. If not accounted for, these can result in severely biased parameter estimates (Driver et al., 2017). Mplus allows users to specify the length of time intervals between observations and adds missing values between observations that are farther apart in time. In doing so, a data set with approximately equidistant time intervals is created. In our empirical example, measurement intervals between two consecutive observations were set to represent 1 year.

Model Comparison. To compare the models with each other, Mplus provides the deviance information criterion (DIC). The DIC is a hierarchical modeling generalization of the Akaike information criterion (AIC) in Bayesian modeling. It captures the predictive accuracy of the models, and lower DICs indicate a better model. Notably, the DIC can be used for model comparison only when the models to be compared have the same latent variables (McNeish & Hamaker, 2020, p.614). This was the case for Models 1 to 4. More specifically, in Models 1 to 4, we specified latent variables to depict individuals' initial wages α, their growth rates ϕ, and the random shocks that may affect their wage trajectories ζ.The models differed in how the fixed and random effects were specified for these latent variables. For example, the variances of α, ϕ, and ζ across individuals were restricted to zero in Model 1, partly restricted to zero in Model 2, and freely estimated in Models 3 and 4. Of note, even when the models that are being compared are based on the same set of latent variables, the DIC can provide nonsensical results when posterior distributions are not well summarized by their means (Gelman et al., 2014). McNeish and Hamaker (2020) further pointed out the DIC's tendency to be unstable, which can result in different conclusions for different seed values for the MC chains. In our examples, all posterior distributions were unimodal with the majority of data distributed around the mean values (see Figure 3), a finding that supports the application of the DIC for model comparisons. Although our models met the prerequisites for the application of the DIC, we advise the reader to interpret the model comparisons with caution.

Model Evaluation. In accordance with Schultzberg and Muthén's (2018) and McNeish's (2019) recommendations, we assessed five evaluation measures that were based on 500 replications (i.e., 500 simulated data sets) for each parameter of the fully hierarchical model (i.e., Model 3; see below): the relative bias, mean squared error (MSE), SE/SD ration, 95% coverage, and non-null detection rate (power).[5] A detailed description of each criterion can be found in the Online Supplemental Material.

Results

To facilitate the interpretation of the results, we employed an exponential transformation by applying Feng, Wang, Lu, and Tu's (2012, p. 2) bias correction[6] to all parameter estimates associated with log-transformed hourly wages (Feng et al., 2012). Thus, the results presented in the text correspond to units of $ instead of log($). The original results for log($) can be found in the Online Supplemental Material (Table A4).

[5] Please note that the simulations were requested during the peer-review process and were not preregistered as part of the original study.
[6] $E(Y) = \exp(\mu + \sigma^2/2)$, $\mathrm{Var}(Y) = \exp(2\mu + \sigma^2)\,(\exp(\sigma^2)-1)$

First, we assessed the notion of between-person heterogeneity in wage dynamics in terms of initial wages (as depicted by α_i) and autoregressive wage growth rates (i.e., as depicted by ϕ_i) in Models 1 to 3 (Table 1). Relative to Models 1 and 2, Model 3 provided the best fit (as indicated by the DIC). In addition, the point estimates as well as the 95% CIs of α and ϕ (as obtained for Model 3) demonstrated heterogeneity in people's (a) initial wages α_i and (b) growth rates ϕ_i. Finally, we used the model parameters obtained from Model 3 as population values in a simulation study to assess the estimation performance of the applied Bayesian model. The model was excellent in recovering point estimates of fixed and random effects of all parameters, as well as the covariance between α_i and ϕ_i (relative bias near 1, MSE near 0, high non-null detection rate; details in the OSM). Estimates for the 95% credibility intervals for the fixed effect of α_i, fixed and random effects of ϕ_i, and the covariance between α_i and ϕ_i were also recovered well (values for 95% coverage between 0.92 and .98); estimates for the 95% credibility intervals for the random effects of α_i, however, fell outside of the acceptable range of 0.92 to 0.98 (α_i: 0.86). This is most likely due to underestimated standard errors (i.e., deviance of SE/SD more than 15%; details in the OSM), which resulted in 95% credibility intervals that were too narrow to capture the true value with 95% probability. Taken together, the simulations revealed that the DSEM procedure provided reliable estimates, but that the interval estimate (i.e., the precision of the point estimate) for the random effects estimate of α_i was less trustworthy. Thus, in the following, the width of the 95% CI for the empirical random effects of α_i needs to be interpreted with caution.

Bayesian posterior probability distributions of initial wage levels α_i and wage growth rates ϕ_i are depicted in Figure 3. Based on the parameter estimates in Model 3, Figure 4 depicts the substantial heterogeneity between persons in initial wage levels α_i and autoregressive wage growth rates ϕ_i.

In accordance with the results presented in Table 1, the point estimate for the mean initial wage level was β_{00}= \$17.42. The mean autoregressive growth parameter of wages was β_{10} = .622. For example, a person starting with an average wage of \$17.42 when entering the labor market would be expected to earn \$17.42 + .622 × \$17.42 = \$28.26 after 1 year, \$17.42 + .622 × (\$17.42 + .622 × \$17.39) = \$34.98 after 2 years, and so on. In other words, after 1 year, a person receives an additional 62 cents for every dollar of their initial hourly wage (Y_0). After 2 years, in addition to their initial wage Y_0 and the additional 62 cents for every dollar of Y_0 (=Y_1), the person also receives an additional 0.62 × 0.62 = 0.38 = 38 cents for every dollar of Y_0; likewise, after 3 years, the person receives an additional 0.62 × 0.62 × 0.62 = 0.24 = 24 cents for every dollar of Y_0. Hence, the person's wage grows over time, although the gain from one measurement occasion to the next declines. In this way, the logarithmic growth pattern of steeper increases in wage levels at the beginning than at the end of a career emerges for $\phi_i < 1$.

Strict CA processes of $\phi_i > 1$ were present in only a tiny fraction (i.e., 0.5% of individuals) of the sample (Figure 4). The covariation between initial wages and autoregressive wage growth was slightly negative (Cov(α_i, ϕ_i) = -0.011), yielding a correlation between α_i and ϕ_i of r = -.072 (Table 1). Thus, we found little evidence that wage growth depends on the initial level of wages in terms of "within-cohort CA" (Cheng, 2014). Taken together, most people in the present sample demonstrated a logarithmic (i.e., diminishing) wage growth over time (as shown in Figure 1, Panels C.1 and C.2) rather than exponential growth corresponding to strict CA.

Model 4 expands on Model 3 by adding the human capital variables (i.e., *IQ*, *GPA*, *SES*, and *Edu*) as predictors of individual differences in wage dynamics. As proposed by human capital theory, adolescent IQ and the highest level of education a person obtained positively predicted initial wage levels, as well as wage growth rates (Table 1). Interestingly, adolescent GPA and pSES did not yield substantial effects on later wage trajectories. However, additional analyses revealed substantial effects of adolescent GPA and pSES if the highest levels of education in adulthood were not included in the models.[7] This suggests that grades and parental resources may serve as the "gatekeepers" of access to higher levels of education (correlation between GPA and education: $r = .48$; correlation between pSES and education: $r = .37$; Table A1).

To obtain more thorough insights into what the coefficients actually mean, we translated the unstandardized coefficients presented in Table 1 into natural metric effect size estimates in Table 2. Table 2 shows that for an average initial wage of $17.17 per hour ($\alpha_i$, Table 1), an increase of one standard deviation (SD) in IQ/GPA/SES/years of education was associated with about $1.45/$0.14/$0.31/$1.61 of additional hourly wages and about 0.97%/0.18%/0.19%/0.74% of additional wage growth per working hour per year (e.g., as for IQ: 0.97% × $17.17 = $0.17/hr/year). At first glance, these numbers may appear small. However, they translate into substantial cumulative individual differences in lifetime wages. We exemplify this with two time series for two hypothetical Persons A and B in Table 2. Specifically, Person A demonstrated average values of IQ, GPA, pSES, and education (corresponding to the average hourly wage of $17.17), whereas Person B had values of IQ, GPA, pSES, and education 2 SDs higher than average (corresponding to an hourly wage of $24.17, composed of the average wage of $17.17 plus $7.00 due to higher human capital). Person B gained up to an hourly wage of $12.31 more than the "average" Person A after the first year (t_1), or $25.35 after 10 years ($t_{10}$; $\Delta Y_A Y_B$). After 10 years (t_{10}), for a 40-hr work week, this would correspond to Person A earning a yearly gross income of $85,440, and Person B earning $134,112, thus earning $48,672 per year more than Person A.

[7] Results for IQ, GPA, and pSES (without years of education) and interaction effects between pSES and the other characteristics (IQ, GPA, years of education) are presented in the Online Supplemental Material of this paper in Table A6.

Accumulated across 38 years (t_{37}, $\Sigma\ \Delta Y_A Y_B$), this would result in a total of a $1,762,535 difference in earnings in favor of Person B.

Discussion

Drawing on U.S. data from the NLSY-79, the major objective of the present paper was to close the gap between theoretical assumptions and empirical investigation in research on wage dynamics and mechanisms underlying wage inequality. To this end, we showed how dynamic structural equation models can provide a versatile statistical framework that can be applied to integrate three major theoretical branches in wage research, namely, human capital theory, the lifespan perspective, and the CA approach. In mapping these theoretical ideals onto statistical terms within the DSEM framework, they become empirically testable and open for further development.

Untangling Different Sources of Within-Cohort Inequality

After individuals enter the labor market, they follow different wage trajectories across their working lives. Over time, these heterogeneous microlevel processes may translate into the aggregate macrolevel pattern of wage inequality within a given cohort at the population level. Crucially, empirical studies that have examined interindividual differences in wage dynamics and mechanisms of intracohort wage inequality are scarce, most likely because researchers have lacked the statistical models that would allow them to depict the various theoretical approaches on wage dynamics and mechanisms underlying wage inequality. In this article, we showed how DSEM can be applied to this end. Specifically, translating theoretical perspectives into testable assumptions via DSEM, we adopted a lifespan perspective on wage dynamics and inequality (e.g., Cheng, 2014) where wage trajectories are shaped by mechanisms that link their outcomes in earlier life stages to those in later life stages. Simultaneously, DSEM allowed us to address the theoretical perspective of CA where the strength of this mechanism may vary between persons, yielding, for example, an exponential (“explosive”) growth in wages (i.e., strict CA) for some individuals. Finally, we were able to integrate and to study key propositions of human capital theory, by which individual differences in human capital (e.g., IQ, GPA, pSES, years of education) predict initial wage levels at labor market entry and growth patterns across the lifespan via the use of conditional models.

Our analyses revealed fundamental differences between people in initial levels of wages and wage growth rates over time. On average, people experienced logarithmic wage patterns across the lifespan. Steeper wage growth in the beginning of a career was followed by increasing wage levels across the lifespan but at a lower rate over time (see also Altonji et al., 2013). Only a few people (0.5%) experienced strict CA processes, that is, unbounded wage growth. Further, on average, we observed a small negative association between initial wages and later wage growth rates, a finding that provides little empirical support for the idea of “within-cohort CA” (Cheng, 2014). Hence, in line with recent literature, most growing inequality over time seems to be a result of between-person differences in human capital variables (“between-group CA”). Adolescent IQ and adult education substantially contributed to the levels and shapes of wage dynamics. Individuals who were more intelligent and obtained higher levels of education earned more, and the wages of more intelligent and educated people also grew more rapidly over time. GPA and pSES yielded positive associations with wage dynamics when education was not included in the models, suggesting a potential “gatekeeping” function of high school grades and parental resources for accessing higher education. Previous studies on this topic (although they used statistical models other than DSEM) have also yielded similar effects for the association between initial wages and growth rates (Cheng, 2014); the positive associations between adolescent IQ, years of education, and wage levels (Hasl et al., 2019; Heckman et al., 2008; Spengler et al., 2018); and wage growth rates (Bagger et al., 2014; Bask & Bask, 2015; Lagakos, Moll, Porzio, Qian, & Schoellmann, 2018).

Importantly, however, future research might benefit from being cautious about interpreting the small (or negligible) negative correlation between initial wages and growth rates as being representative of everyone in the sample. A small percentage of individuals in our sample experienced strict CA processes and explosive wage growth over time. Tentatively assuming that this percentage corresponds to the top-earners or "super-rich" in the 0.05th to 0.01st wage quantiles, the pattern would match one core characteristic of recent rising economic inequality in the US: The divergence in the earnings of the top-earning minority from the wages of the majority of workers (International Monetary Fund, 2015; Saez & Zucman, 2016). This pattern is likely driven by the top income earners' cumulative advantage in obtaining higher earnings (Cheng, 2014). Thus, especially for top incomes, the association between initial wages and wage growth might follow a positive association.

Dynamic Structural Equation Models as a Versatile Empirical Framework for Studying Wage Dynamics

Human capital theory, the lifespan perspective, and the theory of CA are major branches in research on wages and wage dynamics. Yet, they are by far not exhaustive in addressing questions of wage development, and they represent only a small part of the world of literature in wage research. In the following, we provide a brief overview of how other features that typically inform research on wages and inequality can be formalized and subsequently tested in the DSEM framework.

The Coupling of Wages and Other Time-Varying Covariates

In the present paper, we studied IQ, GPA, and parental SES as time-invariant predictors because our archival data did not provide further measures of these characteristics. Of course, these characteristics are likely to change to some extent over time. Particularly interesting for many research questions is thus the possibility that both time-varying and time-invariant covariates can be captured on the within- and the between-person levels using DSEM. Especially in investigations of Mincer's wage equation, the criticism has been put forth that researchers have failed to consider that formal education and training are inherently endogenous variables (Heckman, Lochner, & Todd, 2005) and may change across a person's working life. Further, changes in educational attainment and changes in wages may be coupled over the life course. In our empirical application of DSEM, we followed the approach by Cheng (2014) and did not account for this coupling. However, future research may apply the DSEM framework to account for individuals' levels of education as a second time-varying variable on the within-person level (i.e., Edu_{it}) and the coupling of wages and educational attainment within persons as a random variable (e.g., defining the cross-lagged effects $\phi_{EduWage,i}$ and $\phi_{WageEdu,i}$). In doing so, researchers can also choose to explain between-person heterogeneity in the strength of coupling, for example, as a function of human capital or other individual characteristics on the between-person level.

Time-Varying Wage Growth Rates

At times, CA processes in wage dynamics or other developmental processes may occur only over a specific period or a specific set of stages in the process. Thus, wage growth rates might vary not only between individuals but also from one time period to the next. Formally, we would indicate this assumption by adding an index t to the growth coefficient, that is, ϕ_{it}. First, these variations could be due to interactions with other individual characteristics, which may reduce the impact of the CA process over time (DiPrete & Eirich, 2006). In the case of the Mincer equation, where individuals' wages change as a function of formal education and time, an aging individual might decide to stop investing in his or her human capital because the expected returns from the remaining years as an active workforce participant would not balance out the costs. Thus, the CA process might end. Second, external structural factors may cause a shutdown of a (strict) CA mechanism in wages. In an organizational context, an example might be a person's position on a career ladder. Because career ladders have a finite length, a position on the ladder provides an independent advantage for wages or other benefits only in the early or middle stages of a process. A position's value usually declines at a certain point in the hierarchy because the higher a person climbs the ladder, the lower the number of available positions at the next level (DiPrete & Eirich, 2006; Stewman & Konda, 1983). Hence, even if strict CA and "explosive" growth were present in the early or middle stages of the process, these factors could fade out later on. Researchers can address questions of this kind by investigating CA processes in a "piecewise" manner in discrete-time estimation (e.g., from one time interval or stage—comprising several time intervals—to the next) or by deriving the underlying continuous time function of the process. Especially in applications of this kind, continuous time applications yield huge benefits, which we will get back to later on.

Incorporating "Exposure Processes" in the Investigation of Wage Dynamics

Some theoretical approaches to inequality, such as the Blau-Duncan approach to stratification (Blau & Duncan, 1967) or its extension in the Wisconsin model (Sewell, Haller, & Portes, 1969), frame inequality between individuals or groups as a result of cumulative "exposure" processes. In contrast to strict CA processes, Blau and Duncan (1967) emphasized differences between groups over inequality within a group, cohort, or population. Instead, they proposed that CA is the result of the persistent direct and interaction effects of a status variable. Thereby, the interaction effects of a status variable imply group differences in the returns from a socioeconomic, human capital, or other resource (DiPrete & Eirich, 2006). Examples would be ethnicity or gender, where a certain status (e.g., being black, being a woman) first has a continuing direct effect on wage levels and wage growth rates over time. For example, in their work on the gender pay gap, Gold, Schield, and Geier (2016) found that being a woman had a direct effect on hourly wages. Relative to men, typical women are paid 83 cents on the "male" dollar. Second, the status variable of gender yielded an indirect effect via the interaction, indicating that female workers, even when they were as educated as male workers, received lower wages. This was true at every level of education, and the gap tended to increase with level of education (Gold et al., 2016). In line with the Wisconsin model, which emphasizes not only the importance of status variables but also cumulated effects of social and psychological variables such as childhood mental ability, academic achievement, and socioeconomic status, the same logic applies to the between-person variables of adolescent IQ, GPA, and pSES and the adult levels of education we used in our study. Thus, studies that are interested in group or position effects can easily add status variables with grouping (e.g., Black/Hispanic/White; high/low SES; statistically: nominal or dummy variables) or continuous stratification variables (e.g., IQ, GPA, Edu; statistically: continuous variables) on the between-level in the multilevel formalization of the DSEM framework.

Experimental and Quasi-Experimental Designs

In the last paragraph, we showed how DSEM can incorporate time-invariant "exposure" processes. Similarly, the framework can be extended to assess experimental or quasi-experimental designs. For example, wage earners might face time-varying exposure to treatments. A firm might apply an incentive pay plan as part of their pay structure. Thereby, workers could receive bonuses over and above their hourly wages if they meet certain pre-set requirements or criteria. This "intervention" could be introduced for all employees at the same time (time-invariant onset; e.g., change in incentive structures for the whole company beginning with April 2020) or only when a person attained a certain position (time-variant onset; e.g., after a person got promoted to a management position). Likewise, researchers might be interested in the influence of different payment structures such as performance-based pay versus fixed wages for the wage development or productivity of one or more individuals. Inspired by studies that assess the effectiveness of interventions based on single-case designs (Shadish, 2014; Shadish, Kyse, & Rindskopf, 2013; Shadish & Sullivan, 2011), they could observe the wage levels or productivity of Individuals A and B during the "treatment" phase of incentive pay and during the baseline or maintenance phase of fixed pay. Baseline and treatment measurements are then compared to assess whether a functional relationship exists between the intervention (i.e., incentive pay) and the outcome variable (i.e., wage levels or productivity). Thereby, it is possible to investigate whether wages or productivity change in either level or growth when incentive pay is present but do not when incentive pay is absent. DSEM can incorporate these thoughts by introducing variables denoting the individually time-varying on- and offset of an intervention. For example, a dummy variable "Intervention (Int_{it})" can be created. Such a variable can be both subject-specific (individual *i*) and time-specific (time point *t*). This way, the onset of the intervention (e.g., $Int = 1$) as well as the offset of the intervention (e.g., $Int = 0$) can be clearly defined and modeled accordingly. If the interest is just to statistically control for the onset of a treatment (e.g., a change in incentive structures for everyone working at a company at a specific point in time), the subscript *i* can of course be omitted.

Residual Correlation in Wage Dynamics

Especially when dealing with time-series data, (auto-)correlations among residuals are a common concern. Usually, the goal is to have random error terms, that is, the model residuals should not reveal any relationship or trend outside the defined model equation. Previous studies that modeled wage dynamics oftentimes indirectly included the notion of CA processes via autocorrelation processes in residuals. Altonji et al. (2013), for example, defined their Mincer-based model equations with the extension of an autoregressive residual process, arguing that "The dependence [of the stochastic error component] on its past reflects persistence in the market value of the general skills of [individual] *i* and/or the fact that employers base wage offers on past wages" (p. 1401). Similarly, Bagger et al. (2014) modeled wage dynamics on the basis of human capital accumulation, employer heterogeneity, and individual-level shocks and captured within-job wage growth in an auxiliary AR process. These approaches can be beneficial if trends or cycles (e.g., economic recessions) are expected to bias the results of a substantial research question. If, however, (strict) CA processes are the mechanisms of interest, they should also be modeled as such.

Deliberately depicting CAs in a dynamic modeling framework and including the autoregressive term of current and past wages on the within-person level (instead of capturing them solely in the residual process) allows for the untangling of the multifold reasons for growing population inequality. It further allows researchers to uncover interindividual differences in CA processes over time and to model them on the between-person level. Of course, if the influence of a distinct event on wage development (e.g., mass layoffs due to a worldwide pandemic or the long-term effects of transitioning to parenthood) is of interest, the dynamic SEM framework can be extended accordingly.

Methodological Requirements for DSEMs

In order to properly estimate dynamic structural equation models, it is important to think about general methodological requirements. Although Mplus can estimate nonstationary DSEM and AR coefficients > 1 (L. Muthén, personal communication, February 17, 2021), a systematic analysis of requirements for nonstationary DSEM is, at least to our knowledge, still lacking and should inspire future research. For example, our simulation results suggested that the DSEM framework provided unbiased point estimates of fixed and random effects as well as reliable credibility intervals for the fixed effects of α_i, and fixed and random effects of ϕ_i. However, the standard errors for the random effects of α_i were somewhat underestimated (about 23%). This likely implies that the corresponding empirical 95% CI of the parameter was too narrow and therefore needs to be interpreted with caution. In the future, it might be a worthy endeavor to explore better interval estimates in more detail. Moreover, the simulation study by Schultzberg and Muthén (2018) revealed that in the estimation of two-level DSEMs, a large number of individuals (N) can compensate for a smaller number of measurement occasions (T). Whereas studies that work in the $N = 1$ framework usually need a minimum of 50 to 100 time points to derive valid results without strong priors, two-level DSEM can work with well under 50 time points if the sample size is large enough (> 200 individuals). For example, dynamic panel models (which also operate in a DSEM framework) can already work well with five time points (Bai, 2013). To conclude, the DSEM modeling framework is an interesting and feasible statistical framework with which to study other international panel data sets on wage or educational data yielding the same or a similar structure as the NLSY data. Yet, future simulation studies on nonstationary dynamic structural equation models are needed to determine the conditions (e.g., distributional assumptions of independent and dependent variables, number of individuals [N] and measurement occasions [T]) which ensure reliable estimates of nonstationary AR processes, their standard errors, and credibility intervals.

Limitations and Future Directions

The Challenge of Measurement Equivalence in Wage Time Series

When working with repeated measurements over time, establishing measurement equivalence poses several challenges, especially with wage time series in a life-span context. In 1 cross-sectional year, individuals' wages may be based on different types of work: for example, NLSY participants are simply asked whether they have done any work for pay, which also includes study programs and government-sponsored programs or jobs (U.S. Bureau of Labor Statistics, 2021). Despite the fact that freelance jobs (e.g., lawn mowing or babysitting) are not included, wages can still be earned from holiday jobs or internships. Further, in the first round of interviews in 1979, participants were of different ages, which might be associated with cohort effects.

Although we might not be able to erase the related risk of all possible biases that can result from these challenges, we took several steps to minimize such biases. First, the original NLSY sample was quite heterogeneous with respect to an age span that ranged from 12 to 21. We deliberately made the analytic sample more homogenous with respect to age by focusing on the population of adolescents (aged 14 to 19). Second, although t_0 often represented a different historical year for participants, the age range of 14 to 19 in 1979 was not too broad. Two thirds of participants started working in the years 1979 and 1980. By

1983, more than 90% had entered the labor market. Thus, even in an "extreme" case in which a 14-year-old who started working in 1979 was compared with a 19-year-old (1979) who did not enter the labor market until 1983 at 24 years of age, the lag was not more than 5 historical years. Even though 8% of the sample entered the labor market later than 1983, this fraction of the sample would not be likely to distort the overall results, even if cohort effects were to apply to them. Third, we ensured comparability of the values in adjusting all wage observations for inflation to represent 2019 US $. Fourth, because individuals' wages were stated in gross instead of net terms, historical effects (e.g., effects of changes in government policies on wage taxation) should not bias the wage measures. Finally, we followed Cheng (2014) and eliminated a factor that we would consider one of the biggest distortions in cross-sectional wage measures, namely, the differentiation between full-time and part-time jobs. To avoid this problem, we used hourly pay rates (instead of monthly wages). Hourly pay measures the economic return that an individual receives for 1 hr of labor and is thus not affected by the total number of hours the individual worked.

Shrinkage Phenomena in Estimating AR(1) Coefficients

When working in a multilevel context, the shrinkage phenomenon (i.e., when effect size estimates trend toward the population average) has to be considered. Especially when individual data are sparse (e.g., an individual does not have many observed wage measurements) and offer only a little information about an individual parameter value, the variance of the conditional distribution may be large due to the uncertainty of the individual estimate (Lavielle & Ribba, 2016). The mode of the conditional distribution then "shrinks" to the mode of the population distribution. If this is the case for most individuals, the majority of individual parameters will be concentrated around the population average and will not correctly represent the actual interindividual variability (Lavielle & Ribba, 2016). Longitudinal wage data typically display high proportions of missingness, and the NLSY data are no exception. Thus, in the present example, the model-implied proportion of individuals experiencing strict CA processes ($\phi_i > 1$) may be a lower bound estimate.

Missing Data at the First Measurement Occasion (t_0)

In NLSY (as in any other large-scale survey), participants could have missing values on their hourly wages at the first measurement occasion. Because of our substantive interest in possible nonstationary processes (AR > 1), we could not derive predetermined starting points in individuals' time series from the rest of the time series. However, these are needed in the DSEM estimation procedure. Thus, we decided to impute the first measurement occasion using the EM algorithm. Notably, Enders (2003, 2010) showed that the EM algorithm on individual-level data reproduces values quite accurately (even when the missing values are not completely at random). Further, all other missing values, that is, 37 measurement occasions and covariates, were modeled via Bayesian estimation in DSEM. Nevertheless, our approach has its drawbacks because, with a single imputed value for hourly wages at the first measurement occasion, we likely underestimated the uncertainty related to the imputation of this variable. Thus, the standard errors of coefficients in our study should be interpreted with caution and as lower bound estimates.

Estimation in Continuous Time

Notably, models formalized in the DSEM framework can be estimated in discrete or continuous time. With panel data, and especially wage data, unequally spaced measurement occasions within and between persons are the norm rather than the exception. These may result from missing observations (e.g., if participants did not fill out the NLSY questionnaire in a particular year). Unequal time intervals are of concern when researchers are interested in lagged relationships of wages because the strength of a lagged effect depends on the length of the time interval between measurements (McNeish & Hamaker, 2020; Ryan, Kuiper, & Hamaker, 2018). Of course, researchers have to weigh the costs and benefits of estimation procedures, and discrete-time estimation can be a pragmatic approach (de Haan-

Rietdijk et al., 2017). We have to keep in mind, however, that discrete-time models, even when the measurement occasions are spaced equally, are inherently bound to the time intervals used in a given study (Voelkle, Oud, Davidov, & Schmidt, 2012). Our empirical example captured how CA processes arise for yearly measurements. Being interested in wage or panel data, this can be considered a reasonable resolution of time. Nevertheless, the present results tell us little about wage dynamics and how these processes unfold on a monthly, weekly, or even daily basis. Given that continuous time analyses contain exactly the same information as a discrete-time model and beyond, future research on wage (and other developmental) dynamics may profit considerably from also using continuous time estimation (Driver & Voelkle, 2018; Voelkle et al., 2012).

Summary

The present study's aim was to show how DSEM can serve as a versatile statistical framework for modeling wage dynamics and wage inequality across the lifespan. Specifically, we translated major theoretical branches of research on wage dynamics and wage inequality—the human capital approach, the life course perspective, and, most importantly, the theory of CA—into statistical parameters. In doing so, we translated the assumptions proposed in these theoretical approaches into their statistical equivalents, which opens the window for future refinements of these theories. One of the main advantages of dynamic models is their ability not only to describe individual differences in wage trajectories in a population but to incorporate the underlying mechanisms (e.g., CA) that bring about these differences. Hence, whenever CA processes are expected to occur (e.g., in skill acquisition, management careers, scientific careers, educational achievement, or health), DSEM may provide a powerful modeling framework from which to tackle the developmental dynamics of these vital real-life outcomes and domains.

References

Altonji, J. G., Smith, A. A., & Vidangos, I. (2013). Modeling earnings dynamics. *Econometrica*, *81*(4), 1395–1454. https://doi.org/10.3982/ECTA8415

APA Task Force on Socioeconomic Status. (2007). *Report of the APA Task Force on socioeconomic status*. American Psychological Association.

