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

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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

The overarching goal of the present article 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 et al., 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 article 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 et al., 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 et al., 2008; Heckman & Carneiro, 2003). 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 averages (GPA), and socioemotional skills (e.g., conscientiousness) have repeatedly been shown to positively affect (initial) wage levels and long-term wage growth (Hasl et al., 2019; Heckman et al., 2008; Spengler et al., 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 et al., 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

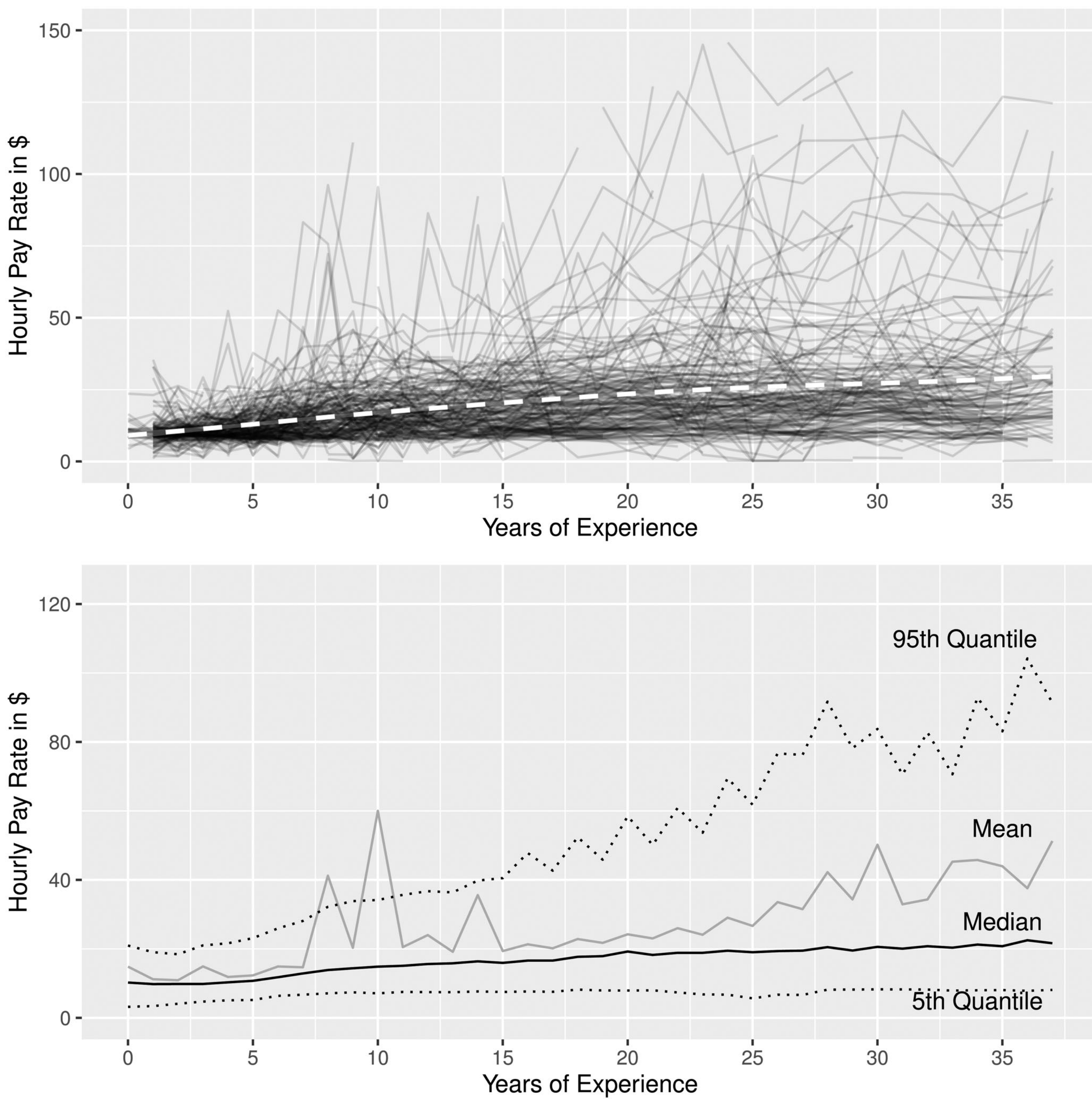

Figure 1. Changes in hourly pay rates across 38 years.
Note. The upper panel represents empirical wage trajectories of a random sample of $N = 300$ individuals across a period of 38 years. The dashed line represents the populations' mean trajectory. The lower panel depicts the mean, median, and the 5th 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).