Asparouhov, T., & Muthen, B. (2003). *Random starting values and multistage optimization*. 8. https://www.statmodel.com/download/StartsUpdate.pdf

Asparouhov, T., & Muthen, B. (2010). *Bayesian analysis using Mplus: Technical implementation*. https://www.statmodel.com/download/Bayes3.pdf

Bagger, J., Fontaine, F., Postel-Vinay, F., & Robin, J.-M. (2014). Tenure, experience, Human capital, and wages: A tractable equilibrium search model of wage dynamics. *American Economic Review*, *104*(6), 1551–1596. https://doi.org/10.1257/aer.104.6.1551

Bai, J. (2013). Likelihood approach to dynamic panel models with interactive effects. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2332992

Baltes, P. B., Reese, H. W., & Nesselroade, J. R. (1988). *Life-span developmental Psychology: Introduction to research methods*. Lawrence Erlbaum Associates.

Bask, M., & Bask, M. (2015). Cumulative (dis)advantage and the Matthew effect in life-course analysis. *PLOS ONE*, *10*(11), e0142447. https://doi.org/10.1371/journal.pone.0142447

Becker, G. S., & Chiswick, B. R. (1966). Education and the distribution of earnings. *The American Economic Review*, *56*(1/2), 358–369. JSTOR.

Cheng, S. (2014). A life course trajectory framework for understanding the intracohort pattern of wage inequality. *American Journal of Sociology*, *120*(3), 633–700. https://doi.org/10.1086/679103

Cingano, F. (2014). *Trends in income inequality and its impact on economic growth* (No. 163; OECD Social, Employment and Migration Working Papers, Vol. 163). https://doi.org/10.1787/5jxrjncwxv6j-en

Crystal, S., Shea, D. G., & Reyes, A. M. (2017). Cumulative advantage, cumulative disadvantage, and evolving patterns of late-life inequality. *The Gerontologist*, *57*(5), 910–920. https://doi.org/10.1093/geront/gnw056

de Haan-Rietdijk, S., Voelkle, M. C., Keijsers, L., & Hamaker, E. L. (2017). Discrete- vs. Continuous-Time Modeling of unequally spaced experience sampling method data. *Frontiers in Psychology*, *8*, 1–19. https://doi.org/doi: 10.3389/fpsyg.2017.01849

Di Domenico, S. I., & Fournier, M. A. (2014). Socioeconomic status, income inequality, and health complaints: A basic psychological needs perspective. *Social Indicators Research*, *119*(3), 1679–1697. https://doi.org/10.1007/s11205-013-0572-8

Diener, E., Ng, W., Harter, J., & Arora, R. (2010). Wealth and happiness across the world: Material prosperity predicts life evaluation, whereas psychosocial prosperity predicts positive feeling. *Journal of Personality and Social Psychology*, *99*(1), 52–61. https://doi.org/10.1037/a0018066

DiPrete, T. A., & Eirich, G. M. (2006). Cumulative advantage as a mechanism for inequality: A review of theoretical and empirical developments. *Annual Review of Sociology*, *32*(1), 271–297. https://doi.org/10.1146/annurev.soc.32.061604.123127

Driver, C. C., Oud, J. H. L., & Voelkle, M. C. (2017). Continuous time structural equation modeling with *R* Package **ctsem**. *Journal of Statistical Software*, *77*(5). https://doi.org/10.18637/jss.v077.i05

Driver, C. C., & Voelkle, M. C. (2018). Hierarchical Bayesian continuous time dynamic modeling. *Psychological Methods*, *23*(4), 774–799. https://doi.org/10.1037/met0000168

Duncan, G. J., Magnuson, K., & Votruba-Drzal, E. (2017). Moving beyond correlations in assessing the consequences of poverty. *Annual Review of Psychology*, *68*(1), 413–434. https://doi.org/10.1146/annurev-psych-010416-044224

Enders, C. K. (2003). Using the Expectation Maximization Algorithm to estimate coefficient Alpha for scales with item-level missing data. *Psychological Methods*, *8*(3), 322–337. https://doi.org/10.1037/1082-989X.8.3.322

Enders, C. K. (2010). *Applied missing data analysis*. Guilford Press.

Feng, C., Wang, H., Lu, N., & Tu, X. M. (2012). Log transformation: Application and interpretation in biomedical research. *Statistics in Medicine*, *32*(2), 230–239. https://doi.org/10.1002/sim.5486

Frankel, M. R., McWilliams, H. A., & Spencer, B. D. (1983). *National Longitudinal Survey of labor force behavior, Youth Survey (NLS) technical sampling report*. https://www.nlsinfo.org/sites/nlsinfo.org/files/attachments/130212/NLSY79%20Tech%20Samp%20Rpt.pdf

Gelman, A., Carlin, J. B., Stern, H. S., Dunson, D. B., Vehtari, A., & Rubin, D. B. (2014). *Bayesian data analysis Third edition (with errors fixed as of 13 February 2020)*. http://www.stat.columbia.edu/~gelman/book/BDA3.pdf

Hallquist, M., Wiley, J., & van Lissa, C. (2018). *Package 'MplusAutomation'* [R]. https://github.com/michaelhallquist/MplusAutomation

Hamaker, E. L., Asparouhov, T., Brose, A., Schmiedek, F., & Muthén, B. (2018). At the frontiers of modeling intensive longitudinal data: Dynamic structural equation models for the affective measurements from the COGITO study. *Multivariate Behavioral Research*, *53*(6), 820–841. https://doi.org/10.1080/00273171.2018.1446819

Hasl, A., Kretschmann, J., Richter, D., Voelkle, M., & Brunner, M. (2019). Investigating core assumptions of the "American Dream": Historical changes in how adolescents' socioeconomic status, IQ, and GPA are related to key life outcomes in adulthood. *Psychology and Aging*, *34*(8), 1055–1076. https://doi.org/10.1037/pag0000392

Heckman, J., & Carneiro, P. (2003). *Human capital policy* (No. w9495; p. w9495). National Bureau of Economic Research. https://doi.org/10.3386/w9495

Heckman, J., Lochner, L., & Todd, P. (2008). Earnings functions and rates of return. *Journal of Human Capital*, *2*(1), 1–31. https://doi.org/10.1086/587037

Heckman, J., Lochner, L., & Todd, P. (2005). *Earnings functions, rates of return and treatment effects: The Mincer equation and beyond* (No. w11544; p. w11544). National Bureau of Economic Research. https://doi.org/10.3386/w11544

International Monetary Fund. (2015). *Uneven growth: Short- and long-term factors*. International Monetary Fund. https://www.imf.org/en/Publications/WEO/Issues/2016/12/31/Uneven-Growth-Short-and-Long-Term-Factors

Lagakos, D., Moll, B., Porzio, T., Qian, N., & Schoellman, T. (2018). Life cycle wage growth across countries. *Journal of Political Economy*, *126*(2), 797–849. https://doi.org/10.1086/696225

Lavielle, M., & Ribba, B. (2016). Enhanced method for diagnosing pharmacometric models: Random sampling from conditional distributions. *Pharmaceutical Research*, *33*(12), 2979–2988. https://doi.org/10.1007/s11095-016-2020-3

McArdle, J. J. (1988). Dynamic but structural equation modeling of repeated measures data. In J. R. Nesselroade & R. B. Cattell (Eds.), *Handbook of Multivariate Experimental Psychology* (pp. 561–614). Springer US. https://doi.org/10.1007/978-1-4613-0893-5_17

McArdle, J. J. (2007). Dynamic structural equation modeling in longitudinal experimental studies. In K. v. Montfort, J. H. Oud, & A. Satorra (Eds.), *Longitudinal models in the* *behavioral and related sciences* (pp. 159–188). Lawrence Erlbaum Associates Publishers.

McArdle, J. J. (2009). Latent variable modeling of differences and changes with longitudinal data. *Annual Review of Psychology*, *60*(1), 577–605. https://doi.org/10.1146/annurev.psych.60.110707.163612

McNeish, D. (2019). Two-level dynamic structural equation models with small samples. *Structural Equation Modeling: A Multidisciplinary Journal*, *26*(6), 948–966. https://doi.org/10.1080/10705511.2019.1578657

McNeish, D., & Hamaker, E. L. (2020). A primer on two-level dynamic structural equation models for intensive longitudinal data in Mplus. *Psychological Methods*, *25*(5), 610–635. https://doi.org/10.1037/met0000250

Merton, K. (1968). The Matthew effect in science. *Science*, *159*(3810), 56–63.

Mincer, J. (1958). Investment in Human capital and personal income distribution. *Journal of Political Economy*, *66*(4), 281–302. JSTOR.

Muthén, L. K., & Muthén, B. O. (1998). *Mplus user's guide* (8th ed.). Muthén & Muthén.

OECD. (2017). *Preventing ageing unequally*. OECD. https://doi.org/10.1787/9789264279087-en

OECD. (2019). *Education at a glance 2019: OECD indicators*. OECD. https://doi.org/10.1787/f8d7880d-en

Pareto, V. (1896). La curva delle entrate e le osservazioni del Prof. Edgeworth. *Giornale Degli Economisti*, *13*(7), 439–448. JSTOR.

Ryan, O., Kuiper, R. M., & Hamaker, E. L. (2018). A continuous-time approach to intensive longitudinal data: What, why, and how? In K. van Montfort, J. H. L. Oud, & M. C. Voelkle (Eds.), *Continuous time modeling in the behavioral and related sciences* (pp. 27–54). Springer International Publishing. https://doi.org/10.1007/978-3-319-77219-6_2

Saez, E., & Zucman, G. (2016). Wealth inequality in the United States since 1913: Evidence from capitalized income tax data. *The Quarterly Journal of Economics*, *131*(2), 519–578. https://doi.org/10.1093/qje/qjw004

Schultzberg, M., & Muthén, B. (2018). Number of subjects and time points needed for multilevel time-series analysis: A simulation study of dynamic structural equation modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, *25*(4), 495–515. https://doi.org/10.1080/10705511.2017.1392862

Sewell, W. H., Haller, A., & Portes, A. (1969). The educational and early occupational attainment process. *American Sociological Review*, *34*(1), 82–92.

Shadish, W. R. (2014). Statistical analyses of single-case designs: The shape of things to come. *Current Directions in Psychological Science*, *23*(2), 139–146. https://doi.org/10.1177/0963721414524773

Shadish, W. R., Kyse, E. N., & Rindskopf, D. M. (2013). Analyzing data from single-case designs using multilevel models: New applications and some agenda items for future research. *Psychological Methods*, *18*(3), 385–405. https://doi.org/10.1037/a0032964

Shadish, W. R., & Sullivan, K. J. (2011). Characteristics of single-case designs used to assess intervention effects in 2008. *Behavior Research Methods*, *43*(4), 971–980. https://doi.org/10.3758/s13428-011-0111-y

Spengler, M., Brunner, M., Damian, R. I., Lüdtke, O., Martin, R., & Roberts, B. W. (2015). Student characteristics and behaviors at age 12 predict occupational success 40 years later over and above childhood IQ and parental socioeconomic status. *Developmental Psychology*, *51*(9), 1329–1340. https://doi.org/10.1037/dev0000025

Spengler, M., Damian, R. I., & Roberts, B. W. (2018). How you behave in school predicts life success above and beyond family background, broad traits, and cognitive ability. *Journal of Personality and Social Psychology*, *114*(4), 620–636. https://doi.org/10.1037/pspp0000185

Stewman, S., & Konda, S. L. (1983). Careers and organizational labor markets: Demographic models of organizational behavior. *American Journal of Sociology*, *88*(4), 637–685.

U.S. Bureau of Labor Statistics. (2021). *National Longitudinal Survey of Labor Force Behavior. Youth Survey, 1979*. https://www.nlsinfo.org/sites/nlsinfo.org/files/attachments/121212/NLSY79_1979_Quex_size%20reduced.pdf

Voelkle, M. C., Gische, C., Driver, C. C., & Lindenberger, U. (2018). The role of time in the quest for understanding psychological mechanisms. *Multivariate Behavioral Research*, *53*(6), 782–805. https://doi.org/10.1080/00273171.2018.1496813

Voelkle, M. C., Oud, J. H. L., Davidov, E., & Schmidt, P. (2012). An SEM approach to continuous time modeling of panel data: Relating authoritarianism and anomia. *Psychological Methods*, *17*(2), 176–192. https://doi.org/10.1037/a0027543

Vyas, S., & Kumaranayake, L. (2006). Constructing socio-economic status indices: How to use principal components analysis. *Health Policy and Planning*, *21*(6), 459–468. https://doi.org/10.1093/heapol/czl029

Zyphur, M. J., Voelkle, M. C., Tay, L., Allison, P. D., Preacher, K. J., Zhang, Z., Hamaker, E. L., Shamsollahi, A., Pierides, D. C., Koval, P., & Diener, E. (2020). From data to causes II: Comparing approaches to panel data analysis. *Organizational Research Methods*, *23*(4), 688–716. https://doi.org/10.1177/1094428119847280

Tables

Table 1

Point Estimates (Posterior Means) and 95% Credibility Intervals for Fixed Effects (i.e., Means) and Random Effects (i.e., Variances) of Initial Wage Levels, Wage Growth Rates, and their Regression on IQ, GPA, pSES, and EDU

	Unconditional models												Conditional model			
	Model 1				Model 2				Model 3				Model 4			
Variable	Fixed effect (mean)		Random effects (variances)		Fixed effect (mean)		Random effects (variances)		Fixed effect (mean)		Random effects (variances)		Fixed effect (mean)		Random effects (variances)	
	Est	95% CI	Est	95% CI	Est	95% CI	Est	95% CI	Est	95% CI	Est	95% CI	Est	95% CI	Est	95% CI
α_i	**17.476**	[17.389, 17.564]			**17.406**	[16.808, 17.616]	**212.792**	[200.560, 225.848]	**17.415**	[17.001, 17.820]	**213.521**	[201.265, 226.074]	**17.173**	[16.782, 17.572]	**192.773**	[181.685,204.120]
ϕ_i	**0.755**	[0.750, 0.760]			**0.740**	[0.734, 0.748]			**0.622**	[0.611, 0.634]	**0.046**	[0.042, 0.051]	**0.616**	[0.605, 0.627]	**0.039**	[0.035, 0.043]
Between person (Level 2)																
	α_i		ϕ_i		α_i		ϕ_i		α_i		ϕ_i		α_i		ϕ_i	
	Est	95% CI	Est	95% CI	Est	95% CI	Est	95% CI	Est	95% CI	Est	95% CI	Est	95% CI	Est	95% CI
IQ (β_{01}, β_{11})													**0.003**	[0.002, 0.004]	**0.002**	[0.001, 0.002]
GPA (β_{02},β_{12})													0.011	[- 0.039, 0.060]	0.014	[- 0.007, 0.034]
pSES (β_{03}, β_{13})													0.018	[-0.011, 0.047]	0.011	[- 0.002, 0.024]
EDU (β_{04},β_{14})													**0.037**	[0.026, 0.049]	**0.017**	[0.012, 0.022]
Cov(α_i,ϕ_i)												-0.011				-0.027
Cor(α_i,ϕ_i)												-0.072				-0.075
DIC				420434.248				217987.855				207481.675				269448.487

Note. Est = Estimate; 95% CI = 95% Credibility Interval; EDU = years of education; DIC = Deviance Information Criterion. Unconditional Models: Model 1-3. Conditional Model: Model 4. Fixed effects represent means, random effects represent variances of the parameters. Model 1 assumes fixed initial log hourly wages (intercept; α_i) and wage growth rates (slopes; ϕ_i); the variances of α_i and ϕ_i were fixed to zero. Model 2 assumes random initial log hourly wages and fixed growth rates (i.e., the variance of ϕ_i was fixed to zero). Models 3 and 4 assume random means for initial log hourly wages (α_i) and random autoregressive coefficients (ϕ_i). In Model 4, random means for initial log hourly wages (α_i) and random wage growth rates (ϕ_i) were predicted by adolescent IQ, GPA, pSES, and adult highest level of education at the between-level. We applied an exponential transformation with Feng et al.'s (2012, p. 2) bias correction to fixed and random effects of α_i. Thus, the presented results correspond to units of U.S. $ instead of log(U.S. $). Original parameters for α_i in log(U.S. $) as well as parameter estimates for the residuals ζ_{it} can be found in the Online Supplemental Material in Table A3. Significant results are printed in bold font, indicating that the 95% Credibility Interval did not contain zero.

Table 2

Natural Metric Effect Size Estimates and Example Time Series for the Long-Term Influence of IQ, GPA, SES, and Education for Initial Wage Levels and Growth Rates.

Part 1. Individual characteristics		
	Initial hourly wages (α_i)	Wage growth rates (ϕ_i)
+1SD*IQ	$1.45	0.97%
+1SD*GPA	$0.14	0.18%
+1SD*SES	$0.31	0.19%
+1SD*EDU	$1.61	0.74%
Σ	$3.51	2.08%

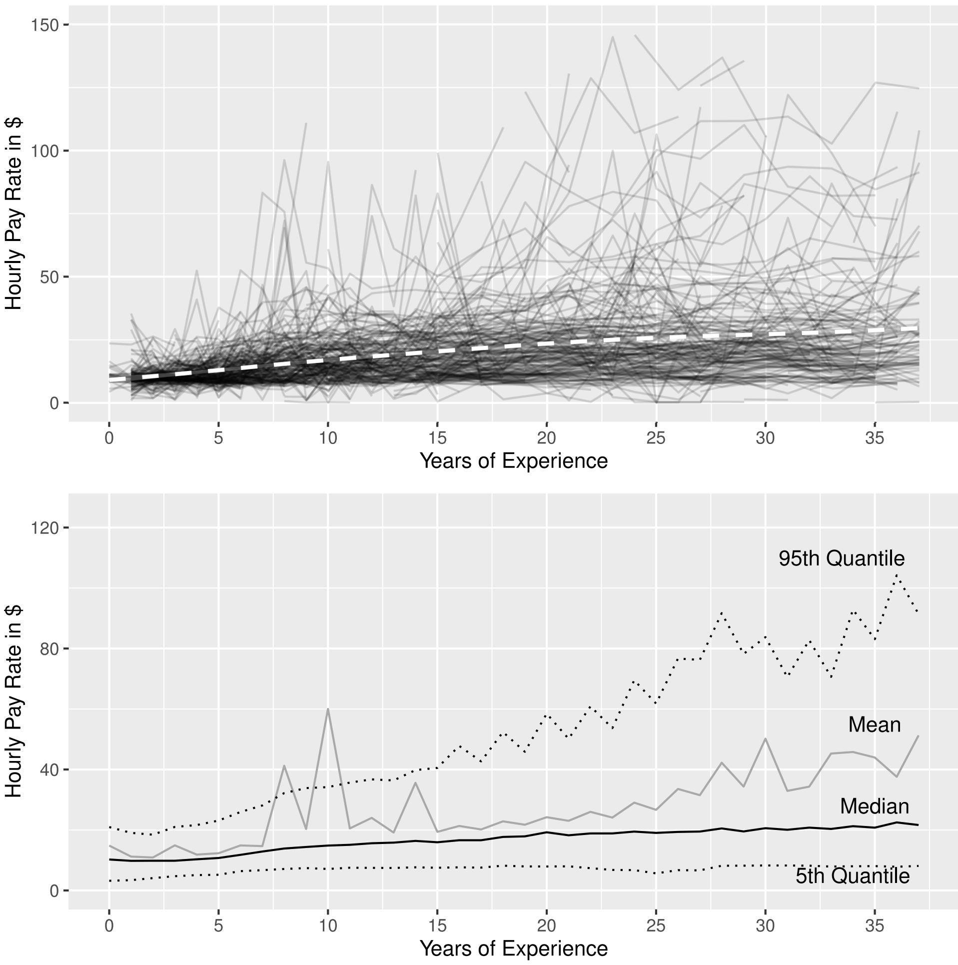
Part 2. Example time series				
Time	Person A (∅) α_i = $17.17 and ϕ_i = 0.62	Person B (+2SD) α_i = $24.17 ϕ_i = 0.66	Δ Y_AY_B	Σ Δ Y_AY_B (Full-Time)
t_0	$17.17	$24.17	$7.00	$13,444
t_1	$27.75	$40.06	$12.31	$37,084
t_2	$34.27	$50.51	$16.24	$68,272
t_5	$42.28	$64.86	$22.58	$188,879
t_{10}	$44.50	$69.85	$25.35	$425,324
t_{15}	$44.70	$70.47	$25.77	$671,660
t_{25}	$44.72	$70.55	$25.83	$1,167,376
t_{35}	$44.72	$70.55	$25.83	$1,663,341
t_{37}	$44.72	$70.55	$25.83	$1,762,535

Note. All transformations into natural metrics are based on the results of Model 4 in Table 1. The units of IQ, GPA, SES, and years of education in Part 1 of this table refer to 1 SD (see Table A2, Online Supplemental Material). Thus, the effect size entries refer to an estimate of the extent to which an increase of 1 SD in IQ (i.e., 28.1 percentile points)/1 SD in GPA (i.e., 0.74 grade points) /1 SD in pSES (i.e., 0.99 SES points)/1 SD in years of education (i.e., 2.53 years) were associated with x additional US$ of initial hourly wages (α_i) and x additional percent of wage growth across the lifespan (ϕ_i). The differences were computed at an average initial hourly wage of α_i = $17.17 by applying b x SD. Part 2 contains two example time series using the model parameters obtained for Model 4. Person A represents an individual with average IQ, GPA, SES, and years of education. Person B represents an individual who is two standard deviations above average in IQ, GPA, SES, and years of education. ΔY_AY_B denotes the differences in hourly wages between Persons A and B at a given time point. Σ Δ Y_AY_B denotes cumulative wage differences on the basis of a full-time job (160 hr/month, 12 months; e.g., t_0: $7.00 x 160 x 12 = $13,444) over time. Over a period of 38 years (t_{37}), Person B earned a total $1,762,535 more than Person A.

Figures

Figure 1

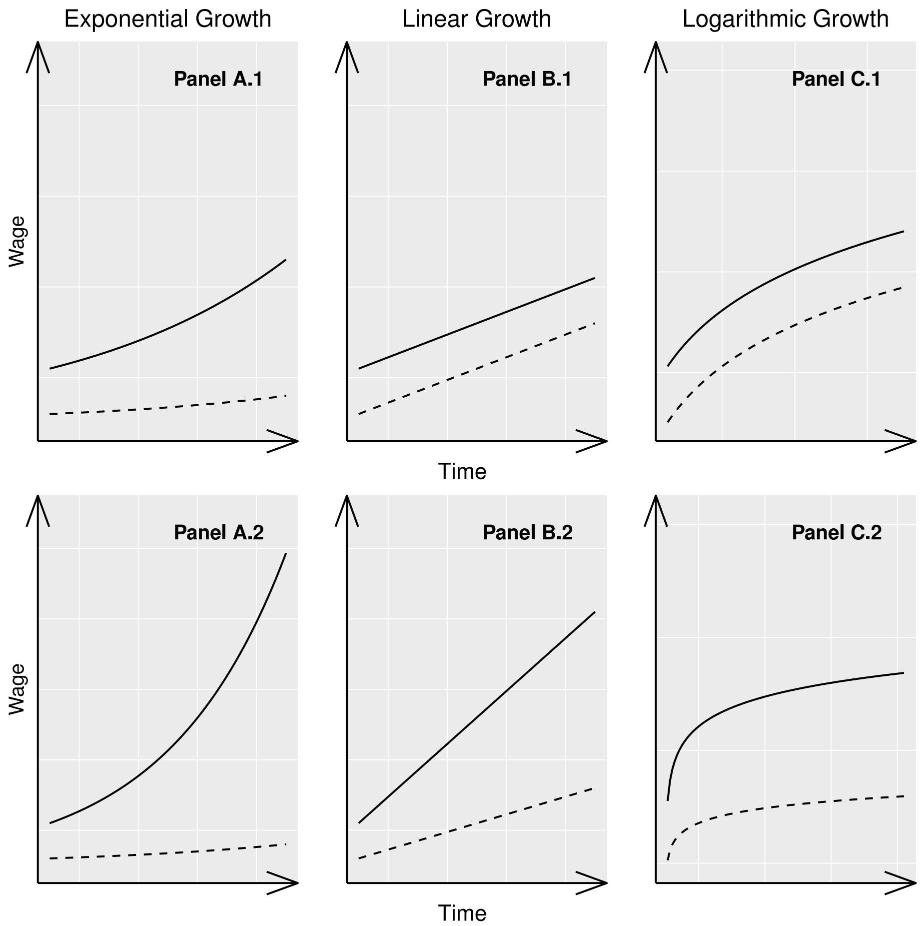
Changes in Hourly Pay Rates Across 38 Years



Note. The upper panel represents empirical wage trajectories of a random sample of $N = 300$ individuals across a period of 38 years. The dashed line represents the populations' mean trajectory. The lower panel depicts the mean, median, and the 5th and 95th quantiles of gross hourly pay rates of all $N = 3{,}720$ individuals across a period of 38 years. All values represent 2019 U.S. \$. Mean and median hourly wages as well as variability between persons grew over time, the latter indicating growing population level inequality. See Figure A1 in the Online Supplemental Material for additional 1st, 99th, and 99.95th quantiles of gross hourly pay rates. The data stemmed from the U.S. National Longitudinal Survey of Youth 1979 (NLSY-79).

Figure 2

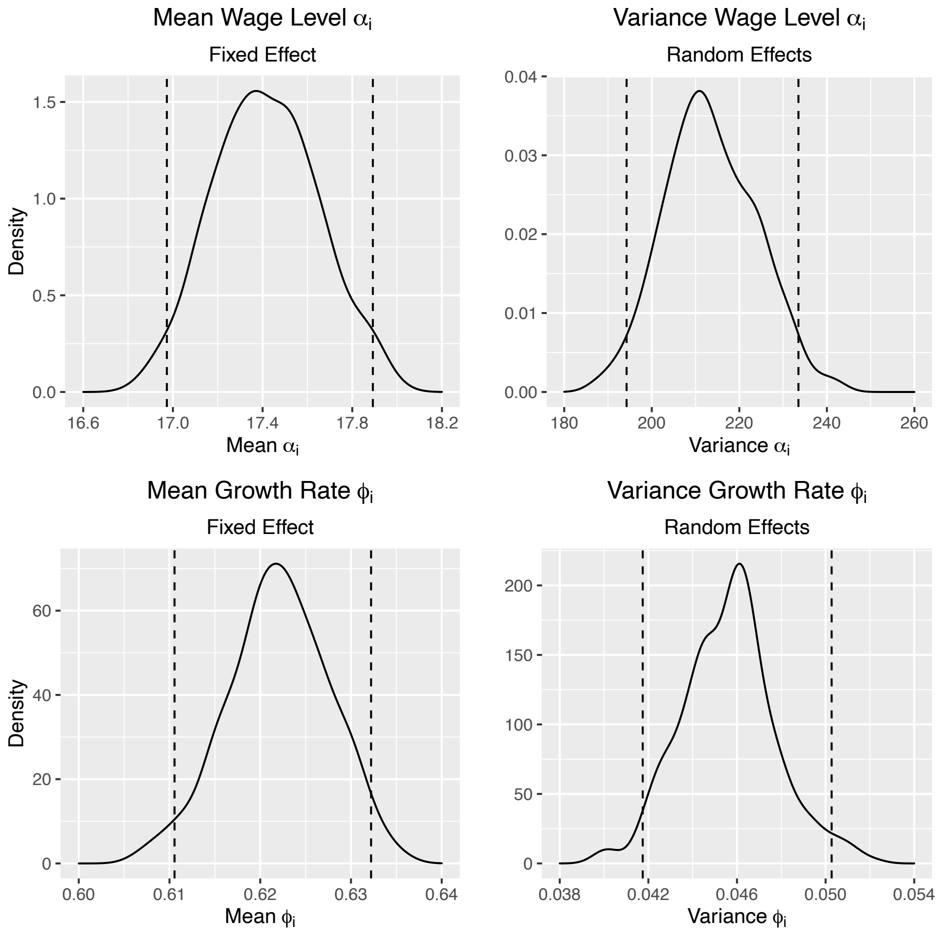
Examples of Between-Person Heterogeneity in Wage Dynamics Showing Exponential, Linear, and Logarithmic Growth



Note. The dashed and solid lines represent two exemplary individuals in each panel. The upper panels (A.1, B.1, C.1) represent between-person differences in initial wages combined with equal growth rates for both people over time. The lower panels (A.2, B.2, C.2) represent the joint effect of between-person differences in initial wages and between-person differences in wage growth rates, where higher initial wages are associated with higher long-term wage growth rates. In Panels A.1, A.2, B.2, and C.2, initial differences between the two individuals became magnified over time, indicating CA processes. Strict CA processes are present in Panel A.2.

Figure 3

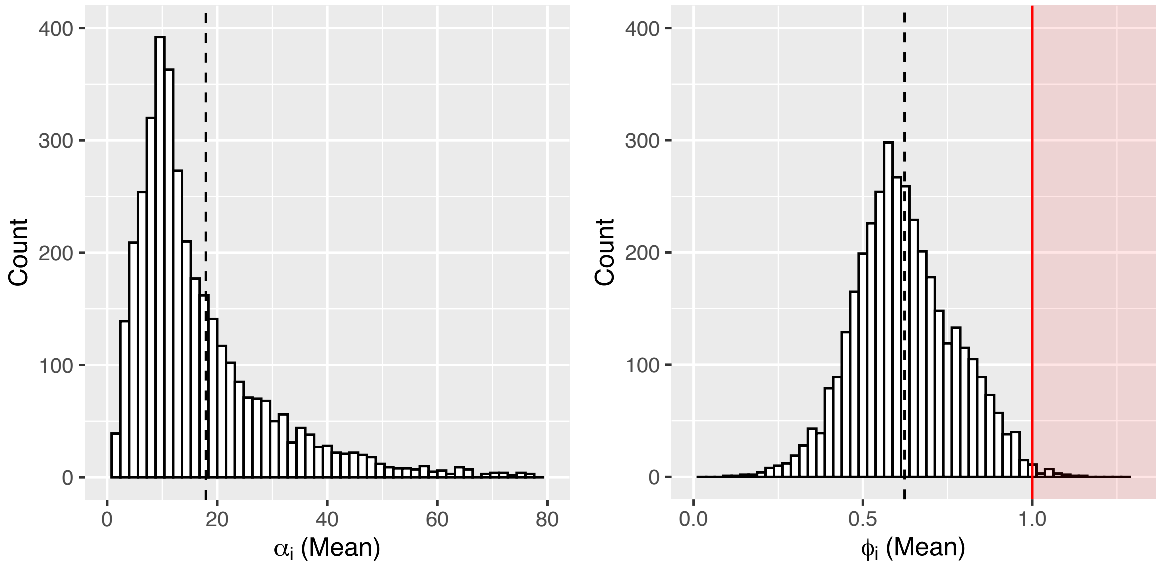
Bayesian Posterior Probability Distributions of Fixed and Random Effects of Initial Wage Levels (α_i) and Autoregressive Wage Growth Rates (ϕ_i)



Note. Bayesian posterior probability distributions of mean levels (i.e., fixed effects) and variances (i.e., random effects) of initial wage level α_i in U.S. \$ (upper panels) and autoregressive wage growth rate ϕ_i (lower panels). The peaks of the distributions correspond to the posterior means of Model 3 in Table 1. The peak variance estimate of α_i corresponds to a standard deviation of \$14.61, the peak variance estimate of ϕ_i corresponds to a standard deviation of 0.214. The dashed lines show the 2.5th and 97.5th quantiles of the posterior distributions to approximate the 95% credibility intervals.

Figure 4

Distribution of Initial Hourly Wage Levels (α_i) and Autoregressive Wage Growth Rates (ϕ_i)



Note. Values based on Model 3. Initial hourly wage levels α_i are given in US $. The vertical dashed line indicates the mean of the distribution in both panels. The majority of individuals experienced logarithmic wage growth over time ($\phi_i < 1$). Those individuals with $\phi_i > 1$ experienced strict CA processes, reflected by exponential growth in their wages across a period of 38 years (0.5% of individuals). Maximum initial hourly wages were $1,333 (not plotted in the panel).

4

Study III

Leveraging Observation Timing Variability to Understand Intervention Effects in Panel Studies: An Empirical Illustration and Simulation Study

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4 Study III: Leveraging Observation Timing Variability to Understand Intervention Effects in Panel Studies: An Empirical Illustration and Simulation Study

Abstract

To examine developmental processes and/or intervention effects, longitudinal studies often aim for measurement intervals that are equally spaced for all participants. In reality, however, this goal is hardly met. While different approaches have been proposed to deal with this issue, few studies have investigated the potential benefits of individual variation in time intervals. In the present paper we examine how continuous time dynamic models can be used to study non-experimental intervention effects in longitudinal studies where measurement intervals vary between and within participants. We empirically illustrate this method by using panel data (N = 2,877) to study the effect of the transition from primary to secondary school on students' motivation. Results of a simulation study also show that the precision and recovery of the estimate of the effect improves with individual variation in time intervals.

Keywords: individually varying time intervals, intervention effects, continuous time models, longitudinal data

Leveraging Observation Timing Variability to Understand Intervention Effects in Panel Studies: An Empirical Illustration and Simulation Study

Longitudinal large-scale assessments and panel studies often aim for equally spaced intervals between measurement occasions. Particularly in the experimental and assessment literature, unequally spaced measurement intervals between observations or measurement waves are often viewed as a potential source of unwanted variance. As a result, standardization or balancing of temporal processes of measurement is frequently attempted (Liu, 2016; Verbeke et al., 2014). In practice, however, time intervals can and do vary between measurement waves, between individuals, and even within individuals, which is often a result of pragmatic constraints (e.g., the available number of test administrators or testing devices) during the process of data collection. If observation intervals in panel studies vary both within and between individuals, they are often referred to as “individually varying” (Voelkle & Oud, 2013). In the present study, we aim to show how these naturally occurring individually varying time intervals (IVTs) can actually be beneficial, by providing additional information about intervention effects from observational data.

The Alignment of Measurement Intervals in Panel Studies of Intervention Effects

Panel studies provide rich data for examining longitudinal target processes or intervention effects that occur at a certain time. Given the manifold research questions these studies may simultaneously address, observation timing is usually not designed around certain expected events, but instead occur at pre-specified points in time (Cooksey, 2018; Hernán et al., 2009). Thus, if an intervention or event of any kind takes place, observations in panel studies may occur close to the onset of the event, or much further away in time. Consider the following example: Throughout schooling, children around the world face certain transitions, one of which is the transition from primary to secondary school. This transition has repeatedly been shown to have social, emotional, and academic consequences for children (Evans et al., 2018). Among other things, it can result in a long-lasting decrease in academic motivation and self-concept (Archambault et al., 2010; Chouinard et al., 2017). According to the stage-environment fit theory (Eccles et al., 1993), poor academic performance, mental health, or academic motivation after the transition may be caused by a mismatch between children's developmental demands at the time of the transition and the social context of secondary schools. When transitioning, children must adjust to larger classrooms and schools, more academic freedom, new peer and teacher interactions, and a greater focus on grades and performance. Due to these differences, students need to adapt to new academic expectations, norms, and evaluation criteria. Subsequently, this can negatively affect young adolescents' academic engagement and motivation, academic self-concept or competence, attitude toward school and learning, and their intrinsic interest in school (Chouinard et al., 2017; Dotterer et al., 2009; Eccles et al., 1993; Evans et al., 2018; Zeedyk et al., 2003). Dotterer et al. (2009) found that the steady decline in academic interest after the transition persisted until the age of 16. From there, it slowly reversed, but never fully recovered to its previous levels. A similar pattern was found for academic motivation (Gottfried et al., 2001).

From a statistical perspective, the transition from primary to secondary school can be considered an intervention that has an effect on all children of a certain cohort at the same time. For example, in Germany, this transition happens as early as after the 4th grade. The German National Educational Panel Study (NEPS; Blossfeld et al., 2011) is the most important German educational large-scale panel study that can be used to examine the effect of the transition on students' motivation. In most cohorts, the NEPS samples students repeatedly once a year. The measurements in primary and secondary school usually take place from November to January, but measurements sometimes occur as late as March or April of a given grade (LIfBi, 2022), leading to between-student variability in measurement timing. Since students are not normally measured the same day or month in every grade, the students' individual measurement intervals across the yearly measurements will vary as well

– sometimes it may be less than a year, sometimes more. Figure 1 presents this idea conceptually. In the upper panel, all students are surveyed at the same time in two consecutive waves, resulting in the same time intervals between their repeated measurement occasions. In the lower panel, students are measured in different months in the two consecutive waves, resulting in IVTs between the repeated observations and with respect to the onset of the intervention. What may also be seen intuitively from Figure 1 is that this naturally occurring continuous sampling of individuals allows us to cover a longer period of time with observations than if students were sampled at the same time each year. Figure A1 (OSM) represents the corresponding empirical example from the NEPS data.

Modeling Approaches to IVTs in Panel Studies

Many statistical models can handle variable timing in measurement and the resulting IVTs well. Latent growth curve models based on structural equation models (LGCM; Bollen & Curran, 2006; McArdle et al., 2009; Sterba, 2014), for example, include time as an exogenous predictor for an outcome; that is, trajectories of outcome variables are modeled as a function of time. Because time is modeled as an exogenous variable, variable timing of measurement is not a problem. Importantly, however, while so-called "static" longitudinal models like the LGCM allow us to describe change over time, a causal interpretation of such models is not possible (Voelkle et al., 2018; Voelkle & Oud, 2015). Thus, when the goal is not only to describe change, but to understand the mechanisms that generate change, so-called "dynamic" models are better suited (Voelkle et al., 2018; Zyphur et al., 2020). Typical dynamic models are autoregressive or change score models, where current states of a system (i.e., the dependent variable) depend on past states and external forces (see e.g., Boker & Nesselroade, 2002; Hasl et al., 2022; McArdle, 2009; Voelkle & Oud, 2015). For example, a student's current level of academic motivation is assumed to depend on his or her past level of academic motivation, but is also influenced by other factors. From a dynamic systems perspective, an intervention such as the transition from primary to secondary school is an event that perturbs the academic motivation system from its normal equilibrium state (Bisconti et al., 2004; Boker & Nesselroade, 2002).

Importantly, discrete-time dynamic models only consider time implicitly by taking into account the order of the measurement, but not the exact time points or time intervals between them (Voelkle et al., 2012). A first problem that arises from this is that it is not possible to compare results of studies to each other if they applied different time intervals to investigate the same substantive process (Voelkle & Oud, 2013). If, for example, a study investigated the effect of the transition from primary to secondary school on academic motivation in intervals of 6 months, and found different effects than a study investigating the same effect with a 12 month interval, which study's estimate is the "correct" one? In such a setting, it is impossible to differentiate between the effect of the measurement intervals and the substantive process itself (Oud & Delsing, 2010). Second, similarly, if panel studies feature IVTs, and these are not accounted for in statistical analyses, it is difficult to interpret the target effect because it represents an average across the individual effects rather than the effect for a certain time interval. Fortunately, the literature identifies a solution to these problems: The application of continuous time (CT) models by means of stochastic differential equations (e.g., Driver & Voelkle, 2018a, b; Oud & Delsing, 2010; Voelkle et al., 2012). Among other things, CT models allow us to separate the measurement process from the process of interest by removing any potential confounding between the two when estimating parameters.

Research Objectives

Considering IVTs a nuisance may represent common practice or intuition rather than statistical necessity (Collins, 2006; Voelkle & Oud, 2013). When panel studies include IVTs, we can cover a larger space in time than we could with equally spaced measurement intervals. This may be helpful when examining longitudinal processes because we can learn more about the temporal course of a process or event. In this paper, we apply this line of thought to the estimation of intervention effects. Whereas previous research focused on how to use IVTs to study continuous processes, in the present paper, we add to this literature by demonstrating how CT models can leverage IVTs in panel studies for investigating *intervention effects*. Second, whereas earlier studies often drew on abstract examples, this study is guided by an empirical example, namely the transition from primary to secondary school and the NEPS data. Thus, although we will focus on simulations to evaluate whether and under which conditions individual variation in time intervals may improve the estimation and recovery of average intervention effects over time, their design and parameters are inspired by real data.

The article will proceed as follows: We will first introduce intervention effects from a dynamic systems perspective, and consider the handling of IVTs in a CT structural equation modeling framework. We will then develop a model using the NEPS data. The parameters from this empirical model will serve as true effects in a subsequent simulation study, where IVTs will be distributed according to different normal and uniform distributions that are linked to the NEPS measurement schedule. Results will be presented and discussed with respect to the existing literature. Lastly, we will show possible limitations of our approach.

Modeling Input Effects in a Continuous Time Framework

Although developmental processes usually happen in continuous time t, their measurement occasions u are necessarily discrete. CT models by means of differential stochastic equations depict the rate of change of a process over infinitesimally small increments of time. This puts the generating mechanism on a continuous time scale and allows us to distinguish the underlying dynamics clearly from the discrete time measurement occasions u (Oud & Delsing, 2010). In the following, we will present CT models in terms of stochastic differential equations as provided in Driver and Voelkle (2018a). We will also define all parameters that are later used in the simulation study. The CT dynamic model is comprised of a latent dynamic model and a measurement model. CT parameters are obtained via structural equation modeling. A detailed step-by-step tutorial explaining each part of the model formulations of CT models can be found in Voelkle et al. (2012).

Latent Dynamic Model

The dynamic system is described by the linear stochastic differential equation:

$$\mathbf{d}\boldsymbol{\eta}(t) = \big(\boldsymbol{A}\boldsymbol{\eta}(t) + \boldsymbol{b} + \boldsymbol{M}\boldsymbol{\chi}(t)\big)\mathbf{d}t + \boldsymbol{GdW}(t) \qquad \text{(Eq. 1)}$$

Vector $\boldsymbol{\eta}(t) \in \mathbb{R}^v$ represents the state of the latent processes at time *t*. The matrix $\boldsymbol{A} \in \mathbb{R}^{v\times v}$ denotes the drift matrix, with auto effects on the diagonal and possible cross effects on the off-diagonals characterizing the temporal dynamics of the process. The continuous time intercept vector $\boldsymbol{b} \in \mathbb{R}^v$ provides a constant fixed input to the latent processes $\boldsymbol{\eta}$. In combination with $\boldsymbol{A}$, this determines the long-term level around which the processes fluctuate.

Time dependent predictors $\boldsymbol{\chi}(t)$ represent exogenous inputs to the system (such as interventions) that may vary over time and are independent of earlier fluctuations in the system. Eq. 2 shows a generalized form for time-dependent predictors that could be treated a variety of ways depending on the predictors' assumed time course or shape. We use a basic impulse form (Driver & Voelkle, 2018, p. 82), in which the predictors are treated as impacting the processes only at a single moment (observation occasion u). The virtue of this form is that many alternative shapes are made possible via augmentation of the system state

$$\boldsymbol{\chi}(t) = \sum_{u\,\in\,\boldsymbol{U}} \boldsymbol{x}_u\,\delta(t - t_u) \qquad \text{(Eq. 2)}$$

matrices.

Here, time dependent predictors $\boldsymbol{x}_u \in \mathbb{R}^l$ are observed at measurement occasions $u \in \boldsymbol{U}$, where $\boldsymbol{U}$ is the set of measurement occasions from 1 to the number of measurement occasions, with $u = 1$ treated as occurring at $t = 0$. The Dirac delta function $\delta(t - t_u)$ is a generalized function that is ∞ at 0 and 0 elsewhere, yet has an integral of 1, when 0 is in the range of integration. It is useful to model an impulse to a system, and here is scaled by the vector of time-dependent predictors $\boldsymbol{x}_u$. The effect of these impulses on processes $\boldsymbol{\eta}(t)$ is then $\boldsymbol{M} \in \mathbb{R}^{v \times l}$.

$\boldsymbol{W}(t) \in \mathbb{R}^{v}$ represents v-independent Wiener processes, with a Wiener process being a random walk in continuous time. $d\boldsymbol{W}(t)$ represents the stochastic error term, an infinitesimally small increment of the Wiener process. Lower triangular matrix $\boldsymbol{G} \in \mathbb{R}^{v \times v}$ represents the effect of this noise on the change in $\boldsymbol{\eta}(t)$. $\boldsymbol{Q}$, where $\boldsymbol{Q} = \boldsymbol{G}\boldsymbol{G}^T \in \mathbb{R}^{v \times v}$, depicts the variance-covariance matrix of this diffusion process in continuous time.

Discrete Time Solution of a Latent Dynamic Model

To derive expectations for discretely sampled data, Eq. 1 may be solved and translated to a discrete time representation, for any observation $u \in \boldsymbol{U}$:

$$\boldsymbol{\eta}_u = \boldsymbol{A}^*_{\Delta t_u}\boldsymbol{\eta}_{u-1} + \boldsymbol{b}^*_{\Delta t_u} + \boldsymbol{M}\boldsymbol{x}_u + \boldsymbol{\xi}_u \qquad \boldsymbol{\xi}_u \sim \boldsymbol{N}(\boldsymbol{0}_v, \boldsymbol{Q}^*_{\Delta t_u}) \tag{Eq. 3}$$

The * notation is used to indicate a term that is the discrete time equivalent of the original for the time interval Δt_u (which is the time at u minus the time at $u - 1$). $\boldsymbol{A}^*_{\Delta t_u}$ contains the appropriate auto and cross regressions for the effect of latent processes $\boldsymbol{\eta}$ at measurement occasion $u - 1$ on $\boldsymbol{\eta}$ at measurement occasion u. $\boldsymbol{b}^*_{\Delta t_u}$represents the discrete-time intercept for measurement occasion u. Because $\boldsymbol{M}$ is conceptualized as the effect of instantaneous impulses $\boldsymbol{x}$, its discrete time form matches the general continuous time formulation in Eq. 1. $\boldsymbol{\xi}_u$ is the zero mean random error term for the processes at occasion u, which is distributed according to multivariate normal with covariance $\boldsymbol{Q}^*_{\Delta t_u}$. The recursive nature of the solution means that at the first measurement occasion $u = 1$, the system must be initialized in some way, with $\boldsymbol{A}^*_{\Delta t_u}\boldsymbol{\eta}_{u-1}$ replaced by $\boldsymbol{\eta}_{t_0}$ and $\boldsymbol{Q}^*_{\Delta t_u}$ replaced by $\boldsymbol{Q}^*_{t_0}$. Please find the functions relating the continuous time parameters to the discrete time-matrices for any time interval Δt_u in Appendix A.

Measurement Model

While non-Gaussian generalizations are possible, in the present work, the latent process vector $\boldsymbol{\eta}(t)$ has the linear measurement model:

$$\boldsymbol{y}(t) = \boldsymbol{\Lambda}\boldsymbol{\eta}(t) + \boldsymbol{\tau} + \boldsymbol{\varepsilon}(t) \quad \text{(Eq. 4)}$$

$\boldsymbol{y}(t) \in \mathbb{R}^{c}$ is the vector of manifest variables, $\boldsymbol{\Lambda} \in \mathbb{R}^{c \times v}$ represents the factor loadings, and $\boldsymbol{\tau} \in \mathbb{R}^{c}$ represents the manifest intercepts. The residual vector $\boldsymbol{\varepsilon} \in \mathbb{R}^{c}$ has covariance matrix $\boldsymbol{\Theta} \in \mathbb{R}^{c \times c}$.

Translation into a Structural Equation Modeling (SEM) Framework

The structural model to obtain continuous time parameters via SEM is as follows:

$$\boldsymbol{\eta} = \boldsymbol{B}\boldsymbol{\eta} + \boldsymbol{\xi} \quad \text{(Eq. 5)}$$

Here, elements of the latent process vector $\boldsymbol{\eta}$ are related to each other via matrix $\boldsymbol{B}$. The residual vector $\boldsymbol{\xi}$ has covariance matrix $\boldsymbol{\Psi}$. Given Eq. 4 and 5, the model-implied covariance matrix Σ (e.g., Bollen, 1989, p. 325) can be derived for parameter estimation.

Empirical Example: Transition from Primary to Secondary School

Sample

The data for the empirical example stemmed from the German National Educational Panel Study, Starting Cohort 2 (Blossfeld et al., 2011). We used data from waves 5 to 9 (i.e., Grades 3 to 7; years 2014 to 2019), yielding observations for N = 2,971 students over a period of five years and five measurements per student (one per grade). Because the transition from primary to secondary school in Berlin and Brandenburg takes place one year later than in all other German counties (Berlin/ Brandenburg: Grade 5 to 6, all other counties: Grade 4 to 5), students from these counties were excluded from the analysis (N = 94). Thus, the final sample was N = 2,877 students. Most students are observed in November and December of a school year; the minimum realized spread of measurement occasions was November to January in wave 5; the maximum realized spread was October to April in waves 6 and 9. Students' motivation was assessed by the same four questionnaire items in each wave (e.g., "I try hard, even when tasks are difficult") with answers ranging from 1 (completely disagree) to 4 (completely agree). A sum score was calculated by adding up the answers. The individual (i.e., person) means for motivation across measurement waves before the transition ranged from 4 points to 16 points (*M* = 13.518, *SD* = 1.850), the within-person standard deviations ranged from 0 points to 10 points (*M* = 1.589, *SD* = 1.427).

Model Specification

Drawing on previous substantive findings, we expected a) a drop in academic motivation after the transition from primary to secondary school, that b) persisted after the transition (up to Grade 7, where children were 12 years old) without reversing to its previous levels before the transition. In methodological terms, we thus specified a level change form for the intervention process in our example. Of course, other scenarios (e.g., a fade-out effect in the input) could be plausible as well, but for reasons of simplicity, we chose the level-change scenario in our present analyses. We did so by setting the intervention effect's drift parameter to zero ($\boldsymbol{A}_{22}$ = 0). All other parameters of interest (i.e., $\boldsymbol{A}_{11}$, $\boldsymbol{M}_{01}$, $\boldsymbol{\tau}$, $\boldsymbol{\Theta}$, $\boldsymbol{Q}_{11}$) were estimated freely. The specific time point of the transition was set to August 2016 (t_{22}), which marked the end of Grade 4.

Parameter Estimates

Empirical estimates revealed a negative auto effect in the drift matrix ($\boldsymbol{A}_{11}$= -0.300). This implies that in the absence of other influences, academic motivation would always revert to a baseline. The average manifest level of motivation at t_0, that is, the manifest intercept $\boldsymbol{\tau}$, is $\boldsymbol{\tau}$ = 13.508. There were, however, substantial other influences, modeled by the additional latent intervention process of the transition from primary to secondary school, as well as by the system noise. The corresponding input effect $\boldsymbol{M}_{01}$= -0.290 shows that the transition indeed had a negative (and, because of its level change form defined by $\mathbf{A}_{22}$, long-term) effect on students' academic motivation. The diffusion term $\boldsymbol{Q}_{11}$ was estimated to be zero, which implied that in this special case, the model did not assume random fluctuations across the repeated measures. The CT parameters can be translated into a discrete time solution for any time interval Δt_u of interest via exponential transformations (Eq. 6-8, OSM, Appendix A). Figure 2 displays the model-implied average level of academic motivation across time as well as a random selection of students' empirical individual trajectories.

In the OSM, Appendix C, we insert the empirical parameters in Equations 3, 4, and 6, and present step-by-step how to calculate a manifest academic motivation time-series from the CT solution for an exemplary student. For discrete time intervals Δt_u = 12 months between measurements, the CT solution would translate into the discrete time autoregressive coefficient of AR(1) = 0.027 of academic motivation, and a decrease in motivation due to the transition from primary to secondary school of -1.088 scale score points 1 year (12 months) after the transition. In comparison to the average between-person SD of 1.850 scale points for motivation across measurement waves prior to the transition and the average within-person SD prior to the transition of 1.589 scale points, this can be regarded as a considerable effect. Figure 3 depicts the CT function for the AR(1) parameters of academic motivation over time, that is, how autoregressive coefficients vary as a function of time intervals Δt_u.

Next, this empirical solution will serve as the true parameters for a simulation set-up. The simulation study's objective is to evaluate whether and how individual variation in time intervals may benefit the estimation of average intervention effects over time.

A Simulation with Conditions Based on the Empirical Example

First, we simulated a CT dynamic model based on our empirical model. Second, we sampled discrete time observations from the CT model using seven different interval conditions. All interval conditions were chosen with potential real-life sampling interval decisions of panel studies such as the NEPS in mind. Third, we fitted a CT model to 1,000 generated datasets under each condition.

Method. A continuous time model as defined in Equation 3 was simulated with drift matrix $\boldsymbol{A} = \begin{pmatrix} -0.300 & 1 \\ 0 & -0.000 \end{pmatrix}$, continuous time input effect $\boldsymbol{M} = \begin{pmatrix} 0 \\ -0.290 \end{pmatrix}$, continuous time intercept vector $\boldsymbol{b} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$, continuous time dynamic error covariance matrix $\boldsymbol{Q} = \begin{pmatrix} 0 & 0 \\ 0 & 0 \end{pmatrix}$, initial mean vector $\boldsymbol{\tau}$ =13.508, and initial error variance $\boldsymbol{\Theta} = 3.486$ (Table 1). Data were generated for N = 2,877 students and 5 time points each (equivalent to the NEPS data example). The interval conditions were chosen such that each measurement point of an individual represented a measurement occasion in a specific grade. Thus, although the individual discrete time intervals sometimes vary dramatically, the compatibility with grade-wise assessment cycles is ensured. Just as in the original NEPS data, t_0 is set to November of Grade 3, when the first empirical observation of the time series took place. Each grade is considered ending in August of a given year, with the new grade starting in September.

Figure 4 represents the resulting distributions of measurement occasions over time under each interval condition. Condition 1 serves as the 'ideal' situation where every student is sampled every month across 5 grades; Condition 2 represents the other 'extreme' ideal standardization case in which everyone is measured once in each grade in the exact same month. In all remaining conditions, intervals were chosen to be individually varying. Conditions 3, 4 and 5 were drawn from normal distributions centered at 12 months, with different standard deviations – 0.5, 0.75, and 2 months, respectively. In Conditions 6 and 7, intervals are sampled from uniform distributions, with Condition 6 possessing a lower limit of 10 months and an upper limit of 14 months between measurements ($\Delta t_{i,j}$ = U ~ (10, 14)), and Condition 7 sampled so that students are randomly assigned a month for their measurement occasion in each of the five grades, U_{grade} ~ (1, 12). Furthermore, in Conditions 2 – 4, t_0 is the same for every student ($t_0 = 1$), in Conditions 5 – 7, t_0 varies between students. In Conditions 5 and 6, a normal distribution of t_0 around $t_0 = 1$ (values varying between $t_0 = 0\ and\ t_0 = 2$) was assumed in order to introduce higher initial levels of variation in time intervals in comparison to Conditions 2 – 4.

Ultimately, Conditions 1- 7 allow us to compare how different degrees of variation in time intervals succeed in recovering the true underlying (i.e., generating) CT process. We applied the following evaluation criteria to the simulated datasets: Relative bias and mean squared error (MSE) were used to evaluate the point estimates' precision; 95% coverage (i.e., the proportion of 95% CIs across replications in which the population value was included in the interval) and SE/SD ratio (i.e., the average SE estimate/ SD of the estimates of the replications) were used to evaluate how well the population parameter's variability was recovered; power indicated the proportion of replications in which a non-null population effect was detected as being non-null (see OSM, Appendix B for details). Relative bias should take values around 1.00 (range 0.90-1.10), MSE should take values close to 0.00, 95% coverage should take values around 0.95 (range 0.925-0.975), and the SE/SD ratio should be close to 1.00. No specific cut-off applies to acceptable power (nun-null detection rates), but higher values are better (McNeish, 2019; Schultzberg & Muthén, 2018). R version 4.1.1 (R Core Team, 2021) was used for data generation and the R package "ctsem" version 3.5.5 (Driver, Oud & Voelkle, 2017) for model estimation.