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

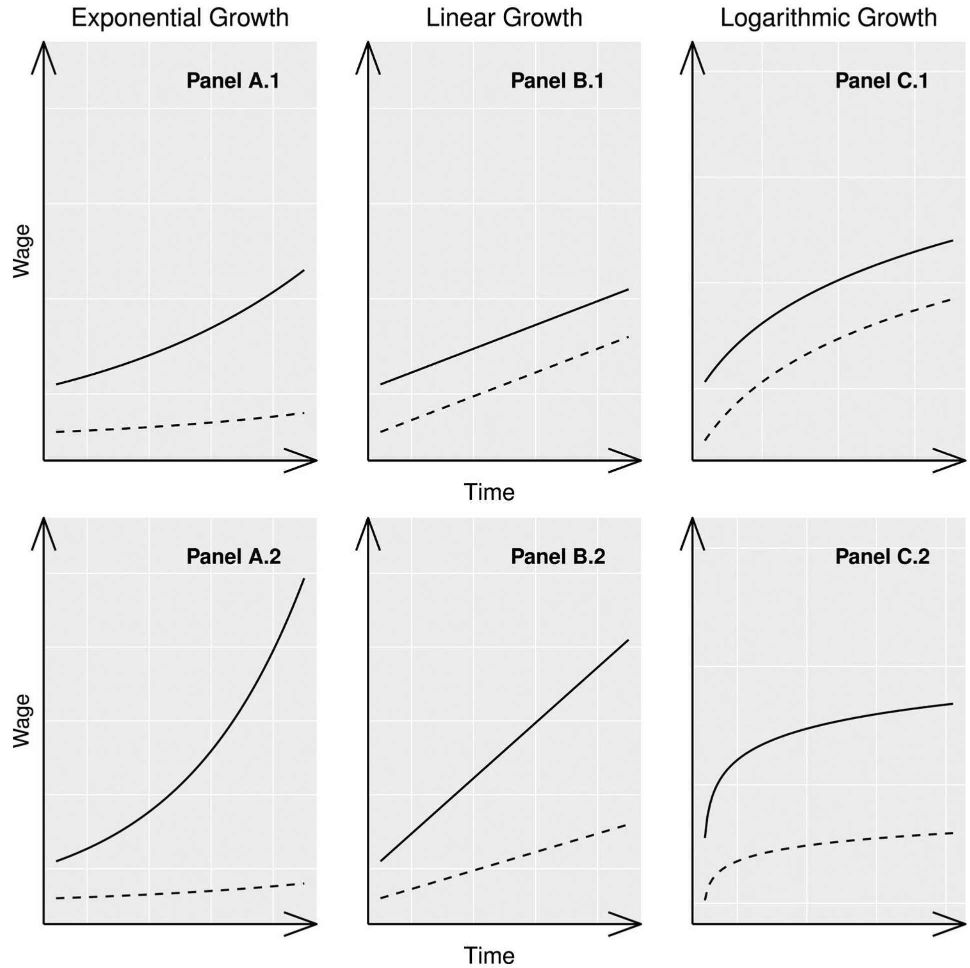

Figure 2. Examples of between-person heterogeneity in wage dynamics showing exponential, linear, and logarithmic growth.
Note. The dashed and solid lines represent two exemplary individuals in each panel. The upper panels (A.1, B.1, C.1) represent between-person differences in initial wages combined 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.

accumulation through the mechanism of compound interest. In its simplest form, it can be formalized as

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

where the current levels of individuals' wages Y_{it} are predicted by previous levels of wages $Y_{i,t-1}$. 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 et al. (2014), who investigated cumulative wage-experience profiles; and Crystal et al. (2017), who cross-sectionally compared income inequality across age groups in different cohorts. Likewise, Tomaskovic-Devey et al. (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 et al., 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 et al. (2014), is the linear or polynomial latent growth curve model (LGCM). In its simplest form, the LGCM can be denoted by

$$Y_{it} = \eta_{0i} + \eta_{1i}t + \zeta_{it}. \tag{2}$$

Current levels of individuals' wages Y_{it} are a function of the initial wage level η_{0i} of individual *i*, a person-specific linear slope η_{1i} 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 $\eta_{1i}t$ 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 article, 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 article, 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):

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

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

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

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

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

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

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[1] (see Panel C in Figure 2); if $\phi_i = 1$, wage growth is

[1]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 α_i /(1- ϕ_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.