Results

How does the (individual) variation in time intervals affect the recovery and precision of CT parameters? Table 1 shows the evaluation measures for auto effect $\boldsymbol{A}_{11}$ and input effect $\boldsymbol{M}_{01}$ for Conditions 1 to 7. Results on the evaluation measures for all CT parameters can be found in the OSM, Table A2. Most importantly, on the basis of our results from Conditions 1 to 7, we can conclude that a certain amount of variation helps the estimation and recovery of average intervention effects over time. In our study, those conditions with higher individual variation in time intervals (Conditions 5-7) offered better recovery of the true auto effect and input parameters than those with lower variation

(Conditions 2-4). As expected, the 'control' condition (1), with every student being measured every month of the sampling period, yielded essentially perfect results. Condition 2, with fixed intervals and only one measurement per year (Δt_j = 12), produced the most biased estimates for input and auto effects. All evaluation measures lay extremely outside of the acceptable ranges, both for point estimates precision (relative bias, MSE) and recovery of the population parameter's variability (95% Cov., SE/SD). Similarly, although power was considerably high with 0.868, it was the lowest across all conditions. Introducing only a little variation ($\Delta t_{i,j}$ = $N \sim$ (12, 0.5); i.e., 2 weeks in Condition 3) was still problematic with respect to MSE ($\boldsymbol{A}_{11}$: MSE= 4.201, $\boldsymbol{M}_{01}$: MSE= 3.103), 95% coverage ($\boldsymbol{A}_{11}$: 95% Cov = 0.800, $\boldsymbol{M}_{01}$: 95% Cov = 0.808), and SE/SD ($\boldsymbol{A}_{11}$: SE/SD = 0.020, $\boldsymbol{M}_{01}$: SE/SD = 0.022), but showed an improvement with respect to the median of the point estimates across 1,000 datasets ($\boldsymbol{A}_{11}$: Rel. Bias (Median) = 1.035; $\boldsymbol{M}_{01}$: Rel. Bias (Median) = 1.034). An increase of variation by only one additional week (SD = 0.75; i.e., 3 weeks in Condition 4) led to an improvement of all evaluation measures. In contrast to Conditions 2 and 3, Condition 4 was the first condition where the MSE was substantially nearer to zero ($\boldsymbol{A}_{11}$: MSE = 0.574, $\boldsymbol{M}_{01}$: MSE = 0.437), indicating that the bias and the standard error were small. Interestingly, although the precision of point estimates (relative bias, MSE) for drift and input parameters improved relatively quickly with the introduction of a little more variation in IVTs, it was not until Condition 5 ($\Delta t_{i,j}$ = $N \sim$ (12, 2)) that the variability of the true auto and input parameter estimates was recovered satisfactorily ($\boldsymbol{A}_{11}$: 95% Coverage = 0.959, SE/SD = 0.965; $\boldsymbol{M}_{01}$: 95% Coverage = 0.954, SE/SD = 0.968). Both subsequent conditions (6 -7) with higher degrees of IVTs also performed well. Conditions 5 and 6 showed fairly similar results, likely due to their similar realized spread of measurement occasions across the whole sampling period (Figure 4). The last condition (7) took a different sampling approach, with students randomly assigned to one of twelve months per grade, resulting in an equal number of measurement occasions per month. The average input and auto effect were recovered as well as in the previous two conditions, with all evaluation measures in the acceptable ranges. Condition 7 had the highest values for power across all conditions ($\boldsymbol{A}_{11}$: Power = 0.994, $\boldsymbol{M}_{01}$: Power = 0.994). To illustrate how these results may have come about, Figure 5 depicts the true CT intervention effect and shows how well measurement occasions resulting from Conditions 2, 6, and 7 might cover its evolution over time. It becomes apparent that Condition 2, with the fewest IVTs, can only capture fractions of the process over time, because it only takes one "snapshot" at exactly the same time each grade. On the other hand, Conditions 6 and 7 have considerably more individual variation in time intervals, and thus cover a broader range of time points across the measurement waves (grades).

Lastly, Table 2 presents the median of the point estimates (averages across 1,000 generated samples) of the CT parameters $\boldsymbol{A}_{11}$, $\boldsymbol{M}_{01}$, $\boldsymbol{\tau}$, $\boldsymbol{\Theta}$, $\boldsymbol{Q}_{11}$, and their respective standard errors under each condition. It also presents discrete time estimates $\boldsymbol{A}^{*}$ for time intervals of Δt_u = 12 months, and discrete time estimates for $\boldsymbol{M}$ at Δt_u = 12 months after the intervention.

Discussion

It was the goal of our study to show how IVTs can contribute to the estimation of average intervention effects over time. For a long time, longitudinal studies have aimed for equally spaced measurement intervals – however, especially in complex samples with many individuals, IVTs are the norm rather than the exception. Although IVTs are often perceived as harmful or unnecessary noise, we were able to demonstrate that we may benefit from IVTs in longitudinal research. To summarize, the results show some amount of individual variation within and between time intervals can improve the estimation of the average intervention effect, both with respect to point estimates and their sampling variability. Two tentative conclusions are as follows: First, the more individual variation within and between individuals across measurement waves, the more we can learn about the evolution of an intervention process across different time intervals (e.g., intervals of 12 months vs. 9 – 15 months). Second, naturally occurring (or planned) individual variation in time intervals can result in a greater realized spread of measurement occasions across the whole sampling period. Inferring from our results, in panel studies with a large *N*, such as the NEPS, the exact choice of IVT sampling distributions might be based on practical considerations. Parameter recovery was not solely dependent on a special IVT distribution (e.g., normal vs. uniform). One possibility may thus be that it is not a certain IVT distribution that matters, but rather that the whole sampling period is sufficiently covered with observations. This claim, however, needs to be investigated systematically in future studies.

IVTs, CT Models, and Staying Agile in an Ever-Changing World

In a world of increasing complexity and unforeseeable events, scientific research needs to stay agile. We need statistical tools that allow us to generate valid knowledge and recommendations for actions, even without a perfect study set-up. When we leverage CT models and IVTs when working with panel data, we obtain several advantages: First, panel studies offer a unique opportunity to study developmental change because they collect data on large, nationally representative samples of individuals (high *N*) repeatedly over time (Andreß, 2017). Without panel data, we might not be able to study the effects of planned or unplanned real-life events such as school transitions, social programs, financial crises, or lock-downs, because no alternative data would allow us to do so, both in terms of availability and data quality. Second, by using IVTs when working with such powerful data, we may be able to obtain significant estimation precision when evaluating the influence of real-life interventions. We can also work more efficiently in terms of resources by reusing existing data (Weston et al., 2019).

From a modeling point of view, by adopting a dynamic system perspective and a CT framework, each time point is simply one point in the continuous evolution of the system. When approximating the underlying path of a system over time via a CT function, we can thereafter easily choose the distances in time we want to make inferences about, according to our specific research question. For example, we could choose to know the parameter estimates for the development of academic motivation before or after an intervention if observations were Δt_u = 1, 6, 12, or 24 months apart. If we were to use discrete time models, we would have to set up a new study to investigate each of these time intervals (Voelkle et al., 2012). Yet, as with any modeling endeavor, due consideration should be given for how far beyond observed cases generalization and inference may be appropriate.

When Do IVTs Provide the Greatest Impact?

We picked a persistent level change form for our input effect in this example, assuming that academic motivation diminishes following the transition from primary to secondary school and remains low thereafter. Of course, depending on how an intervention effect is projected to evolve over time, other shapes of input effects are feasible. For example, if a level change is expected after an intervention but no assumptions are made about whether the effect will last, an initial level change followed by a fade-out shape may be more appropriate. Abenavoli (2019) described such an effect when investigating early childhood education programs, which have been shown to produce immediate positive impacts on children’s cognitive and social-emotional skills. Although participating children began kindergarten with more skills on average than their peers, their skills converged as children progressed through school. Other scenarios are also possible: Bisconti et al. (2004), for example, showed that damped linear oscillator processes could accurately characterize the grief process following the death of a spouse in elderly women. The widows' well-being was subject to frequent ups and downs, with an overall positive trend over time. Conceptually, the more complicated such input processes are, the more crucial it may be to incorporate IVTs when analyzing data. Figure 6 conceptually depicts a fade-out and an oscillating model for the measurement occasions of Condition 2 (no IVTs).

With a level change process like the one we studied, the effect of IVTs on average parameter estimates appeared to be rather small in absolute terms. Yet, even in our "simple" scenario, with no complex evolution of an intervention effect over time, the applied evaluation measures (relative bias, MSE, 95% coverage, SE/SD ratio, power) revealed that the amount of individual variation in time intervals made a difference. Thus, for more advanced cases of input effects, the simulation conditions in our study without (or with little) IVTs would likely not be able to capture the true input effect function, which would lead to even larger differences in parameter estimates (see e.g., Boker & Nesselroade, 2002; Voelkle & Oud, 2013). We thus expect our findings to be rather a "lower bound" for the benefit of integrating IVTs when modeling input effects using panel data.

IVTs and Estimation of Random Intervention Effects

Importantly, for reasons of simplicity, we assumed that an average intervention effect of the transition from primary to secondary school describes the population of students well. In many cases, however, individual differences, or individual reactions to the same intervention, might be the focus of interest. For instance, it might be the goal to identify students who are at risk of suffering a long-term loss in motivation due to a transition from school A to B, and at which point in time a well-placed intervention might help these children. Other examples could be that an intervention, such as a sudden lockdown, might affect students from different socio-economic backgrounds differently. Indeed, individual differences factors such as being female, having parents with higher academic interests, and SES were found to “buffer” the negative effect of transitioning from primary to secondary school (Dotterer et al., 2009; Evans et al., 2018).

To account for such differences, Driver and Voelkle (2018b) extended the CT structural equation modeling approach to accommodate random effects that depict that individuals may respond differently to a certain input process. It is now possible to estimate random effects distributions for all CT parameters, permitting individual variation in strength, persistence, and form of the process in question (e.g., academic motivation) and related intervention processes. With respect to the empirical example, this would imply that the transition from primary to secondary school could result in different input functions for the students, which is likely a more realistic assumption than the “average-fits-all” case. The same benefits of IVTs likely also apply to individual difference estimation, but future work should explicitly test this and examine the extent to which individual difference recovery may also be improved by leveraging IVTs.

Varying IVT Distributions, N, and Intervention Onsets in Future Simulation Studies

Comparing results across all simulation conditions, it became evident that the distributions of IVTs that resulted in a wide spread of measurement occasions across the year performed best with respect to evaluation measures. Although IVT distributions in Conditions 5, 6, and 7 differed in their original set-up – varying from a normal distribution to different kinds of uniform distributions, all of them performed equally well in recovering true parameter estimates and in their confidence intervals. This is an important insight for the following reason: Every large-scale assessment or panel study has its own characteristics and sampling challenges. For example, in educational research, sampling often has to happen in pre-defined school hours. Also, it might not be an easy task to sample as many students during their summer vacation as it is during the school year. Luckily, based on our results, we can see that the exact IVT sampling distribution may be based on practical considerations, as long as the time period in question (e.g., a school year, that is, every month of a time period of 12 months from September in a given year to August next year) is sufficiently covered with observations. Of course, a sampling approach that covers broader periods of time and allows for individual variation in time intervals across waves also makes sense if we do not exactly know when an event might occur. Future studies interested in optimal design decisions could investigate how different IVT configurations interact with sample size, a system's complexity (e.g., coupling, mediation), or the shape of input effects (e.g., oscillation, different time scales).

Limitations

IVTs and Patterns of Missingness

Importantly, IVTs in panel studies may result from different processes. Some individuals (e.g., adults in a panel survey) may select themselves to participate at an earlier or later time, while it may also be possible that the time of participation is set by some authority for all individuals (e.g., students in schools). Thus, in some cases, the IVTs may be considered to be dependent on some variables that are associated with the self-selection process (i.e., missing-not-at-random [MNAR] or missing-at-random [MAR]; Grund et al., 2021), whereas some IVTs can be considered to result from a purely random process (missing-completely-at-random [MCAR]). One core assumption of the presented approach on IVTs is that the sampling of measurement occasions is "exogenous", that is, that any observations that are missing from an equidistant sampling scheme are MCAR or MAR. In our example, we assumed that variability in measurement occasions was due to practical sampling limitations, and therefore unrelated to aspects of the students. In extensive panel studies like the NEPS, it is usually not possible to measure all participants at the same time, which results in natural individual variation of time intervals across measurement waves. Importantly, however, if the M(C)AR assumptions do not hold, inferences from the presented IVT approach should be made with caution and take into account how self-selection processes may affect the results.

Nested (Intervention) Effects

In complex surveys and large-scale assessments, data are usually clustered within different levels. For example, in the NEPS study, students are nested within classes, which are nested within schools. There are two important points resulting from this hierarchical structure: First, students within schools or classes are usually more similar to each other than students between schools or classes with respect to cognitive, socio-emotional, and socio-economic characteristics (Brunner et al., 2018; Dalane & Marcotte, 2022). If this similarity is not statistically accounted for, standard errors of the corresponding parameter estimates are likely underestimated. One possible way to address this is to adjust standard errors by means of a cluster-bootstrap procedure or robust estimates. In the present empirical example, for reasons of simplicity, we did not account for clustering. Thus, its standard errors should be interpreted with caution. Importantly, however, this only affects the substantive interpretation of the empirical example, but does not affect any of the results of the simulation study on IVTs (where data have not been simulated to be clustered). Second, it might be of interest to decompose the effects on different hierarchical levels, in order to differentiate between effects on the school or student level. This is usually done by multilevel modeling. Thus, introducing the multilevel context to modeling input effects in continuous time could be a promising future research endeavor.

CT Modeling Assumptions

In CT models, we assume that every manifest measurement in a time series relates to a continuous time function that “generates” each manifest score. If processes are expected to evolve continuously, this assumption has the advantage of both appropriately representing the processes, and of allowing us to derive discrete time parameters for any time scale (time intervals) we are interested in once the CT function is known – to the degree we trust the model and are willing to generalize. Here, we do not need equally-spaced measurement intervals, and found that it can even be useful if there is individual variation in intervals. If, on the other hand, the true underlying model of a construct is supposed to evolve in discrete time steps, then a discrete time model is a far better approximation. If the purpose is to compare academic achievement from one year to the next, it is crucial to set a specific reference date, and, to this effect, adopt strictly equal time intervals between measurements. Similarly, if we want to pick students who performed best over the previous years (e.g., by examining research questions on top performers), any deviation from equally-spaced measurement intervals may introduce noise and lead to a biased selection. As a result, different research questions require different models, and there is no one-size-fits-all solution.

Conclusion

Often, longitudinal studies aim for equal measurement intervals between observations. In practice, however, this is rarely achieved because of the reality of the measurement process, especially in the case of large-scale panel studies. In this article, it was our goal to examine how individually varying time intervals (IVTs) might benefit the estimation of intervention effects over time. We did so by introducing an empirical example of the German NEPS data, with the transition from primary to secondary school serving as a quasi-experimental intervention. In a subsequent simulation study on the basis of the empirical parameters, we drew on continuous time dynamic models to compare different degrees of individual variation in time intervals between measurement occasions. We found that some amount of individual variation within and between time intervals can improve estimation of the average intervention effect. Importantly, parameter recovery was not dependent on a special distribution of IVTs (e.g., normal vs. uniform) but rather that the time period in question was sufficiently covered with observations as a result of the individual variation. In short, we encourage learning from IVTs for the analyses of intervention effects.

References

Andreß, H.-J. (2017). The need for and use of panel data. *IZA World of Labor*. https://doi.org/10.15185/izawol.352

Archambault, I., Eccles, J. S., & Vida, M. N. (2010). Ability self-concepts and subjective value in literacy: Joint trajectories from Grades 1 through 12. *Journal of Educational Psychology*, *102*(4), 804–816. https://doi.org/10.1037/a0021075

Bisconti, T. L., Bergeman, C. S., & Boker, S. M. (2004). Emotional well-being in recently bereaved widows: A dynamical systems approach. *The Journals of Gerontology: Series B*, *59*(4), 158–167. https://doi.org/10.1093/geronb/59.4.P158

Blossfeld, H.-P., Roßbach, H.-G., & von Maurice, J. (Eds.). (2011). Education as a lifelong process: The German National Educational Panel Study (NEPS) [Special Issue]. Zeitschrift für Erziehungswissenschaft, 14.

Bollen, K. A., & Curran, P. J. (2006). *Latent curve models: A structural equation perspective.* Hoboken, NJ: Wiley.

Boker, S. M., & Nesselroade, J. R. (2002). A method for modeling the intrinsic dynamics of intraindividual variability: Recovering the parameters of simulated oscillators in multi-wave panel data. *Multivariate Behavioral Research*, *37*(1), 127–160. https://doi.org/10.1207/S15327906MBR3701_06

Brunner, M., Keller, U., Wenger, M., Fischbach, A., & Lüdtke, O. (2018). Between-school variation in students' achievement, motivation, affect, and learning strategies: Results from 81 countries for planning group-randomized trials in education. *Journal of Research on Educational Effectiveness*, *11*(3), 452–478. https://doi.org/10.1080/19345747.2017.1375584

Chouinard, R., Roy, N., Archambault, I., & Smith, J. (2017). Relationships with teachers and achievement motivation in the context of the transition to secondary school. *Interdisciplinary Education and Psychology*, *2*(1).

https://doi.org/10.31532/InterdiscipEducPsychol.2.1.001

Collins, L. M. (2006). Analysis of longitudinal data: The integration of theoretical model, temporal design, and statistical model. *Annual Review of Psychology*, *57*(1), 505–528. https://doi.org/10.1146/annurev.psych.57.102904.190146

Dalane, K., & Marcotte, D. E. (2022). The segregation of students by income in public schools. *Educational Researcher*, *51*(4), 245–254. https://doi.org/10.3102/0013189X221081853

Dotterer, A. M., McHale, S. M., & Crouter, A. C. (2009). The development and correlates of academic interests from childhood through adolescence. *Journal of Educational Psychology*, *101*(2), 509–519. https://doi.org/10.1037/a0013987

Driver, C. C., Oud, J. H. L., & Voelkle, M. C. (2017). Continuous time structural equation modeling with *R* Package **ctsem**. *Journal of Statistical Software*, *77*(5), 1–35. https://doi.org/10.18637/jss.v077.i05

Driver, C. C., & Voelkle, M. C. (2018a). Understanding the time course of interventions with continuous time dynamic models. In K. van Montfort, J. H. L. Oud, & M. C. Voelkle (Hrsg.), *Continuous time modeling in the behavioral and related sciences* (S. 79–109). Springer International Publishing. https://doi.org/10.1007/978-3-319-77219-6_4

Driver, C. C., & Voelkle, M. C. (2018b). Hierarchical Bayesian continuous time dynamic modeling. *Psychological Methods*, *23*(4), 774–799. https://doi.org/10.1037/met0000168

Eccles, J. S., Midgley, C., Wigfield, A., Buchanan, C. M., Reuman, D., Flanagan, C., & Iver, D. M. (1993). Development during adolescence. The impact of stage-environment fit on young adolescents' experiences in schools and in families. *The American Psychologist*, *48*(2), 90–101. https://doi.org/10.1037//0003-066x.48.2.90

Evans, D., Borriello, G. A., & Field, A. P. (2018). A review of the academic and psychological impact of the transition to secondary education. *Frontiers in Psychology*, *9*. https://www.frontiersin.org/article/10.3389/fpsyg.2018.01482

Flora, D. B., & Curran, P. J. (2004). An empirical evaluation of alternative methods of estimation for confirmatory factor analysis with ordinal data. *Psychological methods*, *9*(4), 466–491. https://doi.org/10.1037/1082-989X.9.4.466

Gottfried, A. E., Fleming, J. S., & Gottfried, A. W. (2001). Continuity of academic intrinsic motivation from childhood through late adolescence: A longitudinal study. *Journal of Educational Psychology*, *93*(1), 3–13. https://doi.org/10.1037/0022-0663.93.1.3

Grund, S., Lüdtke, O., & Robitzsch, A. (2021). On the treatment of missing data in background questionnaires in educational large-scale assessments: An evaluation of different procedures. *Journal of Educational and Behavioral Statistics*, *46*(4), 430–465. https://doi.org/10.3102/1076998620959058

Hasl, A., Voelkle, M., Kretschmann, J., Richter, D., & Brunner, M. (2022). A dynamic structural equation approach to modeling wage dynamics and cumulative advantage across the lifespan. *Multivariate Behavioral Research*, *0*(0), 1–22. https://doi.org/10.1080/00273171.2022.2029339

Liu, X. (2016). *Methods and applications of longitudinal data analysis*. London: Elsevier. https://doi.org/10.1016/C2013-0-13082-6

McArdle, J. J. (2009). Latent variable modeling of differences and changes with longitudinal data. *Annual Review of Psychology*, *60*(1), 577–605. https://doi.org/10.1146/annurev.psych.60.110707.163612

McArdle, J. J., Grimm, K., Hamagami, F., Bowles, R., & Meredith, W. (2009). Modeling life-span growth curves of cognition using longitudinal data with multiple samples and changing scales of measurement. *Psychological Methods*, *14*(2), 126–149. https://doi.org/10.1037/a0015857

McNeish, D. (2019). Two-level dynamic structural equation models with small samples.

Structural Equation Modeling: A Multidisciplinary Journal, *26*(6), 948–966. https://doi.org/10.1080/10705511.2019.1578657

Oud, J. H. L., & Delsing, M. J. M. H. (2010). Continuous time modeling of panel data by means of SEM. In K. van Montfort, J. H. L. Oud, & A. Satorra (Hrsg.), *Longitudinal research with latent variables* (S. 201–244). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-11760-2_7

Ram, N., & Gerstorf, D. (2009). Time-structured and net intraindividual variability: Tools for examining the development of dynamic characteristics and processes. *Psychology and aging*, *24*(4), 778–791. https://doi.org/10.1037/a0017915

Schultzberg, M., & Muthén, B. (2018). Number of subjects and time points needed for multilevel time-series analysis: A simulation study of dynamic structural equation modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, *25*(4), 495–515. https://doi.org/10.1080/10705511.2017.1392862

Sterba, S. K. (2014). Fitting nonlinear latent growth curve models with individually varying time points. *Structural Equation Modeling: A Multidisciplinary Journal*, *21*(4), 630–647. https://doi.org/10.1080/10705511.2014.919828

Verbeke, G., Fieuws, S., Molenberghs, G., & Davidian, M. (2014). The analysis of multivariate longitudinal data: A review. *Stat Methods Med Res, 23*(1), 42–59. doi:10.1177/0962280212445834

Voelkle, M. C., Gische, C., Driver, C. C., & Lindenberger, U. (2018). The role of time in the quest for understanding psychological mechanisms. *Multivariate Behavioral Research*, *53*(6), 782–805. https://doi.org/10.1080/00273171.2018.1496813

Voelkle, M. C., & Oud, J. H. L. (2013). Continuous time modelling with individually varying time intervals for oscillating and non-oscillating processes: Continuous time modelling. *British Journal of Mathematical and Statistical Psychology*, *66*(1), 103–126. https://doi.org/10.1111/j.2044-8317.2012.02043.x

Voelkle, M. C., & Oud, J. H. L. (2015). Relating latent change score and continuous time models. *Structural Equation Modeling: A Multidisciplinary Journal*, *22*(3), 366–381. https://doi.org/10.1080/10705511.2014.935918

Voelkle, M. C., Oud, J. H. L., Davidov, E., & Schmidt, P. (2012). An SEM approach to continuous time modeling of panel data: Relating authoritarianism and anomia. *Psychological Methods*, *17*(2), 176–192. https://doi.org/10.1037/a0027543

Weston, S. J., Ritchie, S. J., Rohrer, J. M., & Przybylski, A. K. (2019). Recommendations for increasing the transparency of analysis of preexisting data sets. *Advances in Methods and Practices in Psychological Science*, *2*(3), 214–227. https://doi.org/10.1177/2515245919848684

Zeedyk, M. S., Gallacher, J., Henderson, M., Hope, G., Husband, B., & Lindsay, K. (2003). Negotiating the transition from primary to secondary school: Perceptions of pupils, parents and teachers. *School Psychology International*, *24*(1), 67–79. https://doi.org/10.1177/0143034303024001010

Zyphur, M. J., Voelkle, M. C., Tay, L., Allison, P. D., Preacher, K. J., Zhang, Z., Hamaker, E. L., Shamsollahi, A., Pierides, D. C., Koval, P., & Diener, E. (2020). From data to causes II: Comparing approaches to panel data analysis. *Organizational Research Methods*, *23*(4), 688–716. https://doi.org/10.1177/1094428119847280

Tables

Table 1.

Evaluation measures for Conditions 1 – 7

	True Effect	Estimate (Mean)	Estimate (Median)	Rel. Bias (Mean)	Rel. Bias (Median)	MSE	95% Cov.	SE/SD	Power
C1: $\Delta t_j = 1$									
Auto effect (A_{11})	-0.300	-0.299	-0.299	0.998	0.998	0.000	0.945	1.002	0.996
Input effect (M_{01})	-0.290	-0.289	-0.290	0.998	0.999	0.000	0.950	1.004	0.996
C2: $\Delta t_j = 12$									
Auto effect (A_{11})	-0.300	-2.034	-0.339	**6.789**	**1.131**	**8.007**	**0.698**	**0.019**	0.868
Input effect (M_{01})	-0.290	-1.774	-0.327	**6.116**	**1.129**	**5.880**	**0.701**	**0.020**	0.868
C3: $\Delta t_{i,j} = N \sim (12, 0.5)$									
Auto effect (A_{11})	-0.300	-1.143	-0.310	**3.814**	1.035	**4.201**	**0.800**	**0.020**	0.971
Input effect (M_{01})	-0.290	-1.012	-0.300	**3.489**	1.034	**3.103**	**0.808**	**0.022**	0.971
C4: $\Delta t_{i,j} = N \sim (12, 0.75)$									
Auto effect (A_{11})	-0.300	-0.438	-0.300	**1.461**	1.000	0.574	**0.920**	**0.049**	0.989
Input effect (M_{01})	-0.290	-0.408	-0.290	**1.407**	0.999	0.437	**0.918**	**0.053**	0.989
C5: $\Delta t_{i,j} = N \sim (12, 2)$									
Auto effect (A_{11})	-0.300	-0.303	-0.298	1.011	0.995	0.002	0.959	0.965	0.954
Input effect (M_{01})	-0.290	-0.292	-0.287	1.008	0.990	0.002	0.954	0.968	0.955
C6: $\Delta t_{i,j} = U \sim (10, 14)$									
Auto effect (A_{11})	-0.300	-0.302	-0.299	1.007	0.997	0.002	0.937	0.940	0.964
Input effect (M_{01})	-0.290	-0.291	-0.289	1.005	0.997	0.002	0.940	0.952	0.964
C7: $U_{grade} \sim (1, 12)$									
Auto effect (A_{11})	-0.300	-0.306	-0.300	1.017	1.001	0.003	0.928	0.912	0.994
Input effect (M_{01})	-0.290	-0.294	-0.289	1.015	0.994	0.002	0.939	0.913	0.994

Note. Results based on 1,000 generated datasets each. Rel. Bias = Relative Bias; MSE = Mean Squared Error; 95% Cov = 95% Coverage; SE/SD = Standard error/ standard deviation. The True Effect denotes the population effect; Estimate (Mean) and Rel. Bias (Mean) refer to the mean of the point estimates across 1,000 datasets; Estimate (median) and Rel. Bias (Median) refer to the median of the point estimates across 1,000 datasets. Measurement intervals are either constant between individuals (C1, C2), or individually varying (C3-C7). Bold font indicates a deviation from the acceptable ranges of the evaluation measures. Please find a complete list of results with diffusion parameters, manifest intercepts and measurement errors in the OSM (Table A1).

Table 2.

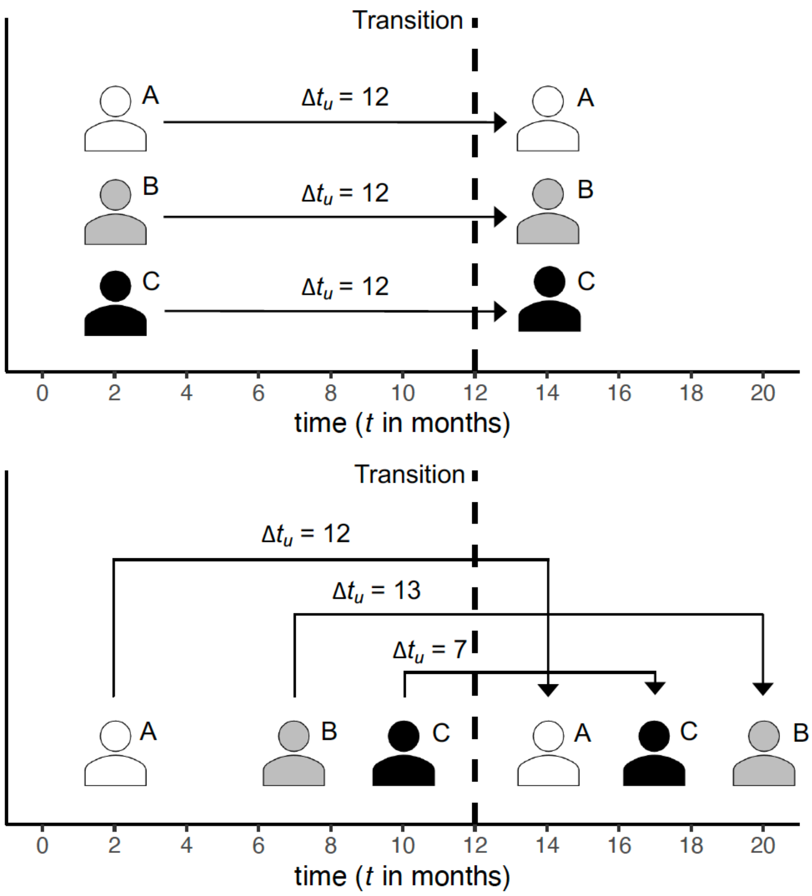
Mean and SE for discrete and continuous time parameters of the Fixed Effect Level Change Model under Conditions 1-7.

	Discrete Time Analysis				Continuous Time Analysis									
	$\boldsymbol{A}^{*}_{\Delta t_u=12}$		$\boldsymbol{M}_{\Delta t_u=12}$		Auto effect ($\boldsymbol{A}_{11}$)		Input effect ($\boldsymbol{M}_{01}$)		Diffusion ($\boldsymbol{Q}_{11}$)		Manifest intercept ($\boldsymbol{\tau}$)		Measurement error ($\boldsymbol{\Theta}$)	
	Est	SE	Est	SE	Est	SE	Est	SE	Est	SE	Est	SE	Est	SE
Empirical NEPS data	0.027	0.057	-1.088	0.338	-0.300	0.094	-0.290	0.090	0.000	0.000	13.508	0.028	3.486	0.058
Simulated Data														
C1: $\Delta t_j = 1$	0.028	0.005	-1.091	0.049	-0.299	0.014	-0.290	0.013	0.000	0.000	13.508	0.007	3.483	0.013
C2: $\Delta t_j = 12$	0.017	0.011	-1.118	0.133	-0.339	0.042	-0.327	0.039	0.173	0.120	13.507	0.025	3.260	0.116
C3: $\Delta t_{i,j} = N \sim (12, 0.5)$	0.024	0.014	-1.098	0.128	-0.310	0.037	-0.300	0.035	0.054	0.056	13.507	0.025	3.402	0.072
C4: $\Delta t_{i,j} = N \sim (12, 0.75)$	0.027	0.015	-1.088	0.131	-0.300	0.037	-0.290	0.035	0.011	0.014	13.507	0.024	3.444	0.046
C5: $\Delta t_{i,j} = N \sim (12, 2)$	0.028	0.019	-1.083	0.151	-0.298	0.043	-0.287	0.040	0.000	0.000	13.507	0.024	3.461	0.042
C6: $\Delta t_{i,j} = U \sim (10, 14)$	0.028	0.017	-1.087	0.143	-0.299	0.040	-0.289	0.038	0.000	0.000	13.506	0.024	3.462	0.042
C7: $U_{grade} \sim (1, 12)$	0.027	0.021	-1.085	0.169	-0.300	0.048	-0.289	0.045	0.001	0.002	13.508	0.024	3.454	0.043

Note. Results based on median of 1,000 generated datasets each. $\boldsymbol{A}^{*}_{\Delta t_u=12}$ = Discrete-time first level autoregressive coefficient with Δt_u= 12 months between measurement occasions; $\boldsymbol{M}_{\Delta t_u=12}$ = Discrete-time intervention effect in scale points of academic motivation Δt_u= 12 months after the transition from primary to secondary school; Est = Estimate; SE = Standard error. Simulated measurement intervals are either constant between individuals (C1, C2), or individually varying (C3-C7).

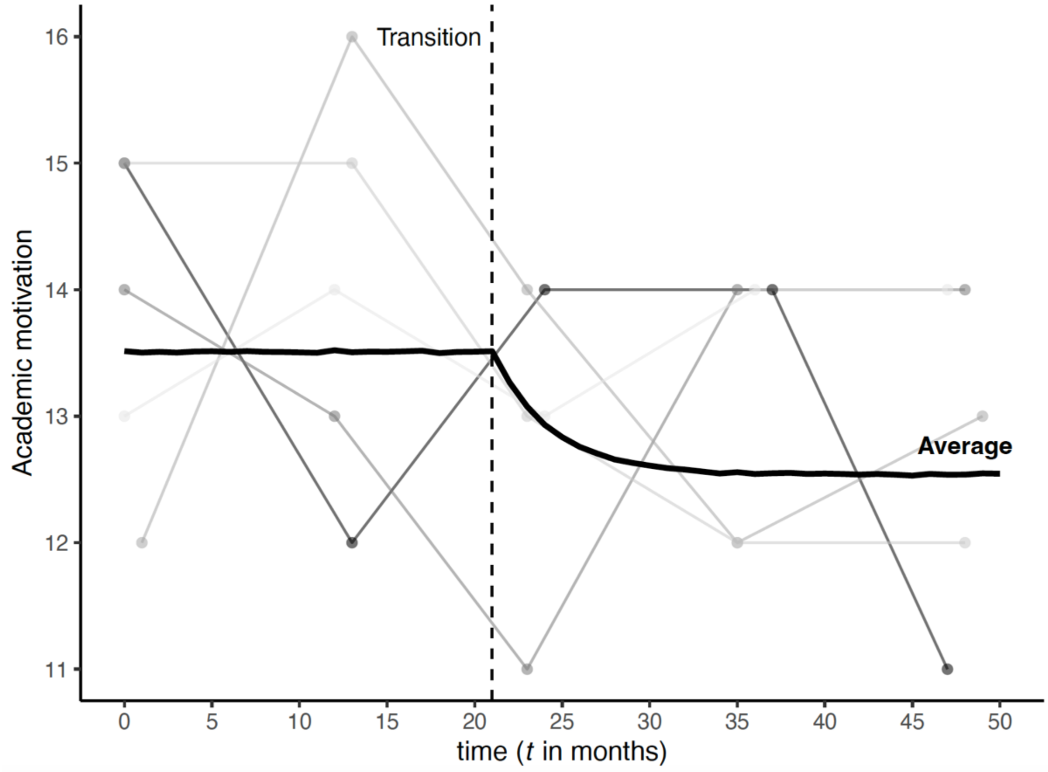
Figures

Figure 1



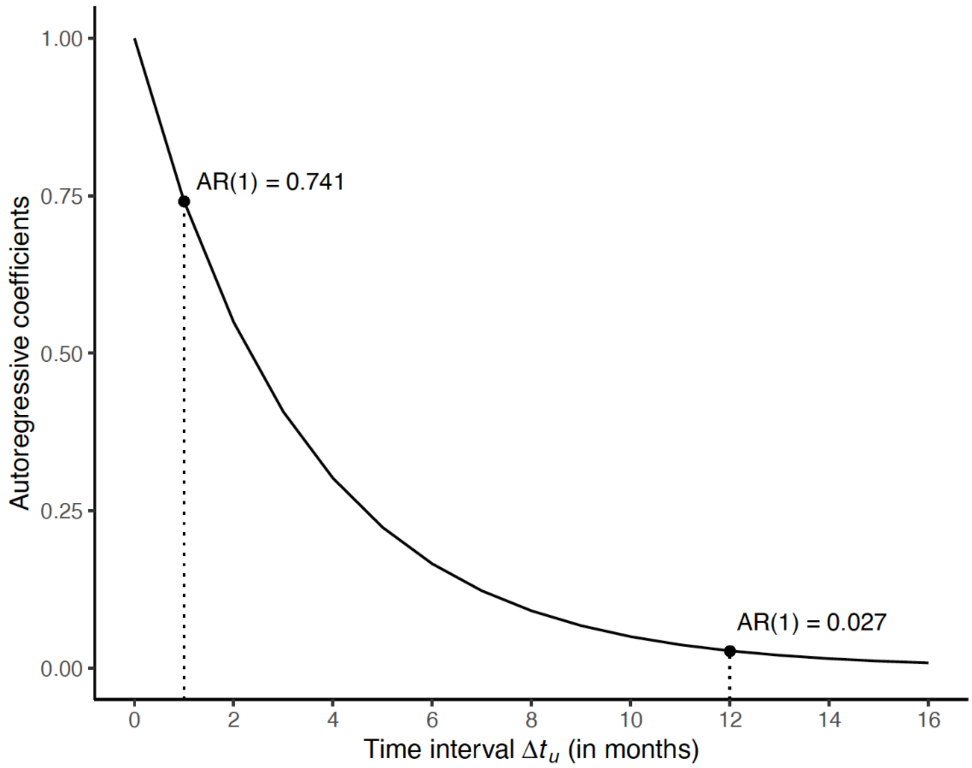
Note. Repeated measurement occasions t_1 and t_2 of three student exemplars: A, B, and C. The dashed line at t_u =12 represents the time point of an intervention (i.e., the month of the transition from primary to secondary school). In the upper panel, all students are surveyed at t_1 = 2 and again at t_2 = 14. In the lower panel, students A, B, and C are measured at different time points t at both measurement occasions. Therefore, the time-intervals (Δt) between the two measurement occasions vary between the individuals and cover different periods of time before the onset of the transition as well as afterwards.

Figure 2



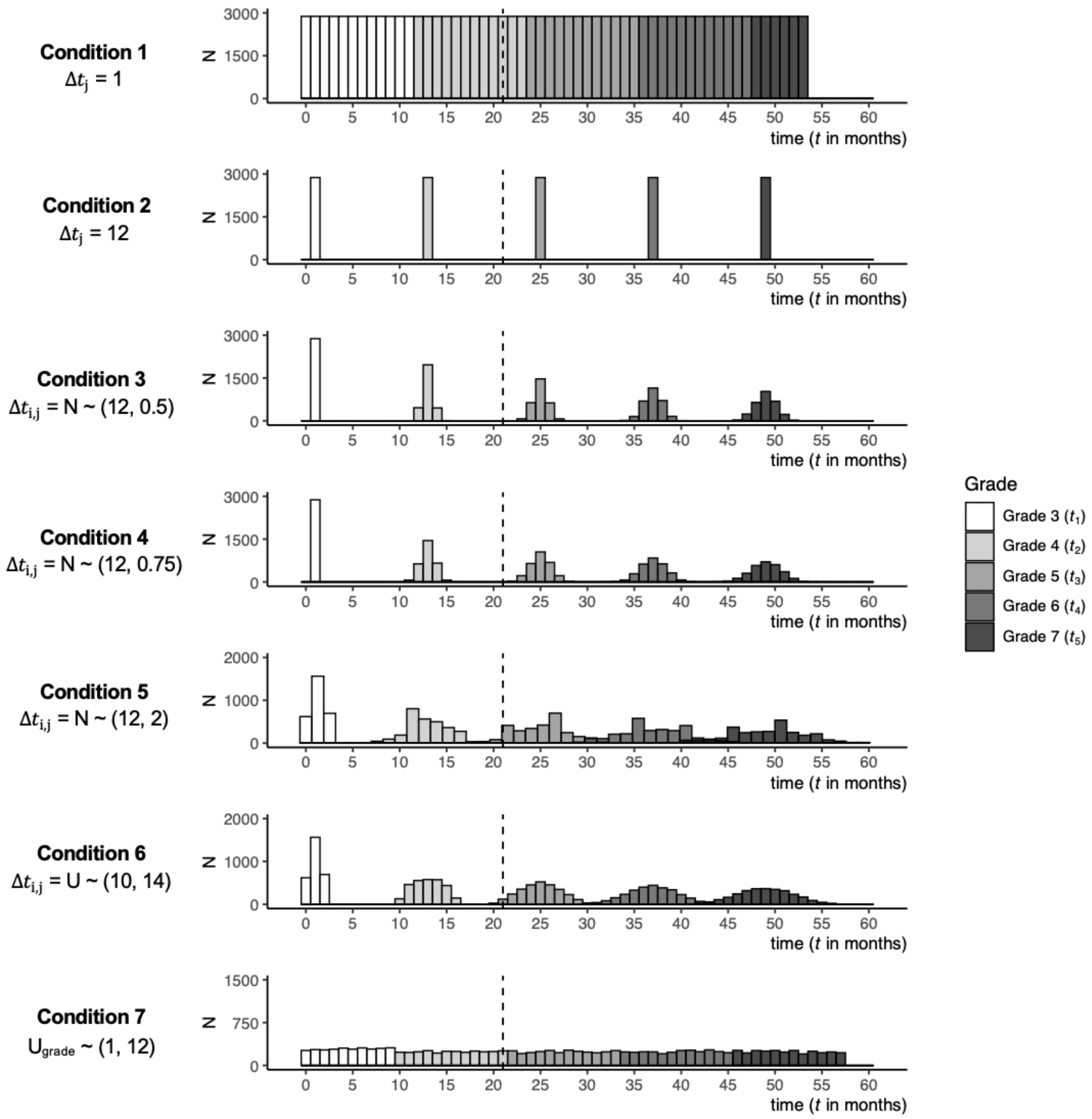
Note. Empirical trajectories of academic motivation of five exemplary students from the German National Educational Panel Study, Starting Cohort 2. The dashed line at t_u = 21 (corresponding to August 2016) represents the time point of the transition from primary to secondary school. The bold line represents the model-implied average expected values of academic motivation as a function of time. Academic motivation drops considerably after the transition and stays at a new lower level afterwards.

Figure 3



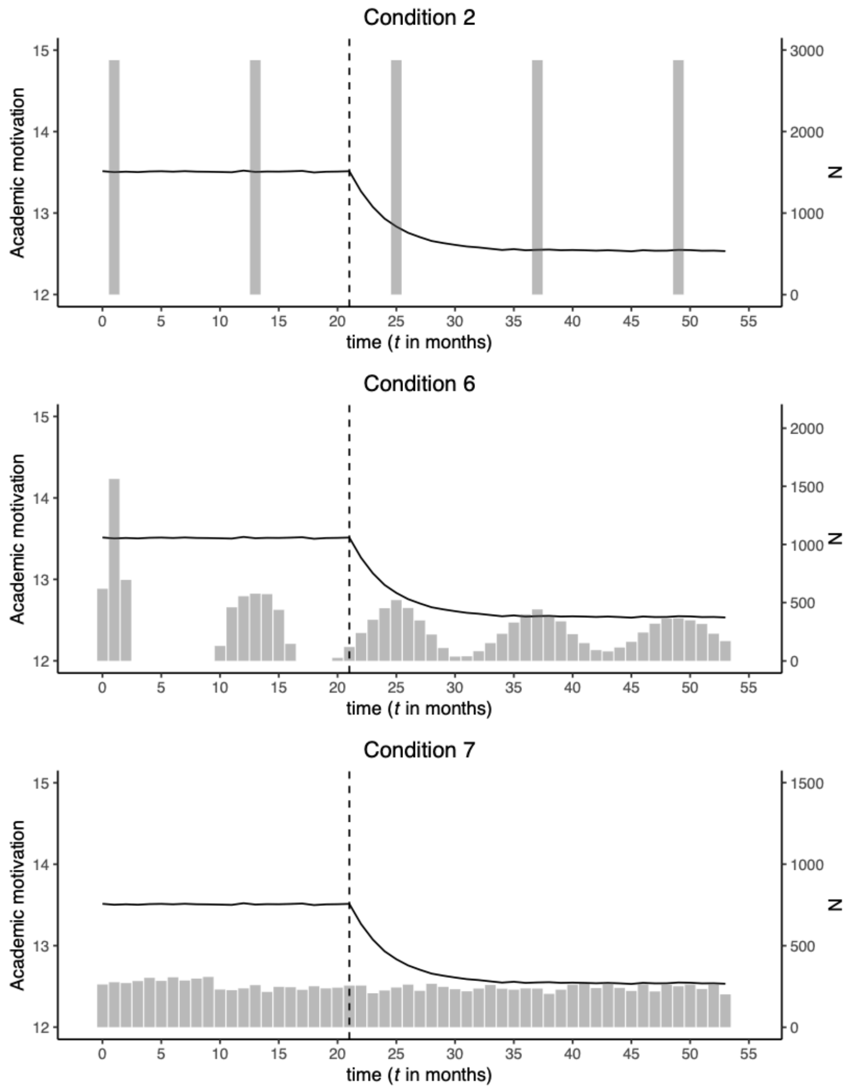
Note. Autoregressive parameters of academic motivation as a function of the time interval between observations. The points on the CT function represent discrete time parameters for time intervals of Δt = 1 month and Δt = 12 months. They differ in absolute values due to different time intervals between measurements, but stem from the same underlying continuous time function.

Figure 4



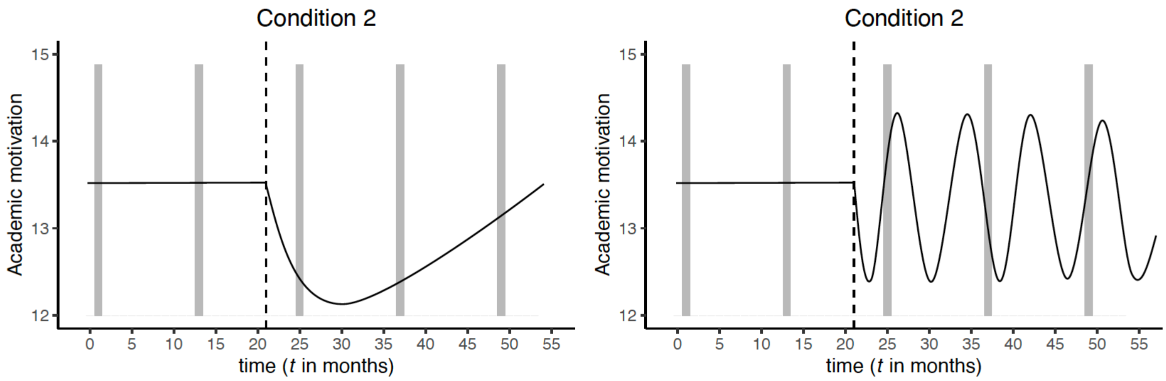
Note. Distributions of measurement occasions resulting from simulation conditions 1 – 7. Time *t* is given in months. t_u= 0 represents November 2014, t_u = 60 represents November 2019. The dashed line at t_u = 21 represents the time point of the transition from primary to secondary school. Conditions 1 and 2 show fixed measurement intervals *j* between individuals, Conditions 3 to 7 display varying degrees of variation in time intervals for each individual *i* and each interval *j* across Grades 3 to 7. In conditions 2 – 7, each student is measured once each grade, resulting in five repeated measurement occasions (t_u= t_1 to t_5). The total *N* of 2,877 students per measurement occasion stays the same in conditions 2- 7.

Figure 5



Note. Exemplary distributions of measurement occasions from Grade 3 to 7 resulting from conditions 2, 6, and 7 plotted against the true model-implied average trajectory of academic motivation over time. Time *t* is given in months, the dashed line at t_u = 21 marks the transition to secondary school. Under condition 2, students are measured once a year at the same time (time intervals *j* fixed). In conditions 6 and 7, time intervals *j* vary between students *i*. From a visual inspection, it becomes apparent that the latter two scenarios result in a greater coverage of the time period before and after the transition with observations. This most likely explains the good performance in recovering average intervention effects in condition 6 and 7 in comparison to condition 2.

Figure 6



Note. Exemplary fade-out and oscillating intervention processes under measurement occasions of condition 2 without individual variation in time intervals. The more complex such input processes become, the more helpful it may be to incorporate IVTs while analyzing data in order to recover the actual shape of the input effects.

5

General Discussion

5 General Discussion

The objective of this doctoral thesis was to study developmental change across the lifespan within the Historical Changes in Developmental Contexts (HIDECO) framework. Its main substantive contributions encompassed the questions of how adolescent skills and parental SES influenced vital life outcomes in adulthood, and how changes in the socioeconomic environment might have affected such relationships over time (Study I). Furthermore, the proposition and presence of cumulative advantage processes in lifespan wage development were examined. In investigating strict CA processes, the influence of adolescent skills and parental SES for initial wage levels and wage growth rates across the lifespan were evaluated (Study II). The dissertation's main methodological contributions encompassed the proposition of a statistical framework, dynamic structural equation models (DSEM), to operationalize and empirically test CA processes (Study II). It furthermore assessed the role of individually varying measurements and time intervals between observations in estimating effect sizes in panel studies, and demonstrated how individually varying time intervals and continuous time dynamic models can help with the examination of real-life intervention effects for developmental processes (Study III). A key strength of this dissertation is that the results of all three studies are based on high-quality, representative panel datasets (NLSY-79, NLSY-97, NEPS), which are some of the most reliable databases to examine individuals' development over the lifespan to date. The thesis further approaches the specified research questions from an innovative and contemporary standpoint by utilizing a wide variety of up-to-date interdisciplinary statistical approaches and a simulation study to examine developmental change.

The general discussion of the thesis will be structured as follows: First, I will first provide a summary of the results organized by the five research questions of this thesis. Secondly, I will discuss substantive and methodological issues that are derivates of Studies

I, II, and III, and are relevant to the presented research strands of this dissertation. The third part will focus on strengths and limitations of the present thesis, and will discuss directions for future research. It will also provide suggestions for how the HIDECO framework might be extended based on the current results. The fourth and last part of the General Discussion will concentrate on implications for policy and practice that can be derived from Studies I to III.

5.1 Summary of the results

5.1.1 Research Questions 1, 2, and 4: Predictive utilities of IQ, GPA, and socioeconomic background across ontological and historical time

Research question 1: How have historical changes in the socioeconomic environment in the 20th century affected the extent to which adolescents' intelligence, grade point average, and socioeconomic background could predict key life outcomes in adulthood?

Research question 2: Did historical changes affect relationships between adolescent characteristics and adult life outcomes differently depending on the individual's location on the outcome distribution?

Research question 4: To what extent do individual differences in individuals' adolescent intelligence, grade point average, socioeconomic status, and adult highest levels of education predict differential initial wage levels and wage growth rates across the lifespan?

Taken together, results from Study I and II showed that adolescent cognitive skills (that is, IQ and grade point average), parental socioeconomic background, and adult educational attainment were important predictors for later life outcomes. First, in Study I, IQ, GPA, parental socioeconomic background, and educational attainment substantially and positively predicted levels of educational attainment, income, occupational prestige, and physical health across a period of 20 years. Second, these relationships reproduced across different birth cohorts, specifically one born in the early 1960s and another born in the early 1980s. Furthermore, cognitive skills in the form of adolescent grade point average gained in importance for the later cohort. This could suggest a greater gatekeeping function of grades in later cohorts where competition in all aspects of life, such as college admissions and labor market entry, was on the rise. In comparing effect sizes of skills and socioeconomic background, it became apparent that, in most cases, IQ was the most impactful predictor of later life outcomes, followed by GPA and parental SES. This pattern also reproduced across different birth cohorts. Third, adolescent IQ, GPA, and SES had positive effects on all quantile values of the respective life outcome distributions (conditional on IQ, GPA, and parental SES; see Wenz, 2005). Fourth, akin to Study I, Study II investigated the effect of adolescent IQ, GPA, and parental SES as one part of its research questions. Importantly, Study II also included (adult) highest levels of education as predictor. Investigating the notion of cumulative advantages and wage inequality in greater detail, results indicated that adolescent IQ and highest educational achievement positively predicted both initial wage levels and wage growth rates across the lifespan. Again, in terms of effect size, IQ was the biggest predictor of wage and wage development. In sum, adolescent skills are important predictors of vital life outcomes with respect to both ontological time and historical time.

5.1.2 Research Question 3: Dynamic structural equation models as a versatile framework to model wage dynamics and cumulative advantage across the lifespan

Research question 3: How can the theoretical mechanism of cumulative advantages be operationalized and translated into a statistical framework in order to make it testable?

Taken together, Study II demonstrated that a statistical framework to operationalize (strict) cumulative advantage (CA) processes had to encompass three key features. First, it had to be able to include an autoregressive (i.e., dynamic) term that could be used to determine the accumulation rate of wages (i.e., their growth rates) over time. Second, unlike traditional time-series models, which typically include only a single time series, the framework needed to be multivariate in order to be able to include multiple time series, one for each panel participant. Third, it had to be able to incorporate random effects parameters to allow for individual differences in wage levels and growth rates, as well as exogenous variables to be included as covariates to explain the resulting heterogeneity. Dynamic structural equation models (DSEM), as proposed by McArdle (1988, 2007) and Hamaker et al. (2018) incorporate all these commodities. When applying DSEM to wage time series of the NLSY, we found evidence for growing population inequality, that is, growing levels of between-person variance in wages over time. Only a small fraction of individuals (0.5% of the sample), however, revealed strict CA in wages, that is, exponential wage growth (AR coefficient > 1) across their working lives. Most wage trajectories had logarithmic shapes, indicating a sharp increase in wage growth early in a person's career that then plateaued, resulting in an equilibrium level. Individual differences in wage levels at labor market entry and subsequent wage growth were primarily predicted by adolescent IQ and educational levels at labor market entry.

5.1.3 Research Question 5: Individually varying time intervals and the estimation of intervention effects over time

Research question 5: Can individually varying time intervals (IVTs) between measurement occasions in panel studies help us learn about the evolution of intervention effects over time?

Taken together, results from Study III revealed that some amount of individual variation in time intervals in panel studies may actually benefit the estimation and recovery of intervention effects over time. Comparing the evaluation measures across 1,000 simulated datasets in each of the seven conditions that gradually increased in their degree of individual variation in time intervals, conditions with more IVTs were able to recover the true intervention parameters better. Whereas point estimates (as evaluated by relative biases and MSE) could be recovered with less IVTs, the estimation of the variability of the estimates (95% coverage, average *SE*/*SD* ratio) in particular benefitted from more individual variation in time intervals. Although statistical power was relatively high in all conditions, it was lowest in the most restrictive condition without any variation at all, and highest in the least restrictive condition with high degrees of IVTs. Importantly, these results contradict the "common wisdom" of seeking equally spaced measurements for all individuals in a longitudinal study, and instead point to the possible benefits of IVTs. Furthermore, based on previous literature, we assumed a persistent level change form for the intervention effect of the transition from primary to secondary school on academic motivation. Such a persistent level change effect is a rather simple input function. Given we were able to find differences in the ability to recover parameters by IVTs even with such a simple effect, it is highly probable that IVTs can provide even greater beneficial effects for more complex intervention effect shapes (e.g., fade-out or oscillation).

5.2 Overarching discussion points

5.2.1 The importance of skills and socioemotional characteristics in the 21st century

Study I revealed the crucial importance of cognitive skills, measured by IQ and grade point average (GPA), for vital life outcomes such as health and occupation across the lifespan. In light of the HIDECO framework, we may differentiate between ontogenetic and historical time when we consider the influence of IQ and grade point average. In ontogenetic time— that is, with respect to developmental changes that evolve across an individual's lifespan— IQ and grade point average were predictive of positive outcome levels (Study I and II) as well as growth rates (Study II) with respect to wages. Although parental SES was a substantial predictor for most outcomes, IQ and GPA outperformed it with respect to many outcomes, such as education, income, and occupational prestige. In Study I, I argued how major changes such as increasing population density, trickle-down economics, and changes in the labor market towards high-skilled labor affected the relationship between adolescent IQ, grade point average, parental socioeconomic background, and later adult life outcomes in the 20th century. I will now address possible trends and their implications for skill development in the 21st century.

The OECD identifies several "megatrends" that are expected to continue throughout the next decades. These include globalization, digitalization, population aging, and migration (OECD, 2019a). Globalization focuses on the emergence of global value chains that allow different parts of production processes to be performed in different geographical locations. Especially in combination with digitalization, the automation of jobs and tasks that require lower-level, routine skills will profoundly transform work environments and might lead to job losses in well-developed economies (Lloyd & Payne, 2019; OECD, 2016, 2019a). Longevity and better health at older ages will allow individuals to participate longer in the workforce; at the same time, the growing needs of the elderly will likely lead to an increased demand for healthcare services and an increased need for interpersonal competencies (OECD, 2019a; World Health Organization, 2015). Lastly, migration flows are likely to increase in the future due to massive demographic and economic imbalances among countries and regions of the world. This increased mobility has the potential to attract new talent and mitigate the effects of aging populations, but also requires a skilled educational system that fosters rapid integration (OECD, 2019a).

The main implications of these megatrends for changing skill needs are an increased demand for higher, non-routine skills and for different sets of skills. This is also related to the need to transition from a front-loaded education system (in which students complete secondary or tertiary education at young ages) to lifelong learning (OECD, 2019a, 2021). Numerous studies, particularly on digitalization, have looked at the critical cognitive skills required to succeed in times of "digital transition.” First are strong technical skills. As technology advances at a quick pace, it is becoming increasingly important for individuals to have strong technical abilities in order to properly use and manage digital tools, systems, and artificial intelligence. This comprises coding and programming language proficiency, as well as a thorough understanding of computer hardware and software (OECD, 2022; van Laar et al., 2017, 2020). Second, data interpretation and analysis will become more vital. This includes the capacity to apply statistical software and tools to make sense of large datasets (e.g., panel data, "big data"), as well as the ability to clearly and effectively explain findings and insights (OECD, 2022). Third is enhanced creativity and problem-solving: Neubert et al. (2015) identify transversal skills such as complex and collaborative problem solving as critical for the workplace of the 21st century. Non-routine and interactive tasks that require active problem solving and collaboration with others are typical for new developments in the working world (Autor et al., 2015; Neubert et al., 2015; OECD, 2021).