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., 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(α_i, ϕ_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(α_i, ζ_{it}) and Cov(ϕ_i, ζ_{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 9 and 10 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}).

$$\alpha_i = \beta_{00} + \beta_{01}\mathrm{IQ}_i + \beta_{02}\mathrm{GPA}_i + \beta_{03}\mathrm{pSES}_i + \beta_{04}\mathrm{Edu}_i + \varepsilon_{0i} \tag{9}$$

$$\phi_i = \beta_{10} + \beta_{11}\mathrm{IQ}_i + \beta_{12}\mathrm{GPA}_i + \beta_{13}\mathrm{pSES}_i + \beta_{14}\mathrm{Edu}_i + \varepsilon_{1i} \tag{10}$$

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 article 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, lifespan 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 et al., 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.[2] 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

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

[2]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.

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, 1998) via R 4.0.3 (using the package *MplusAutomation*; Hallquist et al., 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 et al., 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 3). 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).[3] The number of iterations required to reach convergence and to have sufficient accuracy in estimation depends on the complexity of the 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 & Muthen, 2003; Merkle & Rosseel, 2018). 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 & Muthen, 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 & Muthen, 2003) that could be derived as part of the

[3]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).

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 (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%

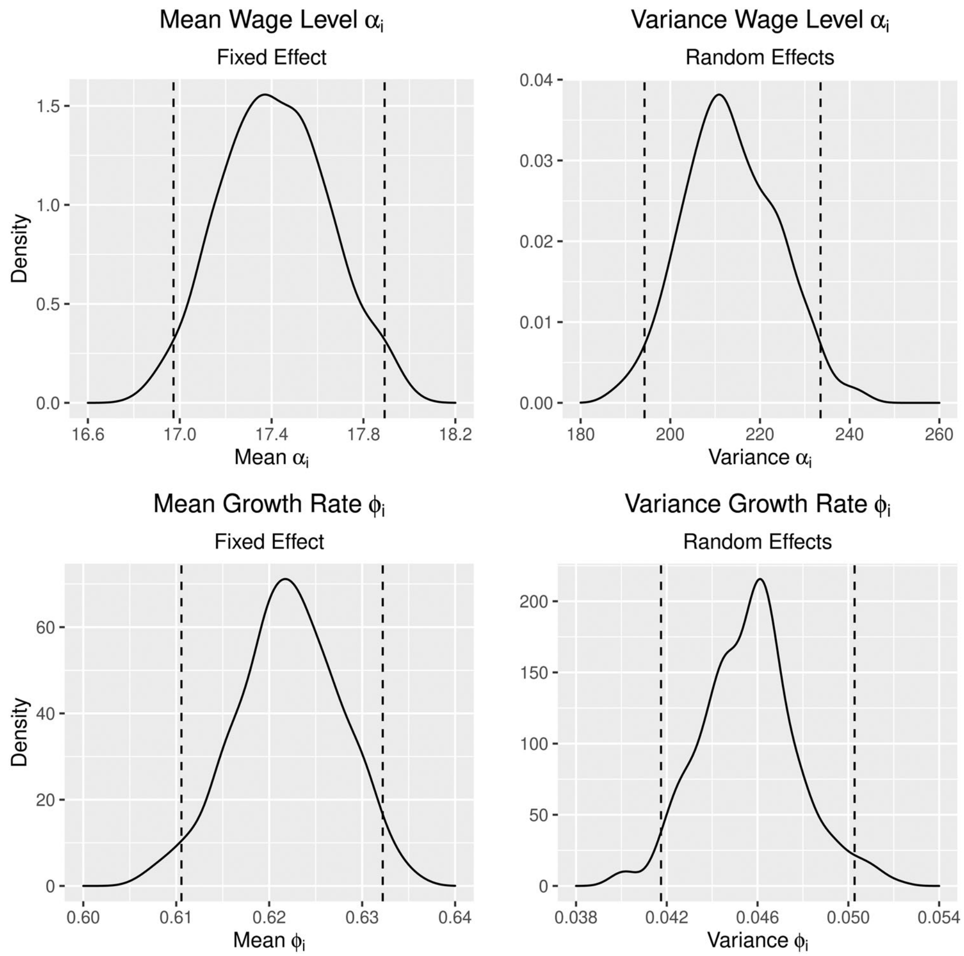

Figure 3. Bayesian posterior probability distributions of fixed and random effects of initial wage levels (α_i) and autoregressive wage growth rates (ϕ_i).

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.

coverage, and non-null detection rate (power).[4] 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 et al. (2013, p. 2) bias correction[5] to all parameter estimates associated with log-transformed hourly wages (Feng et al., 2013). 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).

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

[4]Please note that the simulations were requested during the peer-review process and were not preregistered as part of the original study.

[5]$E(Y) = \exp(\mu + \sigma^2/2)$, $Var(Y) = \exp(2\mu + \sigma^2)\ (\exp(\sigma^2)\text{-}1)$