Importantly, 21st century “skills” include not only cognitive skills, but also a wide spectrum of socioemotional characteristics. Collaboration and communication between people and within teams are becoming increasingly vital in digitalized workplaces (OECD, 2019a, 2019b; Trenerry et al., 2021). Digitalization has made it simpler to work from different geographical places and communicate data in real-time; nonetheless, this distance in working environments necessitates that individuals and groups have excellent communication skills to enable productive work (Trenerry et al., 2021; Weritz, 2022). To negotiate complex new contexts and situations, such as working from home, socioemotional characteristics such as self-regulation and self-management are essential (Kovács & Kálmán, 2021). For example, while many prefer the increased work-life balance and work control that comes with working from home or distance work (Ipsen et al., 2021; Poulsen & Ipsen, 2017), on-site team structures can provide employees with a sense of belonging, and make them feel less isolated and lonely (Poulsen & Ipsen, 2017). Drawing on the HIDECO framework's "Zeitgeist and norms" layer, the concept of well-being has evolved over time to cover far more than the economic and material dimension (Litchfield et al., 2016; OECD, 2020). Future workplaces will have to be designed to actively foster work-life balance, flexibility, and freedom, but to also provide employees with stability, room for innovation, and meaning (Sánchez-Hernández et al., 2019).

Challenges and opportunities that come with megatrends of the 21st century can only be addressed and thrived upon if everyone can participate in the process and, from a very young age, can acquire the skillset required to succeed in the new surroundings. The OECD emphasizes the critical necessity of modern and inclusive educational institutions, for example in the “2030 learning compass” (OECD, 2019c). To flourish in the future, it will require continuing social protection and redistribution policy efforts to address societal inequality (Nozal et al., 2019), as well as highly educated teaching personnel enabling lifelong learning for individuals across all stages of the lifespan, up to old age (Coolahan, 2002; OECD, 2019a, 2021).

5.2.2 Can cumulative advantages and Matthew effects grow continuously?

As was discussed in Study II, strict CA follow the pattern of compound interest effects. Such effects result in exponential individual growth trajectories over time, implying that growth never ends and even accelerates. Also, CA (though not strict ones) that are a result of early advantages in third variables, such as belonging to a high SES or high IQ group, are theoretically assumed to persist and grow larger over time. How realistic, however, is the assumption that an outcome may grow continuously and indefinitely over time? Strict CA are easy to imagine with respect to wealth accumulation. Compound interest effects of a savings deposit may accumulate indefinitely if the interest is constantly reinvested, no money gets removed, and the assets are passed down from generation to generation. Notably, even in this scenario, exogenous events, such as changes in the socioeconomic environment, can influence and change the accumulation rate from time to time. Similarly, although in Study II some cases exhibited strict CA processes in wage growth, the majority of individual revealed income trajectories that followed logarithmic curves. This is also in line with other recent studies on this topic (Cheng, 2014; Heckman et al., 2003, 2005).

Especially when measuring developmental growth in cognitive skills or socioemotional characteristics over time, even though (strict) CA mechanisms are plausible, it might not be a reasonable assumption that unbounded growth in such abilities is possible. Contrary to wealth accumulation, where financial environmental conditions may allow for continuous growth, human ontogenesis and environment are defined by certain boundaries. First, life is finite. By definition, lifespan development spans from gestation to death, and the possibility to grow or develop vanishes once a person dies (Baltes, 1987; Baltes et al., 2006). Second, aging plays a significant role in the acquisition of new knowledge and skills. Learning rates are known to decline from young to old adulthood (Cutler et al., 2021; Hilton et al., 2021). Third, and maybe most important for research on CA in skill acquisition and knowledge gain from childhood to adulthood: Even if an individual had the capacity to grow in an outcome at an explosive rate, the manifestation of such an explosive learning gain might not be possible due to limited learning opportunities in the individual's environment. This becomes even more pronounced when considering how difficult it already is to adequately address the cognitive needs of gifted children in schools (Koshy et al., 2009; van Tassel-Baska & Stambaugh, 2005).

We might consider Peter Scholze as a real-world example. After winning the International Mathematics Olympiad several times during adolescence, his skills were fostered by a professor of mathematics at the FU Berlin beginning at age 16. In 2012, shortly after completing his PhD, he was made full professor at the University of Bonn at the age of 24, becoming the youngest full professor in Germany at that time (Dambeck, 2018; International Mathematics Olympiad, 2023; Max Planck Society, 2018). Peter may have experienced an explosive rate of skill acquisition during adolescence, as he transferred from school mathematics to advanced and university-level mathematics. However, at some point, the question will arise: Are there ever more challenging problems and, for example, mentor supervision available to allow Peter to acquire additional mathematical skills at the same rate? If not, his rate of skill acquisition may eventually reach a nonexplosive equilibrium. A related problem is the problem of measurement. For example, classic intelligence tests often do not measure reliably in the highest percentiles of skill distributions (e.g., because of ceiling effects; Silverman, 2009). As Preckel et al. (2020) point out, higher skills and knowledge might also become increasingly (domain-)specific. This can pose another challenge for measurement: If there are no appropriate measures available, it is not possible to quantify an individual's skill, let alone absolute changes and growth in that skill (Briggs, 2013; for measuring growth with vertical scales, and possible difficulties that can be encountered, see Student, 2022). Thus, even if strict CA mechanisms in skill development were at play, it might not always be possible to reliably observe them because of a lack of quantification and measurement.

For most phenomena, however, the most plausible pattern might be different growth rates at different points in time across an individual's lifespan. Although explosive growth might happen during some (shorter) periods of time, long term it might be more plausible to reach a plateau, resulting in logarithmic growth trajectories (Cheng, 2014). Furthermore, in an extensive meta-analysis on longitudinal studies of personality development, Bleidorn et al. (2022) examined personality stability and change across the lifespan. They found that the rank-order stability of personality traits such as agreeableness, extraversion, and openness considerably increased during early life until plateauing in young adulthood. After the age of 25, there was no substantial increase in rank-order stabilities (Bleidorn et al., 2022). Following these thoughts and expanding on Study II, it may be beneficial to add time-varying growth rates in future dynamic models examining CA mechanisms. Expanding on Study III and modeling input effects in a CT framework, another interesting approach may be to include input effects that are growth-promoting or growth-inhibiting at different periods in time. This could help us better understand the boundaries for continuing growth in learning environments, and could also help us to evaluate whether interventions, such as a giftedness class in primary school, may be able to raise long-term (that is, equilibrium) mean levels of cognitive skills if the growth rate is not deflated early.

5.2.3 The challenge of measurement equivalence in developmental time series

When working with repeated measurements over time, establishing measurement equivalence poses several challenges, especially concerning the investigation of development and change across the lifespan. Measurement equivalence generally assesses whether a measure of a psychological construct has equivalent measurement properties across different ages or times (Baltes et al., 1988; Hertzog & Nesselroade, 2003; Putnick & Bornstein, 2016). If measurement equivalence is not given, it is presumed that a construct has a different structure or meaning to different age groups or at different measurement occasions in the same group (Putnick & Bornstein, 2016). Longitudinal measurement equivalence, that is, measurement equivalence with respect to time, is thus one of the fundamental assumptions for statistical models examining change or growth over time (Hertzog & Nesselroade, 2003; McArdle et al., 2009). We can only attribute growth in observed scores over time to actual development or change in the construct of interest

(Baltes et al., 1988; Labouvie, 1980), instead of for example measurement errors, if there is longitudinal measurement equivalence. For repeated measurement data, longitudinal measurement equivalence is usually assumed when the same unidimensional construct is measured on the same person applying the exact same scale of measurement at every measurement occasion (McArdle et al., 2009). Yet, using the exact same scale at every measurement of a panel study is often impractical, and hardly ever achieved.

In Study II, I used individuals' wage time series across a period of 38 years to assess CA mechanisms. In this length of time, multiple changes in legislation or government policies typically take place that may for example influence wage taxation (U.S. Tax Foundation, 2021). Furthermore, yearly inflation levels influence absolute wage levels, which do not represent real wage increases. If not taken into account, these factors may contribute to biases in the projected long-term wage parameters, such as mean levels and wage growth rates. Importantly, these two concerns can be easily addressed by using gross wages rather than net wages (thereby excluding the effects of new taxing strategies) and adjusting the time series for inflation. Yet, when it comes to measuring and operationalizing psychological constructs over the lifespan, the issue is frequently more complicated. Here, we typically wish to include a wide range of ages or, in case of meta-analyses, to combine different studies based on different groups of individuals measured on similar constructs (McArdle et al., 2009). Two typical challenges of longitudinal measurement equivalence that were present in the dissertation's studies are discussed in the following.

First, if possible, many longitudinal researchers are careful to use exactly the same tests (or items) at every repeated measurement occasion. However, even when such precautions are taken, the meaning and function of the test(s) can change (McArdle & Cattell, 1994; Schaie et al., 2005). In Study III, based on the NEPS data, the same four questions were used to assess academic motivation across grades 3 to 7, a developmental period when students were about 9 to 13 years old. Although this is a rather small time-window compared to the whole lifespan of an individual, it could be that same questionnaire implies different things to children who are 9 years old as compared to adolescents who are 13 years old. Similarly, if the measurement of academic motivation took place across even longer periods of time, for example from early adulthood to old age, the construct "academic motivation" might mean something significantly different to individuals in their twenties or their eighties. Thus, it is critical to keep this in mind when evaluating constructs over the lifetime, and to be aware that some constructs, their factorial structure, or their definitions only apply to specific age groups (Meredith & Horn, 2001; Moersdorf et al., 2022).

Second, in some cases it might not be appropriate to use the same tests or scales repeatedly over time. If we are interested in cognitive development from childhood to adulthood, different age-appropriate tests are required (McArdle et al., 2009; Schaie et al., 2005). Other common reasons for changing primary measures include bad experiences in prior usage of tests and the introduction of new and improved tests (McArdle et al., 2009; Schaie et al., 2005). One of the main challenges associated with such changes in measures is that it is difficult to separate differences in the scales over time from changes in the constructs over time (McArdle et al., 2009). Comparing the NLSY cohorts in Study I, I faced a similar problem. NLSY-79 used seven items from the Center for Epidemiologic Studies Depression Scale (CES-D) to assess depressive symptoms, whereas the NLSY-97 applied a five-item short version of the Mental Health Inventory (MHI-5). Although not a repeated measurement case, it was important to ensure the comparability of the values between historical cohorts. Because Study I concerned the comparison between relative relationships between skills and later life outcomes (such as depressive symptoms), rather than the comparison between absolute mean levels between the cohorts, we approached the problem by *z*-standardizing the sum scores within cohorts.

Future studies should address longitudinal measurement equivalence of psychological constructs in greater depth, for example by applying process analyses when participants answer the questions of a test. Furthermore, psychometric modeling (e.g., Bauer et al., 2013; Curran et al., 2021) or frameworks such as proposed by McArdle et al. (2009) linking Item Response Theory and latent growth curve models, are promising approaches to dealing with threats to construct validity over time and across different independent samples. Both approaches might be promising to consider in future research.

5.2.4 Introducing the time dimension to substantive theory development and measurement

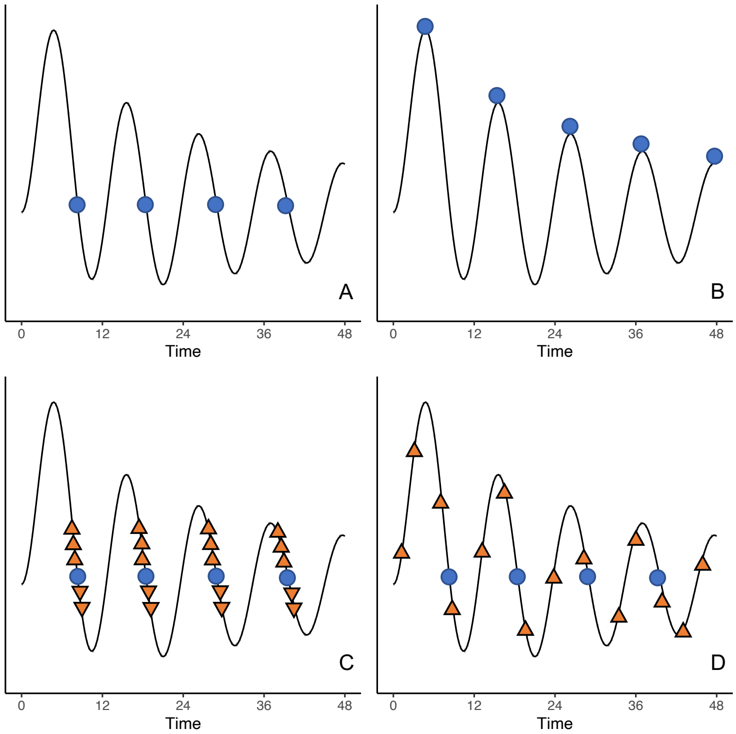
In recent years, a number of psychological researchers have called for an increasing focus on theories describing how psychological processes evolve over time within individuals and a complimentary increase in empirical approaches that collect and analyze psychological time series to gain insight into these processes (Hamaker et al., 2018; Molenaar, 2004; Robinaugh et al., 2020; Ryan et al., 2018). According to Dubin (1978), theory building includes four key elements: the identification of the constructs in question, the explanation of *how* and *why* they are related, the specification of to *whom* they apply, and the specification of *where* and *when* they are applicable (George & Jones, 2000; Whetten, 1989). The last two elements, namely the context in which the theory is applied and the time frame in which it is applicable, are often treated as mere boundary conditions and not given much further consideration (George & Jones, 2000). However, when it comes to longitudinal or developmental change processes, this approach may be insufficient (Collins, 2006; McGrath & Tschan, 2004). For example, developmental trajectories of phenomena may differ in shape or intensity over time and in response to exogenous interventions, and it may be important to understand why this occurs and on what time scale we can expect to see certain types of change (Collins & Graham, 2002; Timmons & Preacher, 2015). The theoretical model of change can significantly impact the propositions that can be derived from a theory (George & Jones, 2000). Therefore, the theoretical model of change should also consider expected meaningful intraindividual variability, relations to time-varying and time-invariant covariates, and how such relations evolve over time (Collins 2006; McGrath & Tschan, 2004).

The theory of cumulative advantages (CA), as considered in Study II, explicitly incorporates time as an element by describing the mechanism by which a system (e.g., wages) is expected to change over time. Many theories in psychology or the educational sciences, however, only consider time implicitly, if at all. Importantly, as was shown in Study III, the theoretical model of change is also closely intertwined with the measurement of change, more specifically the temporal design choices that ought to be made when interested in investigating a construct's change over time (Boker & Nesselroade, 2002). Collins (2006) argues that design choices for longitudinal studies must be made with great care, because some designs will result in a detailed and unobstructed view of the change phenomenon, whereas others will provide an unsatisfying or even misleading view. An effective longitudinal design depends on capturing the theoretical process that is consistent with the temporal change being investigated (Dormann & Griffin, 2015). The most appropriate temporal design is thus one chosen not primarily based on logistics, but instead based on correspondence with the theoretical model of change (Collins, 2006; Hertzog & Nesselroade, 2003; Timmons & Preacher, 2015). Based on Boker and Nesselroade (2002) as well as Voelkle and Oud (2013), we might consider an (damped) oscillatory process presented in Figure 3. Here, the values are expected to fluctuate over time— for example if a student's academic motivation changes depending on the semester cycle—but the changes get smaller across school years. A panel data collection that samples individuals once a year at the same time will be unable to represent such a change pattern. Thus, although academic motivation might actually face several ups and downs throughout a year if a smaller time-scale was considered, the yearly trajectories might represent a (curvi-)linear shape (see panels A and B in Figure 3), underestimating any temporal organization and leaving the actual change of the intrinsic dynamic undetected (Boker & Nesselroade, 2002; Nesselroade & Ghisletta, 2003).

Several studies have attempted to determine the appropriate interval or “lag” between measurements. Dormann and Griffin (2015) discuss optimal time lags for cross-lagged effects, and Boker and Nesselroade (2002) tackle the same question with respect to oscillating dynamics. Although temporal designs in line with the theoretical model of change of a phenomenon are highly desirable, they are not always viable. This might be either because there is no sufficient model of change deductible from a theory, resulting in random time intervals, or due to practical reasons such as economic considerations and staff availability. Especially in panel contexts, Study III showed that individually varying time intervals (IVTs) might help in recovering process dynamics even if no “ideal” study set-up was available. If taken into account, IVTs might also help detect intrinsic dynamics that happen on smaller timescales (e.g., months) than the original measurement intervals (e.g., years) would allow us to detect. Panels C and D in Figure 3 present this idea conceptually (see also Voelkle & Oud, 2013). Similarly, to tackle the challenge of optimal time lags between measurements, mini-longitudinal studies (Nesselroade & Ghisletta, 2003) or “shortitudinal” studies (Dormann & Griffin, 2015) have been recommended, where many data points are collected over a shorter period of time (resulting in far shorter time-lags between measurements).

Figure 3

Theoretical model of change and measurement process



Note. Given is a damped oscillatory function of an outcome of interest over time. The points exemplify regular measurement occasions of the outcome once a year, that is, every twelve months. From the upper two panels A and B, it becomes apparent that the yearly measurements, dependent on when they are taken, falsely represent either a linear trajectory (Panel A) or a curvilinear trajectory (Panel B) of the outcome because the sampling is not frequent enough to detect the actual oscillatory process. In Panels C and D, the triangles represent observations that vary around the regular yearly measurements. By taking such observation timing variability into account, the true oscillatory function might be detected better than without (individual) variation in measurement occasions and the resulting variation in time intervals between measurements.

5.3 Strengths, limitations, and directions for future research

In the following, I will discuss strengths and limitations of the doctoral thesis, and reflect on the presented findings within the context of the overarching theoretical framework, the HIDECO framework of lifespan psychology. Directions for future research and possible implications for the further advancement of the HIDECO framework will be discussed.

5.3.1 Strengths and limitations

Strengths of the present thesis

Some of the major strengths of the present dissertation are as follows:

First, across the three studies of the dissertation, all layers of the HIDECO model are addressed, reflecting the diverse and multidimensional nature of lifespan development. Study I is one of the few existing studies examining how the historical dimension represented by the “Zeitgeist and norms” layer of the HIDECO framework (Drewelies et al., 2019) has influenced the relationships between adolescent characteristics and vital adult life outcomes, thereby linking historical and ontogenetic time. Study II focused on the development of wages across the lifespan, focusing on individual level characteristics, represented by the “individual resources” layer. Importantly, this last layer was represented in all three studies of the thesis, although in different forms (e.g., cognitive skills, grade point average, academic motivation). Study III further took into account institutional contexts influencing students’ experiences (i.e., the “social embedding” layer in the HIDECO model), and focused on methodological aspects and the “micro/macro time” layer of the HIDECO model in order to lay the foundations for future research on longitudinal design decisions. Thus, the research questions of this dissertation not only addressed several layers of developmental change across the lifespan, but also focused on the proposed interrelationships and interactions between different areas of life and research. In their entirety, the research questions are well-suited to represent part of the complexity and versatility of lifespan research.

Second, the international longitudinal databases used in the present thesis are of high quality, thereby enabling meaningful results. Both the US National Longitudinal Surveys of Youth (1979, 1997) as well as the German National Educational Panel Study provide data from clearly defined populations, and are sampled (approximately) representatively and repeatedly over time. Thereby, they not only allow us to reliably compare mean levels of variables or relationships of interest, but also to track intraindividual change over time. Because of their large sample sizes, they also yield high power and precision for statistical analyses. The measuring instruments used in the panel studies are rigorously tested and evaluated, and meet high psychometric standards. Furthermore, in the NLSY samples, grade point averages could be computed based on original data from actual high school transcripts instead of self-reports. Because both the NLSY and the NEPS sample different cohorts simultaneously, they allow the investigation of historical differences in the measured characteristics, and their reaction to historical changes. Lastly, because of both samples' (approximate) representativity, it is further possible to generalize to the greater population based on the derived results. Thus, the NLSY and NEPS data were some of the internationally strongest available databases to answer my research questions.

Third, the diversity of research on lifespan development is matched by the diversity of statistical-methodological approaches that have been developed to investigate questions in the field. In this thesis, I draw on multiple state-of-the-art methods of data analyses across the three conducted studies. For example, in Study I, quantile regressions were used to learn more about different quantiles of the outcome distributions of vital life outcomes dependent on IQ, GPA, and pSES. In Study II, I used dynamic structural equation models, which incorporate strengths of state-space modeling, dynamic factor analysis, and multilevel modeling (Hamaker et al., 2018). Study III complemented the pluralism of methods by utilizing both continuous-time modeling analyses and a rigorous simulation study to investigate different possible scenarios of distributions of measurement intervals in panel studies. Frequentist (Study I, III) and Bayesian (Study II) estimation approaches, and complex missing data methodology such as multiple imputation were used to answer the research questions. In sum, capitalizing on methods from both the static and dynamic modeling families, the discrete and continuous time modeling families, as well as simulation studies, made it possible to investigate developmental change processes from many different angles.

Fourth, the substantive and methodological approaches I used in this thesis are truly interdisciplinary. For example, inequality—its precursors and effects— are phenomena that relate to many different scientific disciplines. In order to define and lay the foundations for the concept of cumulative advantages, I incorporated literature from developmental and educational psychology, life-course sociology, and economics. In light of the HIDECO model, developmental change across the lifespan needs to be understood as a puzzle of many different aspects (e.g., on the individual, institutional, and historical level). Thereby, each aspect may be a topic of research in different disciplines with different foci, and to get the full picture, boundaries need to be fluid. The statistical methods used in this dissertation also stem from different scientific disciplines. For example, whereas multivariate intraindividual change modeling (Study II, III) is typically situated in the psychological research methods tradition, quantile regression analyses are more based in econometric analyses. This interdisciplinary approach allowed me to gain a more complete picture with respect to my research questions compared to staying in only one discipline.

Limitations of the present thesis

When conducting research, it is not only important to point out strengths, but also to be aware of the limitations and drawbacks. Some limitations of the present thesis are as follows:

First, although the data properties of the US NLSY and German NEPS study are excellent databases to study developmental change, both samples stem from highly developed, industrialized Western countries. Especially with respect to Study II, findings on the mechanisms of inequality and accumulation, especially with respect to growth parameters across the lifespan, might differ for individuals from countries with lower general socioeconomic status. Because of their representative composition, the samples represent individuals of different socioeconomic, educational, ethnic, age, and gender backgrounds within the US and German population. However, from the perspective of international development, the samples might still be considered WEIRD samples (White, Educated, Industrialized, Rich, and Democratic; Henrich et al., 2010). Thus, the external validity and generalizability of the dissertation's empirical results in Studies I, II, and III to non-WEIRD populations might be limited. Importantly, the simulation's results on IVTs in Study III are likely not affected, although the empirical parameters that served as population parameters might be.

Second, although all layers of the HIDECO framework have been more or less represented in the research questions of the present thesis, it is not always easy to differentiate between them empirically. Especially in Study I, where historical changes in the socioeconomic environment of the 20th century were discussed, the layers "Zeitgeist and norms" and "Science and technology" often overlapped. For example, the breakthrough of the internet in the 1990s might be located in the "Science and technology" layer, however its effects might be represented in the "Zeitgeist and norms" part of the model. Similarly, when speaking of changes in the historical environment, the cause-effect relationships between such changes and their combined effects on the relationships between adolescent skills and adult life outcomes leave open for interpretation which of the many changes might have been the strongest drivers. Although it was our goal to capture the "net" effect of changes in the twentieth century, it is likely that specific factors (e.g., the introduction of the internet, market liberalization legislation) influenced the investigated relationships differently at different points in time. Study I's study design did not allow for such a differentiated investigation.

Third, time scales in panel studies are usually located on the “macro time” level of years. Although Study III pointed to interesting ways to learn about average intervention effects on a smaller time scale when time intervals vary between participants, developmental change does not only happen yearly or monthly, but also on much smaller time scales such as weeks or even across a single day or hour (“micro time” in the HIDECO framework). The present dissertation focused on the lifespan context and examined trajectories across many years, but did not consider high-density data such as from experience sampling methods. To fully comprehend the evolution of developmental processes such as cumulative advantages through time, it is necessary to consider data measured on much smaller time scales in order to capture possible process patterns and forms that we would not be able to identify otherwise. For example, a systematic pattern of daily oscillations in a variable might not be captured with monthly intervals, even if we applied continuous time models and used information on monthly IVTs provided in a panel study. Measurement burst designs across one or two consecutive days, on the other hand, may be able to provide such information. Importantly, however, such data is not as readily available as panel data, and might not fulfill other important criteria such as representativity.

5.3.2 Directions for future research

In the following sections, I will discuss selected overarching directions for future research based on Studies I, II, and III. These encompass (1) Causal inference from an interventionist and mechanistic perspective, (2) random effects, person-specific data analysis and $N = 1$ time series, (3) skill development and the knowledge-is-power hypothesis, and (4) possible future advances in the HIDECO framework.

Causal inference from an interventionist and mechanistic perspective

An aspect that has been only implicitly discussed in the dissertation so far is the notion of causal inference. Very broadly, it is possible to differentiate between two points of view on causality: the “interventionist” and the “mechanistic” view (Aalen et al., 2012). The interventionist view focuses on an intervention, and a given counterfactual, as the core of the causality terminology and constitution (Woodward, 2003, 2004). A causal effect is evaluated by comparing the evolution of a system, for example academic motivation, when the intervention is or is not present. In causal inference research based on observational data, counterfactuals may be constructed by a population’s mean baseline, that is, how the population’s level in an outcome would persist if no external event or intervention had occurred (Pearl, 2000, 2009; Woodward, 2004). To evaluate the causal effect, the level of an outcome after an intervention is compared to this baseline (Pearl, 2009). On the other hand, we can adopt a “mechanistic” or process-based understanding of causality, which may also be seen as causality from a dynamic viewpoint. Here, the emphasis is on mechanisms, that is, the wish to understand how the effects come about (Aalen et al., 2012; Machamer et al., 2000). Aalen et al. (2012) give Newton’s explanation of the tides being due to the gravitational effect of the moon on the waters on Earth as an example of such a mechanism. This may be viewed as a causal relationship, although it is difficult to imagine intervening in this system. Importantly, there are many scenarios where we can understand mechanisms, even if experimental intervention would not be realistic, practical, or ethical (Aalen et al., 2012).

In this dissertation, I focused on the latter process-based element of causality when drawing on dynamic models in Studies II and III. The interventionist perspective of causality has the advantage of having a very explicit definition of causal effects, which can be stated a priori, and the definition may also be used to characterize confounders and selection (see e.g., Emsley et al., 2010). At the same time, a mechanistic view of causality may allow for a higher degree of causal exploration (*how* and *why* an intervention yields an effect) as opposed to confirmation (*if* an intervention yields an effect; Aalen et al., 2012; Machamer et al., 2000). With respect to modeling input effects in a CT dynamic SEM framework as applied in Study III, Driver and Voelkle (2018a, p. 106) state that " to the extent that a model is accurately specified and the observed input effects are exogenous to the system processes, causal interpretations of the input effects and their time course may be reasonable." Importantly, however, as in classical experimental manipulations, when input effects are not exogenous, that is, when individuals have some influence over the event, the interpretation of the effect becomes less clear. For example, if a student decides to transfer from school A to school B on the same academic track, it may still be interesting to model the observed response (e.g., in the individual's self-concept); however, the resulting effect cannot be assumed to be due to the event specifically, as it may instead be due to antecedents that gave rise to the event (e.g., being an outsider).

Future research could focus on several aspects. First, the potentials and limitations of the process-based view of causality should be thoroughly examined (Aalen et al., 2012; Machamer et al., 2000). Second, the interventionist and mechanistic perspectives are not mutually exclusive. It might thus be investigated how different conceptions of causality might complement each other when it comes to deriving causal inferences from longitudinal observational data. One possible approach could be to extend Study III by defining a system of relationships between two variables such as academic motivation and joy of learning (as given e.g., in the NEPS SC 2), and to evaluate the effect of a non-experimental exogeneous intervention, such as the Covid-lockdown of schools in 2020, from different angles. Graph-based models (e.g., directed acyclic graphs and their extensions; Aalen et al., 2016; Gische & Voelkle, 2022), propensity score matching (Fuentes et al., 2022; Kretschmann et al., 2014) or marginal structural models (Robins et al., 2000; Zheng et al., 2018) could be used to evaluate the interventionist side of the event. The mechanistic view could be evaluated by (CT) dynamic SEM frameworks as in Studies II and III, or related approaches such as neural networks and neural ordinary differential equations (NODEs; Bonnaffé et al., 2021; Gwak et al., 2020). Doing so may shed light on intersections in different views on causality and stimulate ongoing debate. Third, on a philosophical level, it could be worthwhile to consider whether different perspectives on causality might be useful at different stages of a research field's development. If a field is relatively new, research might focus on "which treatment works." Later, it may be more appropriate to inquire as to how and why certain treatments work. This progression can be seen, for example, in the field of psychotherapy research (see Cuijpers et al., 2019).

Random effects, person-specific data analysis, and N = 1 time series

Not all individuals are the same. For example, they may have different baseline levels in outcomes such as academic motivation, and they may react differently to one and the same input or intervention. Especially in developmental research, examining individual differences and explaining heterogeneity of change processes are of interest because they are closely connected to person- or group-specific interventions. Interestingly, however, although the individual is often the core of substantive theories on such subjects, the field of psychology has a tradition of nomothetic research, that is, research that focuses on population values and distributions. Therefore, Molenaar (2004, 2013), Molenaar and

Campbell (2009), and Nesselroade et al. (2007) have repeatedly argued for a paradigm shift from nomothetic (interindividual, population-based) to idiographic (intraindividual, person-based) approaches. The main argument is that in classic inter-individual approaches, the estimated mean parameter often does not reflect the true parameter or trajectory of any individual in a sample. Furthermore, to be able to infer from inter-individual results to intra-individual effects, the ergodicity assumption has to be met (Molenaar, 2004, 2013; Schmiedek et al., 2020). However, because one requirement for ergodicity is that means and variances must be stationary over time, Molenaar (2013) argues that in developmental research, such an inference per definition is not possible, because development implies change and altered means over time. If lifespan developmental research aims to learn about individual pathways and to help individual persons, its focus should thus shift to intraindividual variation and development.

Statistically, this problem translates to a spectrum of methods. On one end of the spectrum are panel models with a single set of fixed-effects parameters that govern the dynamics of every individual (Driver & Voelkle, 2018b). Such fixed effects models are extreme in that they assume that individuals in a sample are basically the same, or that individuals react in exactly the same way to an intervention. On the other end of the spectrum, there are purely individual-specific models as proposed by Molenaar (2013) or Steele et al. (2014). Here, it is assumed that individuals are not similar at all and in a statistic estimation procedure, and the trajectory or information of one individual cannot inform any aspect of the subject-specific estimate of any other individual because they are assumed to be completely unique. Random effects or hierarchical (Bayesian) approaches, such as in Driver and Voelkle (2018a, 2018b) or Hamaker et al. (2018), define the middle ground between these extremes. Individuals are assumed to follow different trajectories, in strength or form of effects of an intervention. Yet, in the statistical estimation procedure, the trajectory or information of individuals who are similar to each other in some characteristics also inform the person-specific estimates for other individuals. The latter approach is very useful for panel data, because it provides subject-specific estimates while not needing the vast number of repeated measures per individual (e.g., $T > 50$; Liu, 2017) that is needed for purely idiographic approaches (Driver & Voelkle, 2018b).

In this dissertation, the first part of Study I and the empirical example in Study III were assumed to be fixed effect models. Especially in Study III, this was a simplified assumption due to the focus on subsequent simulations on IVTs. Study II took to the realm of hierarchical Bayesian modeling, that is, included random effects with covariates, and allowed us to learn about individual CA trajectories. There are several fruitful directions for future research: First, with respect to historical changes in Study I, it would be interesting to investigate the impact of single events, such as an election result, in greater detail. Based on panel data and hierarchical models, individual time series prior and after the event could be included in a model, with variables like SES and cognitive skills as covariates, as a first approximation of subject- (or subgroup-) specific effects. Second, for reasons of simplicity, Study III assumed fixed effects of academic motivation. In future studies, academic motivation trajectories and the input effect of the transition from primary to secondary school should be investigated on a random-effects level to both derive more realistic substantive results and to investigate whether or under which conditions individually varying time intervals might also help the estimation and recovery of such random effects (as opposed to average fixed effects). Third, by setting up intensive longitudinal data collections next to typical panel data, it would further be possible to model truly person-specific parameters. For example, if students were prompted to regularly answer questions about their well-being around a transition in a Smartphone App, it might be possible to model student-specific trajectories in real-time and thus to identify students at risk of struggling at the transition, and to intervene accordingly. Fourth, a related approach is $N = 1$ and single case experimental designs. In special needs education, it has been argued that such experimental approaches are helpful to establish evidence-based instructional practices (Dowdy & Jessel, 2021; Plavnick & Ferreri, 2013). By focusing on one individual, such designs are highly adaptive and can identify both practices that work, and necessary changes to accommodate for instances where previously effective treatments fail to work with a specific individual (Plavnick & Ferreri, 2013). Future research could evaluate how input effects, as investigated in CT models, might inform the empirical evidence drawn from such designs. There is also methodological work that helps to integrate *N*=1 studies with meta-analytic methods to derive more general conclusions (Pustejovsky & Ferron, 2017; Shadish et al., 2014).

Skill development and the knowledge-is-power hypothesis

One of the most prominent hypotheses in educational and developmental psychology is the so-called "knowledge-is-power" hypothesis. The hypothesis relates prior knowledge to the learning performance, specifically implying that domain-specific knowledge is among the strongest determinants of later performance and learning (Simonsmeier et al., 2022). Domain-specific knowledge, or specialized knowledge on a topic, is also known as memorized knowledge that can motivate action and enable the accomplishment of specific tasks over indefinite periods of time (Tricot & Sweller, 2014). The "knowledge-is-power" hypothesis turns up in many different disciplines in slightly different forms, though the assumption behind it is always similar. For example, research on memory has shown that how new information is processed in working memory and recorded in long-term memory depends on prior contents of long-term memory (Brod et al., 2013). In developmental psychology, Brod and Shing (2019) compared groups of children, younger adults, and older adults to evaluate the effects of prior knowledge on memory across the lifespan. In all age groups, they found that prior knowledge improved memory for elements encoded in a congruent context. Furthermore, educational psychological hypotheses included prior knowledge as key components for academic achievement, and it has been shown to reveal positive effects even if other possible important predictors such as course attendance or homework were controlled for (Moehring et al., 2018; Thompson & Zamboanga, 2003). One interesting direction for future research could be the application of the dynamic structural equation models as proposed in Study II (DSEM) or III (DSEM in continuous time [CT]) to this question. Because the knowledge-is-power hypothesis might also be framed as a question of possible cumulative advantages in the development of knowledge or skills (see e.g., Baumert et al., 2012), it is readily testable via such models. In their extensive meta-analysis on the hypothesis, Simonsmeier et al. (2021) differentiate between methodological approaches that relate absolute levels of prior knowledge in a domain to later absolute levels of knowledge in that domain via correlation analysis, and those studies that operationalize the hypothesis by relating levels of prior knowledge to (relative) knowledge gains, that is, learning rates, over time. They argue that only the latter approach is appropriate for testing the knowledge-is-power hypothesis, which could be investigated by examining the correlation between the intercept and slope parameter in a random effects dynamic structural equation model, as done with initial wage levels and wage growth rates across the lifespan in Study II. Interestingly, although many studies found positive effects of prior knowledge on learning, the entirety of studies included in Simonsmeier et al.'s (2012) meta-analysis revealed a large heterogeneity when estimating such an effect for the knowledge-is-power hypothesis, ranging from negative effects (e.g., Bilalic et al., 2010) to positive effects (e.g., Moehring et al., 2018; Thompson & Zamboanga, 2013), and centered around zero. The authors thus called for systematic future research on the conditions under which prior knowledge reveals such differential effects on learning. Among other things, they propose that prior knowledge might affect learning through the positive mediation of some pathways and the negative mediation of others. This might happen simultaneously, and ignoring the simultaneous pathways may lead to net effects around zero (Simonsmeier et al., 2012). Processes positively mediating the effects of prior knowledge on domain-specific learning could be attention to learning outcomes (Tanaka et al., 2008), a more efficient interpretation and encoding of new information (Brod et al., 2013), or a better evaluation of the plausibility of new information (Lombardi et al., 2016); processes negatively mediating the effects could be non-efficient problem constructions (Gulacar et al., 2022) or interferences of similar elements in a knowledge domain (Castel et al., 2007; Smith et al., 2000). It would be straightforward to include these as exogenous predictors in hierarchical (Bayesian) dynamic structural equation modeling frameworks (DSEM; DSEM in CT) when estimating heterogeneity in knowledge growth parameters. Importantly, the mediators could also be defined to have different onsets or durations, which may seem plausible depending on the learning situations. Similarly, processes underlying individuals' habit formation across the lifespan, and research questions relating past behaviors to future behaviors (e.g., Ouellette & Wood, 1998) could be translated onto to this framework.

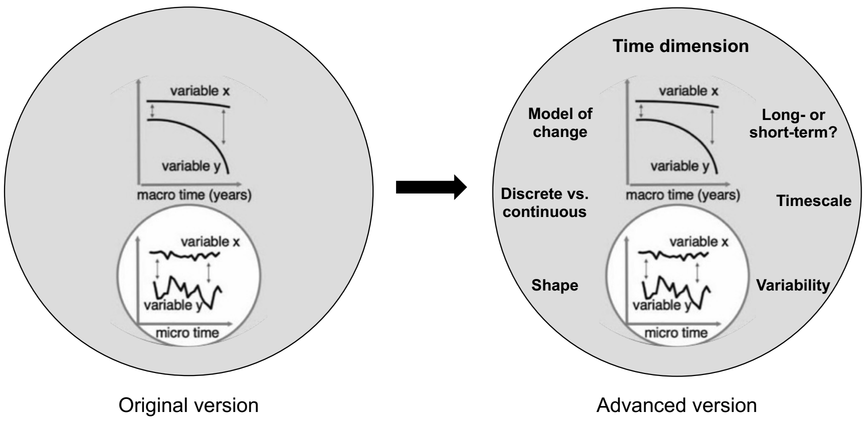
Possible future advances in the HIDECO framework

The HIDECO model is the overarching framework for the three studies of this dissertation. It embedded both the individual and the contextual factors constituting the research questions and hypotheses of the thesis, and allowed for differentiation between ontogenetic and historical time. This last differentiation is crucial when addressing lifespan developmental questions and analyzing change over time. Four of the five main layers of the model (i.e., the individual resources, social embedding, technology and science, and Zeitgeist and norms) encompassed all my substantive variables of interest. Because the model also explicitly stated the dynamic nature of change and development across the lifespan by establishing interaction paths between the different layers, it was well-suited to evaluate for example how changes in the greater socioeconomic environment interacted with individual differences in personal characteristics and resources over time. Thus, it succeeds in depicting the developmental context of individual change, that is, the environmental conditions relevant to understanding the evolution of a specific individual characteristic or behavior (see also Drewelies et al., 2019). During the course of the dissertation and the exploration of questions of Studies I, II, and III, however, it became apparent that the fifth and “core” layer of the model, the time layer, may benefit from a more differentiated perspective. When addressing mechanisms and pathways of development within the context layers of the HIDECO framework, Drewelies et al. (2019, p. 1023) state that “These sets of factors operate on how developmental processes unfold both over micro time scales and macro time scales and how such processes are intertwined.” Drewelies et al. (2019) also give a short example of each timescale (micro time: days; macro time: years), but do not extend any further on this topic than that. Especially when (causal) mechanisms are concerned, the time dimension of such processes, as proposed both in Studies I through III and in the discussion of this thesis, is of utmost importance to understand lifespan development and change.

Accordingly, some possible future advances in the model might be as follows: It could be added that, if researchers are interested in development across the lifespan, they should not only be aware of the general classification of micro /or macro time, but ask themselves “What is the model of change of the phenomenon I am interested in?” First, this encompasses the question of whether there are possible differences in change patterns, or shapes of trajectories, when the phenomena are examined in the short- or long-term; second, it encompasses the question of whether the change in question is expected to happen in discrete time steps or across continuous time; and third, as already shown graphically in the HIDECO framework (Drewelies et al., 2019), it could be made explicit whether there are assumptions about the variability of developmental processes based on other moderating or mediating variables or with respect to parallel processes of other variables over time. Figure 4 proposes one possibility of how the advances in the model could look graphically. Most probably, Drewelies et al. (2019) implicitly assumed these questions when designing the micro /macro time layer. Making these assumptions explicit, however, could enhance the framework's aim for researchers to be able to embed testable hypotheses in the framework in the future.

Figure 4

Possible advancements in the time dimension of the HIDECO framework



Note. Adapted from Drewelies, J., Huxhold, O., & Gerstorf, D. (2019). The role of historical change for adult development and aging: Towards a theoretical framework about the how and the why. *Psychology and Ageing, 34*(8), p. 1024 (http://dx.doi.org/10.1037/pag0000423). Copyright 2019 by American Psychological Association. Reprinted with permission.

Another possible advancement of the framework might be to set a greater focus on individual differences in lifespan development across the different contextual layers of the framework. Understandably, in setting up a framework that focuses on the influences of historical changes and how they affect individual development over time, the main focus lay on cohort differences in components of the different layers of the framework. These comprised differences such as cohort differences in individual resources, transformations of social embedding, or changes in the Zeitgeist over time. Importantly, at the same time, early ontogenetic development, but also adult development and aging, are subject to great heterogeneity, even though historical changes or societal mega-trends (e.g., OECD, 2019a, 2021) might affect everyone simultaneously. This was, for example, one of the motivations for including quantile regression analyses in Study I of this dissertation, and to examine random effects estimates of wage growth parameters across the lifespan in Study II. Future extended versions of the framework might thus explicitly address how individual differences in ontogenetic development are understood within the greater framework of historical changes in developmental contexts.

Lastly, the proposition of open data and open science in general becomes central in the context of the HIDECO framework and lifespan research. In order to examine the impact of historical changes on human development over time, it is crucial to have data on different historical cohorts, and to grant researchers access to this kind of data. Only if continuing access to such data is given can research can address implications of long-term changes in the historical context (such as megatrends; OECD, 2019a) or short-term specific historical events (such as the financial crisis of 2007 or the lockdown of schools in 2020) over time. Open data and open science with respect to cohort data allows research to continuously monitor and evaluate changes in the historical environment and their impact on ontogenetic development, which would not be possible in the necessarily bounded lifetime of one researcher alone. A future advancement of the HIDECO framework might thus be to explicitly address the necessity of open data and open science to be able to address research questions posed within the framework.

5.4 Implications for policy and practice

In the following, I will present selected implications for policy and practice on the basis of the thesis's findings. First, I will discuss the malleability of skills and implications for the design of effective policies; second, I will address how cumulative advantages in wages across the lifespan might be addressed with suitable tax policies; and third, I derive several suggestions from Studies I through III for how to complement future panel studies with respect to measuring change.

5.4.1 Malleability of skills and implications for the design of effective policies

As was shown in Studies I and II, skills are highly important for individual development across the lifespan. Higher cognitive skills, measured by IQ and school grades, were not only predictive for key life outcomes such as years of education, health, and income development in ontogenetic time, but also across different cohorts –that is, across historical time. The greater the cognitive skills in adolescence, the more educated, physically and mentally healthy, and financially secure individuals were later in life. This is in line with the OECD repeatedly pointing out the importance of skill development for the success of society as a whole. Only a skilled workforce that also feels well and knows how to foster individual well-being can help master future challenges in school, work, and personal domains.

One promising potential of skills for the design of effective policies is their malleability. Skills and skill development are not set in stone at birth (Kautz et al., 2014). Cognitive skills and social and emotional characteristics are malleable capacities, and can be built upon and extended through learning (Bleidorn et al., 2022; OECD, 2015; Uttal et al., 2013; Zhang et al., 2019). Cognitive skills such as intelligence have a hereditary, that is, genetic, component (Plomin & Deary, 2015; Sauce & Matzel, 2018). To a lesser degree, this has also been established for socioemotional characteristics (e.g., Zwir et al., 2020). Yet, the development and manifestation of such skills and characteristics is crucially formed by individuals' environments, such as peers, parents, teachers, schools, and social environments (OECD, 2015; Roberts, 2018). Policies that aim to foster and raise cognitive skills or socioemotional characteristics thus always need to work at the intersection of the child, family, community, and school. Because cognitive skills and socioemotional characteristics are learned in a variety of contexts both within and outside of formal education, collaborative efforts have a higher chance of succeeding than working in isolation (Clarke et al., 2015; OECD, 2015). Studies conducted in OECD countries identified four common characteristics of effective intervention programs targeting skill development (OECD, 2015): First, the relationship quality between parents, teachers, and the child should be warm and supportive. By emphasizing attachment, children experience trust and stability, enabling them to focus on learning and exploring (see also e.g., Bergin & Bergin, 2009). Second, consistency in the quality of learning settings should be ensured across contexts (e.g., family, school). Gains made by a child can thus be carried over into new circumstances. Third, if training is provided for children or teachers, learning approaches that are sequenced, active, focused, and explicit produce the greatest advantages. Actively drawing on prior knowledge when acquiring new knowledge, enhancing collaborative learning opportunities, and creating interdisciplinary projects are known to support academic capacity and efficacy (Cantor et al., 2019). Fourth, the onset of the policies and interventions should be between early childhood and adolescence, and their effectiveness should be evaluated and changes made, if necessary (OECD, 2015).

There are multiple reasons to seek to foster cognitive skills and socioemotional characteristics as early as possible. From a developmental psychological perspective, both cognitive skills and socioemotional characteristics are relatively more malleable in the early years and childhood (OECD, 2015; Kautz et al., 2014). During the adolescent years, socioemotional characteristics have shown to be more malleable than cognitive skills (Kautz et al., 2014). Interventions that target skill development at an early stage in life are thus likely to have the highest return on investment (Heckman, 2000, 2011; OECD, 2012). From a CA perspective, early high-quality care and education in kindergarten or primary school lays the foundation for further skill development. Such early intervention and investments in cognitive skills and socioemotional characteristics can thus be key drivers of the improvement of the life prospects of disadvantaged persons, and reduce socioeconomic inequality (Heckman, 2011; OECD, 2015).

5.4.2 Ideas to complement future panel studies with respect to measuring change

Complementing temporal designs to measure historical and ontogenetic change

Historical and ontogenetic development and change happen on different timescales simultaneously. The HIDECO model conceptualizes these different time levels of change by differentiating between micro and macro levels of time. This refers to processes (e.g., academic motivation) fluctuating on a daily or even hourly basis, as well as revealing a developmental trajectory across years or decades. To fully understand a (psychological) phenomenon is also to understand its developmental trajectories and change patterns over time and on different time scales. Many authors have thus argued that longitudinal studies should include far shorter time lags between measurements than those found in the literature (e.g., Dormann & Griffin, 2015) or pointed out the benefits of intensive measurement designs such as experience sampling or measurement bursts, where individuals are sampled repeatedly over a short period of time (Hamaker & Wichers, 2017; Rast et al., 2012). Based on the results of Study III and the examination of intervention effects on academic motivation, it may help a great deal to complement typical yearly measurements of panel studies with such *"shortitudinal" measurement approaches* when thinking about the optimal time lags in longitudinal study design to capture change in a substantive phenomenon. Such "shortitudinal" approaches could be implemented either on a regular basis for all participants in the panel study's sampling scheme, or in the form of *innovation samples*. Innovation samples are used because it is often not feasible to exert new measurement approaches to a whole panel sample, for example due to financial or time reasons. In this case, it may be possible to draw a random subset of households or individuals in a panel to examine new measurement approaches or learn about certain substantive phenomena in greater detail. For example, the UK Household Longitudinal Study included an "Innovation Panel" of participants that are asked the same questions as in the main survey, but also participate in experiments to test new survey questions and evaluate new methodologies (University of Essex, Institute for Social and Economic Research, 2021). Innovation samples could also be applied to measuring change, and making use of "shortitudinal" measurements in an innovation panel could allow for idiographic time-series analyses in order to learn about individual persons or groups and design interventions accordingly.

Another important related question, based on considerations in Study I, is how to actually measure historical changes, and more specifically how to identify which historical changes might have caused observed changes in an outcome of interest. Because historical change does not happen in a vacuum and the economic, political, and social environment usually change simultaneously, it is difficult to assess the exact driving forces. Classic panel cohort designs with yearly measures, such as the NLSY-79 and NLSY-97, are the crucial cornerstones of assessing the combined effects of historical changes on certain outcomes. High(er) resolution repeated measurement data, even if not in the form of classic intensive longitudinal data (e.g., measurement bursts), but for example in quarterly intervals, might help to identify the impact of distinct events, because some forces in the historical environment would be held constant while evaluating the impact of others that are changing simultaneously (see e.g., Legewie, 2013).

Socioemotional characteristics, use of technology, and documentation

The importance of socioemotional characteristics has been widely acknowledged in the last two decades (e.g., Heckman, 2011; Roberts et al., 2007). However, earlier panel studies historically focused primarily on measures of cognitive skills, especially targeting intelligence (e.g., the ASVAB battery in the NLSY), and largely omitting systematic personality and social-emotional measures. Thus, it could prove to be valuable to include more, multifaceted, and repeated *measures of socioemotional characteristics in panel studies* in the future. Newer panel studies such as the NEPS regularly included measures of self-concept, self-efficacy, or academic motivation in their surveys. Furthermore, the systematic and repeated measurement of personality traits and socioemotional characteristics, particularly when combined with economic or health time-series data, is desirable. Although some panel studies, such as the GSOEP, already include repeated measurements of facets of the Big 5 personality model in their survey, they are still the exception rather than the norm. Given the potential and significance of socioemotional characteristics for key life outcomes, their regular inclusion in representative panel studies will be key to gain a more complete understanding of their development, change, and affecting factors.

As proposed in many studies with experience sampling methods, *mobile technology* can play a key role in facilitating measurement (van Berkel et al., 2017). For example, Starting Cohort 2 of the NEPS samples around 3,000 students each year. If only 200 of them were randomly selected to answer the same set of questions repeatedly across a school year and summer break using their smartphone, more detailed information on ongoing processes (e.g., the evolution of academic motivation) as well as (unforeseen) interventions (e.g., the impact of a sudden change in learning settings due to a lockdown) could be attained utilizing IVTs and CT modeling approaches. Across waves, this would result not only in a dense observation coverage within a school year, but also a high degree of individual variation in time intervals across waves. This might not be feasible for achievement tests, but could successfully be applied for socioemotional constructs. Similarly, if researchers have defined their model of change and decided the “correct” time intervals to investigate the phenomenon of interest (e.g., capture an oscillatory process in the short run, logarithmic in the long run), it might be helpful to give them the possibility of *submitting some of their own items to be included in the data collection of the regular panel sample*, for example based on an application procedure, that then also allows them to collect data on a random subsample of the regular sample repeatedly in line with their defined time intervals (e.g., as realized in the GSOEP). The facilitated access to the subsample and the habituation and trust of the individuals in the sample to the regular sampling process might help obtain good response rates.

The last point concerns the *exact documentation of time information* in panel studies. Whenever possible, panel data should make the date and times of measurement occasions available as exactly as possible. The more information we have on the exact time point of measurement occasions of a construct of interest in a given dataset, the better can we use the information that these variables may provide for a research question on change over time. Of course, providing such information should never harm participants of a study, that is, the exact time information should not allow for personal identification of study participants. If exact time information, however, does not allow for personal identification, there is no obvious reason why the time of response should not be provided with exact year, month, day, hour, minute, or even second. Especially with the use of computerized questionnaires, this should be easy to attain, and could provide researchers relatively easily with valuable information about the time course of the phenomenon or phenomena in question.

5.5 Conclusions

The present doctoral thesis contributes to the field of lifespan psychology both substantively and methodologically. Based on three empirical studies, I first investigated how historical changes in the socioeconomic environment of the 20th century affected the relationships between adolescent cognitive skills (measured by IQ and GPA) and parental socioeconomic status (pSES) and participants' adult educational, occupational, and health outcomes (Study I). Overall, adolescent IQ, GPA, and pSES were all positively associated with adult educational attainment, wages, and mental and physical health. Importantly, levels of cognitive skills were generally more positively associated with these outcomes than pSES. Furthermore, while the regression weights of IQ and pSES for adult life outcomes remained relatively stable across cohorts, GPA gained in importance over historical time. Second, it was my goal to examine the mechanisms underlying lifespan inequalities in key life outcomes over time (Study II). To do so, I proposed dynamic structural equation models (DSEM) as a versatile statistical framework to operationalize and empirically test so-called strict cumulative advantage (CA) processes as drivers for inequality in wages. Interestingly, only 0.5% of the sample revealed strict CA processes shown in exponential wage growth rates, with the majority of individuals showing logarithmic wage trajectories over time. Akin to Study I, higher levels of IQ, GPA, and pSES, as well as adult educational levels, were positively associated with both initial wage levels at labor market entry, and subsequent wage growth rates across the (working) lifespan. Third, I investigated how observation timing variability in panel studies might be leveraged to enhance estimation precision and recovery of nonexperimental intervention effects (Study III). Although longitudinal and panel studies often aim at equally spaced measurement occasions between their observations, this goal is hardly ever met. By utilizing continuous time dynamic structural equation models and conducting a simulation study based on a real-life empirical example of the effects of the transition from primary to secondary school on students' academic motivation, I showed that some degree of such individual variation, or individually varying time intervals (IVTs), could actually benefit parameter estimation and recovery.

5.6 References

Aalen, O. O., Røysland, K., Gran, J. M., & Ledergerber, B. (2012). Causality, mediation and time: A dynamic viewpoint. *Journal of the Royal Statistical Society*, *175*(4), 831–861. https://doi.org/10.1111/j.1467-985X.2011.01030.x

Aalen, O., Røysland, K., Gran, J., Kouyos, R., & Lange, T. (2016). Can we believe the DAGs? A comment on the relationship between causal DAGs and mechanisms. *Statistical Methods in Medical Research*, *25*(5), 2294–2314. https://doi.org/10.1177/0962280213520436

Autor, D. H., Dorn, D., & Hanson, G. H. (2015). Untangling trade and technology: Evidence from local labour markets. *The Economic Journal*, *125*(584), 621–646. https://doi.org/10.1111/ecoj.12245

Baltes, P. B. (1987). Theoretical propositions of life-span developmental psychology: On the dynamics between growth and decline. *Developmental Psychology*, *23*, 611–626. https://doi.org/10.1037/0012-1649.23.5.611

Baltes, P. B., Lindenberger, U., & Staudinger, U. M. (2006). Life span theory in developmental psychology. In W. Damon & R. Lerner (Eds.), *Handbook of child psychology: Theoretical models of human development* (pp. 569–664). John Wiley & Sons Inc.

Baltes, P. B., Reese, H. W., & Nesselroade, J. R. (1988). *Life-span developmental psychology: Introduction to research methods*. Lawrence Erlbaum Associates.