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. (2013, 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 A4. Significant results are printed in bold font, indicating that the 95% Credibility Interval did not contain zero.

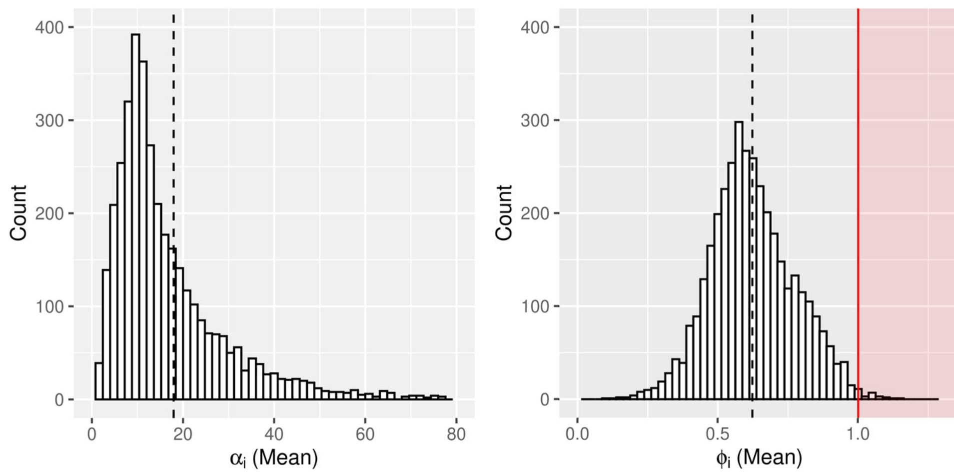

Figure 4. Distribution of initial hourly wage levels (α_i) and autoregressive wage growth rates (ϕ_i).
Note. Values based on Model 3. Initial hourly wage levels α_i are given in US $. The vertical dashed line indicates the mean of the distribution in both panels. The majority of individuals experienced logarithmic wage growth over time ($\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).

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 + 0.622 × $17.42 = $28.26 after 1 year, $17.42 + 0.622 × ($17.42 + 0.622 × $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 $0.62 \times 0.62 = 0.38 = 38$ cents for every dollar of Y_0; likewise, after 3 years, the person receives an additional $0.62 \times 0.62 \times 0.62 = 0.24 = 24$ 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 ($\mathrm{Cov}(\alpha_i, \phi_i) = -0.011$), 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

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 $\phi_i = 0.62$	Person B (+2SD) α_i = \$24.17 $\phi_i = 0.66$	$\Delta\ Y_AY_B$	$\Sigma\ \Delta\ Y_AY_B$ (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 A1, 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 deviation 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. $\Sigma\ \Delta\ Y_AY_B$ 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.

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.[6] 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 (α_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. 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 article 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

[6]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.

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 et al., 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 0.05^{th} to 0.01^{st} 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 article, 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 et al., 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, Gould et al. (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 (Gould 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 et al., 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 lifespan 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 et al., 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 et al., 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. *(Word Count: 11,662)*

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