Bauer, D. J., Howard, A. L., Baldasaro, R. E., Curran, P. J., Hussong, A. M., Chassin, L., & Zucker, R. A. (2013). A trifactor model for integrating ratings across multiple informants. *Psychological Methods*, *18*(4), 475–493. https://doi.org/10.1037/a0032475

Baumert, J., Nagy, G., & Lehmann, R. (2012). Cumulative advantages and the emergence of social and ethnic inequality: Matthew effects in reading and mathematics development within elementary schools? *Child Development*, *83*(4), 1347–1367. https://doi.org/10.1111/j.1467-8624.2012.01779.x

Bergin, C., & Bergin, D. (2009). Attachment in the classroom. *Educational Psychology Review*, *21*(2), 141–170. https://doi.org/10.1007/s10648-009-9104-0

Bleidorn, W., Schwaba, T., Zheng, A., Hopwood, C. J., Sosa, S. S., Roberts, B. W., & Briley, D. A. (2022). Personality stability and change: A meta-analysis of longitudinal studies. *Psychological Bulletin*, *148*, 588–619. https://doi.org/10.1037/bul0000365

Boker, S. M., & Nesselroade, J. R. (2002). A method for modeling the intrinsic dynamics of intraindividual variability: Recovering the parameters of simulated oscillators in multi-wave panel data. *Multivariate Behavioral Research*, *37*(1), 127–160. https://doi.org/10.1207/S15327906MBR3701_06

Bonnaffé, W., Sheldon, B. C., & Coulson, T. (2021). Neural ordinary differential equations for ecological and evolutionary time-series analysis. *Methods in Ecology and Evolution*, *12*(7), 1301–1315. https://doi.org/10.1111/2041-210X.13606

Briggs, D. C. (2013). Measuring growth with vertical scales. *Journal of Educational Measurement, 50*(2), 204–226. https://doi.org/10.1111/ jedm.12011

Brod, G., & Shing, Y. L. (2019). A boon and a bane: Comparing the effects of prior knowledge on memory across the lifespan. *Developmental Psychology*, *55*, 1326–1337. https://doi.org/10.1037/dev0000712

Brod, G., Werkle-Bergner, M., & Shing, Y. L. (2013). The influence of prior knowledge on memory: A developmental cognitive neuroscience perspective. *Frontiers in Behavioral Neuroscience*, *7*, 139. https://doi.org/10.3389/fnbeh.2013.00139

Cantor, P., Osher, D., Berg, J., Steyer, L., & Rose, T. (2019). Malleability, plasticity, and individuality: How children learn and develop in context. *Applied Developmental Science*, *23*(4), 307–337. https://doi.org/10.1080/10888691.2017.1398649

Castel, A. D., McCabe, D. P., Roediger, H. L., & Heitman, J. L. (2007). The dark side of expertise: Domain-specific memory errors. *Psychological Science*, *18*(1), 3–5. https://doi.org/10.1111/j.1467-9280.2007.01838.x

Cheng, S. (2014). A life course trajectory framework for understanding the intracohort pattern of wage inequality. *American Journal of Sociology*, *120*(3), 633–700. https://doi.org/10.1086/679103

Clarke, A. M., Morreale, S., Field, C.-A., Hussein, Y., & Barry, M. M. (2015). *What works in enhancing social and emotional skills development during childhood and adolescence?* World Health Organization Collaborating Centre for Health Promotion Research, National University of Ireland Galway.

Collins, L. M. (2006). Analysis of longitudinal data: The integration of theoretical model, temporal design, and statistical model. *Annual Review of Psychology*, *57*(1), 505–528. https://doi.org/10.1146/annurev.psych.57.102904.190146

Collins, L. M., & Graham, J. W. (2002). The effect of the timing and spacing of observations in longitudinal studies of tobacco and other drug use: Temporal design considerations. *Drug and Alcohol Dependence*, *68*, 85–96. https://doi.org/10.1016/s0376-8716(02)00217-x

Coolahan, J. (2002). *Teacher education and the teaching career in an era of lifelong learning* (OECD Education Working Papers No. 2). OECD Publishing. https://www.oecd-ilibrary.org/education/teacher-education-and-the-teaching-career-in-an-era-of-lifelong-learning_226408628504

Cuijpers, P., Reijnders, M., & Huibers, M. J. H. (2019). The role of common factors in psychotherapy outcomes. *Annual Review of Clinical Psychology*, *15*(1), 207–231. https://doi.org/10.1146/annurev-clinpsy-050718-095424

Curran, P. J., Georgeson, A. R., Bauer, D. J., & Hussong, A. M. (2021). Psychometric models for scoring multiple reporter assessments: Applications to integrative data analysis in prevention science and beyond. *International Journal of Behavioral Development*, *45*(1), 40–50. https://doi.org/10.1177/0165025419896620

Cutler, J., Wittmann, M. K., Abdurahman, A., Hargitai, L. D., Drew, D., Husain, M., & Lockwood, P. L. (2021). Ageing is associated with disrupted reinforcement learning whilst learning to help others is preserved. *Nature Communications*, *12*(1), Article 1. https://doi.org/10.1038/s41467-021-24576-w

Dambeck, H. (2018, August 1). Peter Scholze gewinnt Fields-Medaille: “So jemanden habe ich noch nie erlebt.” *Der Spiegel*. https://www.spiegel.de/wissenschaft/mensch/peter-scholze-gewinnt-fields-medaille-so-jemanden-habe-ich-noch-nie-erlebt-a-1214439.html

Dormann, C., & Griffin, M. A. (2015). Optimal time lags in panel studies. *Psychological Methods*, *20*(4), 489–505. https://doi.org/10.1037/met0000041

Dowdy, A., & Jessel, J. (2021). Single case research designs. In B. Hott, F. Brigham, & C. Peltier (Eds.), *Research methods in special education* (pp. 165–198). SLACK Incorporated.

Drewelies, J., Huxhold, O., & Gerstorf, D. (2019). The role of historical change for adult development and aging: Towards a theoretical framework about the how and the why. *Psychology and Aging*, *34*(8), 1021–1039. https://doi.org/10.1037/pag0000423

Driver, C. C., & Voelkle, M. C. (2018a). Understanding the time course of interventions with continuous time dynamic models. In K. van Montfort, J. H. L. Oud, & M. C. Voelkle (Eds.), *Continuous time modeling in the behavioral and related sciences* (pp. 79–109). Springer International Publishing. https://doi.org/10.1007/978-3-319-77219-6_4

Driver, C. C., & Voelkle, M. C. (2018b). Hierarchical Bayesian continuous time dynamic modeling. *Psychological Methods*, *23*(4), 774–799. https://doi.org/10.1037/met0000168

Dubin, R. (1978). *Theory building*. Free Press.

Fuentes, A., Lüdtke, O., & Robitzsch, A. (2022). Causal inference with multilevel data: A comparison of different propensity score weighting approaches. *Multivariate Behavioral Research*, *57*(6), 916–939. https://doi.org/10.1080/00273171.2021.1925521

George, J. M., & Jones, G. R. (2000). The role of time in theory and theory building. *Journal of Management*, *26*(4), 657–684. https://doi.org/10.1177/014920630002600404

Gische, C., & Voelkle, M. C. (2022). Beyond the mean: A flexible framework for studying causal effects using linear models. *Psychometrika*, *87*(3), 868–901. https://doi.org/10.1007/s11336-021-09811-z

Gulacar, O., Mann, H. K., Mann, S. S., & Vernoy, B. J. (2022). The influence of problem construction on undergraduates' success with stoichiometry problems. *Education Sciences*, *12*(12), 867. https://doi.org/10.3390/educsci12120867

Gwak, D., Sim, G., Poli, M., Massaroli, S., Choo, J., & Choi, E. (2020). *Neural ordinary differential equations for intervention modeling*. arXiv:2010.08304v1; arXiv:2010.08304v1. arXiv:2010.08304v1

Hamaker, E. L., Asparouhov, T., Brose, A., Schmiedek, F., & Muthén, B. (2018). At the frontiers of modeling intensive longitudinal data: Dynamic structural equation models for the affective measurements from the COGITO study. *Multivariate Behavioral Research*, *53*(6), 820–841. https://doi.org/10.1080/00273171.2018.1446819

Hamaker, E. L., & Wichers, M. (2017). No time like the present: Discovering the hidden dynamics in intensive longitudinal data. *Current Directions in Psychological Science*, *26*(1), 10–15. https://doi.org/10.1177/0963721416666518

Heckman, J. J. (2000). *Invest in the very young*. Ounce of Prevention Fund and University of Chicago Harris School of Public Policy Studies.

Heckman, J. J. (2011). The economics of inequality: The value of early childhood education. *American Educator*, *35*(1), 31–36.

Heckman, J. J., Lochner, L., & Todd, P. (2003). *Fifty years of Mincer earnings regressions* (No. w9732). U.S. National Bureau of Economic Research. https://doi.org/10.3386/w9732

Heckman, J. J., Lochner, L., & Todd, P. (2005). *Earnings functions, rates of return and treatment effects: The mincer equation and beyond* (No. w11544). U.S. National Bureau of Economic Research. https://doi.org/10.3386/w11544

Henrich, J., Heine, S. J., & Norenzayan, A. (2010). The weirdest people in the world? *The Behavioral and Brain Sciences*, *33*(2–3), 61–83; discussion 83-135. https://doi.org/10.1017/S0140525X0999152X

Hertzog, C., & Nesselroade, J. R. (2003). Assessing psychological change in adulthood: An overview of methodological issues. *Psychology and Aging*, *18*(4), 639–657. https://doi.org/10.1037/0882-7974.18.4.639

Hilton, C., Johnson, A., Slattery, T. J., Miellet, S., & Wiener, J. M. (2021). The impact of cognitive aging on route learning rate and the acquisition of landmark knowledge. *Cognition*, *207*, 104524. https://doi.org/10.1016/j.cognition.2020.104524

International Mathematics Olympiad. (2023). *Internationale Mathematik-Olympiade*. https://www.imo-official.org/participant_r.aspx?id=7867

Ipsen, C., van Veldhoven, M., Kirchner, K., & Hansen, J. P. (2021). Six key advantages and disadvantages of working from home in Europe during COVID-19. *International Journal of Environmental Research and Public Health*, *18*(4), Article 4. https://doi.org/10.3390/ijerph18041826

Kautz, T., Heckman, J. J., Diris, R., Ter Weel, B., & Borghans, L. (2014). *Fostering and measuring skills: Improving cognitive and non-cognitive skills to promote lifetime success*. OECD Publishing. http://www.oecd.org/education/ceri/Fostering-and-Measuring-Skills-Improving-Cognitive-and-Non-Cognitive-Skills-to-Promote-Lifetime-Success.pdf

Koshy, V., Ernest, P., & Casey, R. (2009). Mathematically gifted and talented learners: Theory and practice. *International Journal of Mathematical Education in Science and Technology*, *40*(2), 213–228. https://doi.org/10.1080/00207390802566907

Kovács, Z., & Kálmán, C. (2021). The role of self-regulation and perceived self-efficacy in adaptation to home-office work during the pandemic. *Journal of Adult Learning, Knowledge and Innovation*, *4*(2), 88–98. https://doi.org/10.1556/2059.2021.00048

Kretschmann, J., Vock, M., & Lüdtke, O. (2014). Acceleration in elementary school: Using propensity score matching to estimate the effects on academic achievement. *Journal of Educational Psychology*, *106*(4), 1080–1095. https://doi.org/10.1037/a0036631

Labouvie, E. W. (1980). Identity versus equivalence of psychological measures and constructs. In L. Poon (Ed.), *Aging in the 1980s: Psychological issues* (pp. 493–502). American Psychological Association. https://doi.org/10.1037/10050-036

Legewie, J. (2013). Terrorist events and attitudes toward immigrants: A natural experiment. *American Journal of Sociology*, *118*(5), 1199–1245. https://doi.org/10.1086/669605

Litchfield, P., Cooper, C., Hancock, C., & Watt, P. (2016). Work and Wellbeing in the 21st Century. *International Journal of Environmental Research and Public Health*, *13*(11), 1065. https://doi.org/10.3390/ijerph13111065

Liu, S. (2017). Person-specific versus multilevel autoregressive models: Accuracy in parameter estimates at the population and individual levels. *British Journal of Mathematical and Statistical Psychology*, *70*(3), 480–498. https://doi.org/10.1111/bmsp.12096

Lloyd, C., & Payne, J. (2019). Rethinking country effects: Robotics, AI and work futures in Norway and the UK. *New Technology, Work and Employment*, *34*(3), 208–225. https://doi.org/10.1111/ntwe.12149

Lombardi, D., Nussbaum, E. M., & Sinatra, G. M. (2016). Plausibility judgments in conceptual change and epistemic cognition. *Educational Psychologist*, *51*(1), 35–56. https://doi.org/10.1080/00461520.2015.1113134

Machamer, P., Darden, L., & Craver, C. F. (2000). Thinking about mechanisms. *Philosophy of Science*, *67*(1), 1–25.

Max Planck Society. (2018). *Fields Medal awarded to Peter Scholze*. https://www.mpg.de/12166322/fields-medal-awarded-to-peter-scholze

McArdle, J. J. (1988). Dynamic but structural equation modeling of repeated measures data. In J. R. Nesselroade & R. B. Cattell (Eds.), *Handbook of multivariate experimental psychology* (pp. 561–614). Springer US. https://doi.org/10.1007/978-1-4613-0893-5_17

McArdle, J. J. (2007). Dynamic structural equation modeling in longitudinal experimental studies. In K. v. Montfort, J. H. Oud, & A. Satorra (Eds.), *Longitudinal models in the behavioral and related sciences* (pp. 159–188). Lawrence Erlbaum Associates Publishers.

McArdle, J. J., & Cattell, R. B. (1994). Structural equation models of factorial invariance in parallel proportional profiles and oblique confactor problems. *Multivariate Behavioral Research*, *29*(1), 63–113. https://doi.org/10.1207/s15327906mbr2901_3

McArdle, J. J., Grimm, K., Hamagami, F., Bowles, R., & Meredith, W. (2009). Modeling life-span growth curves of cognition using longitudinal data with multiple samples and changing scales of measurement. *Psychological Methods*, *14*(2), 126–149. https://doi.org/10.1037/a0015857

McGrath, J. E., & Tschan, F. (2004). *Temporal matters in social psychology: Examining the role of time in the lives of groups and individuals*. American Psychological Association. https://doi.org/10.1037/10659-000

Meredith, W., & Horn, J. (2001). The role of factorial invariance in modeling growth and change. In L. M. Collins & A. Sayer (Eds.), *New methods for the analysis of change* (pp. 203–240). American Psychological Association. https://doi.org/10.1037/10409-007

Moehring, A., Schroeders, U., & Wilhelm, O. (2018). Knowledge is power for medical assistants: Crystallized and fluid intelligence as predictors of vocational knowledge. *Frontiers in Psychology*, *9*. https://www.frontiersin.org/articles/10.3389/fpsyg.2018.00028

Moersdorf, L., Freund, A. M., & Daum, M. M. (2022). Spelling out some unaddressed conceptual and methodological challenges in empirical lifespan research. *Acta Psychologica*, *226*, 103585. https://doi.org/10.1016/j.actpsy.2022.103585

Molenaar, P. C. M. (2004). A manifesto on psychology as idiographic science: Bringing the person back into scientific psychology, this time forever. *Measurement: Interdisciplinary Research & Perspective*, *2*(4), 201–218. https://doi.org/10.1207/s15366359mea0204_1

Molenaar, P. C. M. (2013). On the necessity to use person-specific data analysis approaches in psychology. *European Journal of Developmental Psychology*, *10*(1), 29–39. https://doi.org/10.1080/17405629.2012.747435

Molenaar, P. C. M., & Campbell, C. G. (2009). The new person-specific paradigm in psychology. *Current Directions in Psychological Science*, *18*(2), 112–117. https://doi.org/10.1111/j.1467-8721.2009.01619.x

Nesselroade, J. R., Gerstorf, D., Hardy, S. A., & Ram, N. (2007). Idiographic filters for psychological constructs. *Measurement: Interdisciplinary Research and Perspectives*, *5*(4), 217–235. https://doi.org/10.1080/15366360701741807

Nesselroade, J. R., & Ghisletta, P. (2003). Structuring and measuring change over the life span. In U. M. Staudinger & U. Lindenberger (Eds.), *Understanding human development* (pp. 317–337). Springer US. https://doi.org/10.1007/978-1-4615-0357-6_14

Neubert, J. C., Mainert, J., Kretzschmar, A., & Greiff, S. (2015). The assessment of 21st century skills in industrial and organizational psychology: Complex and collaborative problem solving. *Industrial and Organizational Psychology*, *8*(2), 238–268. https://doi.org/10.1017/iop.2015.14

Nozal, A., Martin, N., & Murtin, F. (2019). *Creating opportunities for people's well-being and economic growth*. OECD Publishing.

OECD (2012). *Equity and quality in education: Supporting disadvantaged students and schools*. OECD Publishing. https://doi.org/10.1787/9789264130852-en

OECD (2015). *Skills for social progress: The power of social and emotional skills*. OECD Publishing. https://doi.org/10.1787/9789264226159-en

OECD (2016). *OECD Science, technology, and innovation outlook 2016*. OECD Publishing. https://doi.org/10.1787/sti_in_outlook-2016-en

OECD (2019a). *OECD Skills strategy 2019: Skills to shape a better future*. https://read.oecd-ilibrary.org/education/oecd-skills-strategy-2019_9789264313835-en

OECD (2019b). *OECD Skills outlook 2019. Thriving in a digital world.* https://www.oecd-ilibrary.org/sites/df80bc12-en/index.html?itemId=/content/publication/df80bc12-en

OECD (2019c). *OECD Learning Compass 2030*. OECD Publishing.

OECD (2020). *How's life? 2020: Measuring well-being*. OECD Publishing. https://www.oecd-ilibrary.org/economics/how-s-life/volume-/issue-_9870c393-en

OECD (2021). *OECD Skills outlook 2021: Learning for life*. https://www.oecd.org/education/oecd-skills-outlook-e11c1c2d-en.htm

OECD (2022). *Skills for the digital transition: Assessing recent trends using big data*. OECD Publishing. https://doi.org/10.1787/38c36777-en

Ouellette, J. A., & Wood, W. (1998). Habit and intention in everyday life: The multiple processes by which past behavior predicts future behavior. *Psychological Bulletin*, *124*, 54–74. https://doi.org/10.1037/0033-2909.124.1.54

Pearl, J. (2000). *Causality: Models, reasoning, and inference*. Cambridge University Press.

Pearl, J. (2009). *Causality*. Cambridge University Press.

Plavnick, J. B., & Ferreri, S. J. (2013). Single-case experimental designs in educational research: A methodology for causal analyses in teaching and learning. *Educational Psychology Review*, *25*(4), 549–569. https://doi.org/10.1007/s10648-013-9230-6

Plomin, R., & Deary, I. J. (2015). Genetics and intelligence differences: Five special findings. *Molecular Psychiatry*, *20*(1), 98–108. https://doi.org/10.1038/mp.2014.105

Poulsen, S., & Ipsen, C. (2017). In times of change: How distance managers can ensure employees' wellbeing and organizational performance. *Safety Science*, *100*, 37–45. https://doi.org/10.1016/j.ssci.2017.05.002

Preckel, F., Golle, J., Grabner, R., Jarvin, L., Kozbelt, A., Müllensiefen, D., Olszewski-Kubilius, P., Schneider, W., Subotnik, R., Vock, M., & Worrell, F. C. (2020). Talent development in achievement domains: A psychological framework for within- and cross-domain research. *Perspectives on Psychological Science*, *15*(3), 691–722. https://doi.org/10.1177/1745691619895030

Pustejovsky, J. E., & Ferron, J. M. (2017). Research synthesis and meta-analysis of single-case designs. In *Handbook of Special Education* (2nd ed.). Routledge.

Putnick, D. L., & Bornstein, M. H. (2016). Measurement invariance conventions and reporting: The state of the art and future directions for Psychological research. *Developmental Review : DR*, *41*, 71–90. https://doi.org/10.1016/j.dr.2016.06.004

Rast, P., MacDonald, S. W. S., & Hofer, S. M. (2012). Intensive measurement designs for research on aging. *GeroPsych*, *25*(2), 45–55. https://doi.org/10.1024/1662-9647/a000054

Roberts, B. W. (2018). A revised sociogenomic model of personality traits. *Journal of Personality*, *86*(1), 23–35. https://doi.org/10.1111/jopy.12323

Roberts, B. W., Kuncel, N. R., Shiner, R., Caspi, A., & Goldberg, L. R. (2007). The power of personality: The comparative validity of personality traits, socioeconomic status, and cognitive ability for predicting important life outcomes. *Perspectives on Psychological Science*, *2*(4), 313–345. https://doi.org/10.1111/j.1745-6916.2007.00047.x

Robinaugh, D. J., Hoekstra, R. H. A., Toner, E. R., & Borsboom, D. (2020). The network approach to psychopathology: A review of the literature 2008–2018 and an agenda for future research. *Psychological Medicine*, *50*(3), 353–366. https://doi.org/10.1017/S0033291719003404

Robins, J. M., Hernán, M. A., & Brumback, B. (2000). Marginal structural models and causal inference in epidemiology. *Epidemiology*, *11*(5), 550–560. https://doi.org/10.1097/00001648-200009000-00011

Ryan, O., Kuiper, R. M., & Hamaker, E. L. (2018). A continuous-time approach to intensive longitudinal data: What, why, and how? In K. van Montfort, J. H. L. Oud, & M. C. Voelkle (Eds.), *Continuous time modeling in the behavioral and related sciences* (pp. 79–109). Springer International Publishing. https://doi.org/10.1007/978-3-319-77219-6_2

Sánchez-Hernández, M. I., González-López, Ó. R., Buenadicha-Mateos, M., & Tato-Jiménez, J. L. (2019). Work-life balance in great companies and pending issues for engaging new generations at work. *International Journal of Environmental Research and Public Health*, *16*, 1–18. https://doi.org/10.3390/ijerph16245122

Sauce, B., & Matzel, L. D. (2018). The paradox of intelligence: Heritability and malleability coexist in hidden gene-environment interplay. *Psychological Bulletin*, *144*, 26–47. https://doi.org/10.1037/bul0000131

Schaie, K. W., Willis, S. L., & Pennak, S. (2005). An historical framework for cohort differences in intelligence. *Research in Human Development*, *2*(1–2), 43–67.

Schmiedek, F., Lövdén, M., von Oertzen, T., & Lindenberger, U. (2020). Within-person structures of daily cognitive performance differ from between-person structures of cognitive abilities. *PeerJ*, *8*, e9290. https://doi.org/10.7717/peerj.9290

Shadish, W. R., Hedges, L. V., & Pustejovsky, J. E. (2014). Analysis and meta-analysis of single-case designs with a standardized mean difference statistic: A primer and applications. *Journal of School Psychology*, *52*(2), 123–147. https://doi.org/10.1016/j.jsp.2013.11.005

Simonsmeier, B. A., Flaig, M., Deiglmayr, A., Schalk, L., & Schneider, M. (2022). Domain-specific prior knowledge and learning: A meta-analysis. *Educational Psychologist*, *57*(1), 31–54. https://doi.org/10.1080/00461520.2021.1939700

Smith, S. M., Ward, T. B., Tindell, D. R., Sifonis, C. M., & Wilkenfeld, M. J. (2000). Category structure and created memories. *Memory & Cognition*, *28*(3), 386–395. https://doi.org/10.3758/BF03198554

Steele, J. S., Ferrer, E., & Nesselroade, J. R. (2014). An idiographic approach to estimating models of dyadic interactions with differential equations. *Psychometrika*, *79*(4), 675–700. https://doi.org/10.1007/s11336-013-9366-9

Student, S. R. (2022). Vertical scales, deceleration, and empirical benchmarks for growth. *Educational Researcher*, *51*(8), 536–543. https://doi.org/10.3102/0013189X221105873

Tanaka, D., Kiyokawa, S., Yamada, A., Dienes, Z., & Shigemasu, K. (2008). Role of selective attention in artificial grammar learning. *Psychonomic Bulletin & Review*, *15*(6), 1154–1159. https://doi.org/10.3758/PBR.15.6.1154

Thompson, R. A., & Zamboanga, B. L. (2003). Prior knowledge and its relevance to student achievement in introduction to psychology. *Teaching of Psychology*, *30*(2), 96–101. https://doi.org/10.1207/S15328023TOP3002_02

Timmons, A. C., & Preacher, K. J. (2015). The importance of temporal design: How do measurement intervals affect the accuracy and efficiency of parameter estimates in longitudinal research? *Multivariate Behavioral Research*, *50*(1), 41–55. https://doi.org/10.1080/00273171.2014.961056

Trenerry, B., Chng, S., Wang, Y., Suhaila, Z. S., Lim, S. S., Lu, H. Y., & Oh, P. H. (2021). Preparing workplaces for digital transformation: An integrative review and framework of multi-level factors. *Frontiers in Psychology*, *12*. https://www.frontiersin.org/articles/10.3389/fpsyg.2021.620766

Tricot, A., & Sweller, J. (2014). Domain-specific knowledge and why teaching generic skills does not work. *Educational Psychology Review*, *26*(2), 265–283. https://doi.org/10.1007/s10648-013-9243-1

University of Essex, Institute for Social and Economic Research. (2021). *Understanding society: Innovation panel, waves 1-13, 2008-2020. [Data collection]. 11th Edition. UK Data Service. SN: 6849*. https://doi.org/10.5255/UKDA-SN-6849-14.

U.S. Tax Foundation. (2021, August 24). *Historical federal individual income tax rates & brackets, 1862-2021*. https://taxfoundation.org/historical-income-tax-rates-brackets/

Uttal, D. H., Meadow, N. G., Tipton, E., Hand, L. L., Alden, A. R., Warren, C., & Newcombe, N. S. (2013). The malleability of spatial skills: A meta-analysis of training studies. *Psychological Bulletin*, *139*, 352–402. https://doi.org/10.1037/a0028446

van Berkel, N., Ferreira, D., & Kostakos, V. (2017). The experience sampling method on mobile devices. *ACM Computing Surveys*, *50*(6). https://doi.org/10.1145/3123988

van Laar, E., van Deursen, A. J. A. M., van Dijk, J. A. G. M., & de Haan, J. (2017). The relation between 21st-century skills and digital skills: A systematic literature review. *Computers in Human Behavior*, *72*, 577–588. https://doi.org/10.1016/j.chb.2017.03.010

van Laar, E., van Deursen, A. J. A. M., van Dijk, J. A. G. M., & de Haan, J. (2020). Determinants of 21st-century skills and 21st-century digital skills for workers: A systematic literature review. *SAGE Open*, *10*(1), 1–14. https://doi.org/10.1177/2158244019900176

van Tassel-Baska, J., & Stambaugh, T. (2005). Challenges and possibilities for serving gifted learners in the regular classroom. *Theory Into Practice*, *44*(3), 211–217. https://doi.org/10.1207/s15430421tip4403_5

Voelkle, M. C., & Oud, J. H. L. (2013). Continuous time modelling with individually varying time intervals for oscillating and non-oscillating processes. *British Journal of Mathematical and Statistical Psychology*, *66*(1), 103–126. https://doi.org/10.1111/j.2044-8317.2012.02043.x

Weritz, P. (2022). Hey leaders, it's time to train the workforce: Critical skills in the digital workplace. *Administrative Sciences*, *12*(94), 1–13. https://doi.org/10.3390/admsci12030094

Whetten, D. A. (1989). What constitutes a theoretical contribution? *The Academy of Management Review*, *14*(4), 490–495. https://doi.org/10.2307/258554

Woodward, J. (2003). *Making things happen: A theory of causal explanation*. Oxford University Press.

Woodward, J. (2004). Counterfactuals and causal explanation. *International Studies in the Philosophy of Science*, *18*(1), 41–72. https://doi.org/10.1080/02698590412331289251

World Health Organization. (2015). *World report on ageing and health*. World Health Organization. https://www.who.int/publications/i/item/9789241565042

Zhang, Q., Wang, C., Zhao, Q., Yang, L., Buschkuehl, M., & Jaeggi, S. M. (2019). The malleability of executive function in early childhood: Effects of schooling and targeted training. *Developmental Science*, *22*(2), e12748. https://doi.org/10.1111/desc.12748

Zheng, W., Luo, Z., & van der Laan, M. J. (2018). Marginal structural models with counterfactual effect modifiers. *The International Journal of Biostatistics*, *14*(1), 1–24. https://doi.org/10.1515/ijb-2018-0039

Zwir, I., Arnedo, J., Del-Val, C., Pulkki-Råback, L., Konte, B., Yang, S. S., Romero-Zaliz, R., Hintsanen, M., Cloninger, K. M., Garcia, D., Svrakic, D. M., Rozsa, S., Martinez, M., Lyytikäinen, L.-P., Giegling, I., Kähönen, M., Hernandez-Cuervo, H., Seppälä, I., Raitoharju, E., … Cloninger, C. R. (2020). Uncovering the complex genetics of human character. *Molecular Psychiatry*, *25*(10), Article 10. https://doi.org/10.1038/s41380-018-0263-6

EIDESSTATTLICHE ERKLÄRUNG

Hiermit erkläre ich an Eides statt, die Dissertationsarbeit „Time matters: Adopting a lifespan developmental perspective on individual differences in skills, cumulative advantages, and the role of dynamic modeling approaches“ selbstständig und ohne unerlaubte Hilfe Dritter angefertigt zu haben. Bei der Abfassung wurden nur die in der Dissertation angegebenen Hilfsmittel benutzt sowie alle wörtlich oder inhaltlich übernommenen Stellen als solche gekennzeichnet. Die Arbeit wird zur Promotion im Fach Psychologie eingereicht. Die Dissertation ist in der gegenwärtigen oder einer anderen Fassung in keinem früheren Promotionsverfahren angenommen oder abgelehnt worden. Ich habe an keiner anderen Hochschule ein Promotionsverfahren eröffnet.

Andrea Hasl
Potsdam, 02. März 2023