A Life Course Trajectory Framework for Understanding the Intracohort Pattern of Wage Inequality[1]

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Much research has been devoted to cross-sectional and intercohort patterns of wage inequality, but relatively little is known about the mechanisms for the *intracohort* pattern of wage inequality. To fill this intellectual gap, this article establishes a life course trajectory (LCT) framework for understanding the intracohort pattern of wage inequality. First, the author proposes and conceptualizes three essential properties of the LCT framework (random variability, trajectory heterogeneity, and cumulative advantage) that are used to establish a mathematical formalization of the LCT framework. Both the conceptualization and the formalization imply that intracohort wage inequality will increase over the life course due to random variability, trajectory heterogeneity, and cumulative advantage. Finally, the author combines the LCT framework with the multilevel growth curve model, then applies the model to data from the NLSY79, and finds support for the significance of random variability, trajectory heterogeneity, and between-group cumulative advantage properties but not the within-group cumulative advantage property.

Understanding patterns of wage inequality is central to stratification research. Prior studies have advanced our understandings of wage inequality using two major approaches: by analyzing cross-sectional variations in wages (e.g., Blau and Duncan 1967; Weeden and Grusky 2012) and by examining intercohort differences in wage inequality—that is, the varying extent of inequality experienced by cohorts who entered the labor market at different historical periods (Kim and Sakamoto 2008*b*; Mouw and Kalleberg 2010*b*; Western and Rosenfeld 2011). These two approaches to wage

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inequality research generally treat individuals as single points of observation, overlooking the processes through which wages change over the life course. As a result, they reveal little about the intracohort pattern of wage inequality—that is, the way wage inequality develops over a cohort's life course. As individuals in a cohort age, do they earn more equal or more unequal wages? What mechanisms contribute to the intracohort pattern of wage inequality, and to what extent? What theoretical perspectives help explain this pattern? To date, these important questions have escaped theoretical investigation and empirical assessment.

Despite this gap in literature, research that examines the intracohort pattern of wage inequality carries sociological significance. First, sociologists have long sought to identify the underlying microlevel mechanisms that generate the macrolevel social phenomena (Granovetter 1978; Coleman 1994). For instance, Abbott (1983, 1995) urged sociologists involved in stratification research to move from using the "individual" as the primary microlevel unit of analysis to the incorporation of "sequence" or "trajectory" as alternative microlevel units of analysis. The intracohort pattern of wage inequality exemplifies a macrolevel phenomenon in the stratification system that stems from individuals' wage trajectories at the microlevel (Elder 1985; Blalock 1989; Huber 1990). After individuals in a single cohort enter the labor market, they follow different wage trajectories influenced by mechanisms that link their outcomes at earlier life stages to those at later life stages. The convergence or divergence of these trajectories as individuals age translates into the aggregate pattern of wage inequality within this cohort. Lack of knowledge about microlevel wage trajectories limits our broader sociological understanding of the macro-micro linkage in the wage stratification system.

Second, research on the intracohort pattern of wage inequality is important to the field of life course research in its examination of how inequality develops over the lifetime. Rather than treat individual outcomes observed at different life stages as separate or disconnected, the life course perspective links the temporal sequence of an individual's life stages into a life course trajectory. In recent decades, theoretical developments in life course research in the fields of sociology, psychology, epidemiology, and economics

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and the growing availability of fine-grained individual-level longitudinal data have spurred sociological interest in how individuals acquire social status, class positions, and economic resources via their life experiences (Elder 1985; Dannefer 2003; Elman and O'Rand 2004; DiPrete and Eirich 2006; Mayer 2009). Studying the intracohort pattern of wage inequality will help create a comprehensive picture of how inequality develops over individuals' life courses.

Third, research on the intracohort pattern of wage inequality addresses recent concerns about how rising economic instability and insecurity contribute to inequality in the current era (Hacker 2006; Western and Bloome 2009; Western et al. 2012). In particular, empirical studies suggest that year-to-year wage volatility in recent decades has become an increasingly important component of earnings inequality (Gottschalk and Moffitt 1994, 2009). Hence, modern-age economic inequality can be understood not simply as a static distribution but also as a temporal pattern along the axis of individual lifetimes. Analyzing wages over time among a cohort of individuals will help explicate the life course economic mobility processes that contribute to patterns of inequality.

Given its sociological significance, research on the intracohort pattern of wage inequality is disappointingly scant, consisting of a small compilation of descriptive ideas and untested hypotheses (DiPrete and Eirich 2006).[2] Prior studies are limited either to comparing a set of discrete trajectory groups or to examining a single mechanism of intracohort inequality without elaborating on the roles of and interconnections among various microlevel mechanisms that shape aggregate wage inequality. Much of the challenge in studying this topic is rooted in the absence of a formal and comprehensive framework that would allow development of research in an established theoretical context and assessment of findings within a body of related empirical work. To help fill this intellectual gap, this analysis establishes a life course trajectory (LCT) framework that scrutinizes the macrolevel intracohort pattern of wage inequality from its microlevel basis.

I posit that the LCT framework for understanding intracohort patterns of wage inequality must account for three essential properties: (1) the random variability in wage attainment (*random variability property*), (2) the heterogeneity in individuals' wage trajectories (*trajectory heterogeneity property*), and (3) the cumulative advantage in wage attainment (*cumulative advantage property*). In the discussion that follows, I draw on prior

[2] In their extensive literature review on this matter, DiPrete and Eirich (2006, p. 280) remarked, "The frequent lack of clarity in models, mechanisms, and tests is a continuing issue in the sociological literature on cumulative advantage processes as potential generators of inequality."

theories and evidence to introduce and explain the significance of these essential properties, develop hypotheses about the implications of these properties for the macrolevel intracohort pattern of wage inequality, and formalize these properties in a mathematical model.

Finally, I will present an empirical application of the LCT framework by studying the intracohort pattern of wage inequality among a specific cohort in the United States. I find strong support for the significance of the random variability, trajectory heterogeneity, and between-group cumulative advantage properties in reality. Yet, my results do not support the existence of the within-group cumulative advantage property. Simulations based on model estimates indicate that the mechanisms of trajectory heterogeneity and cumulative advantage together explain about over half (57.40%) of the growth of wage inequality across the 20-year life span, and the accumulation of random variability explains 42.60% of the growth of wage inequality over this period. I will also present auxiliary analyses that aid interpretation of the main results and discuss the generalizability and implications of the study.

LIFE COURSE TRAJECTORY AS THE BASIS FOR THE INTRACOHORT PATTERN OF WAGE INEQUALITY

Two processes are examined in stratification research on temporal trends in wage inequality: *intercohort* and *intracohort* patterns. The intercohort pattern is driven by the variation of inequality across cohorts who enter the labor force at different historical times; the intracohort pattern is driven by the variation of inequality across ages among individuals within the same cohort (Ryder 1965; Alwin and Krosnick 1991; Lynch 2003). That is, the intracohort pattern emphasizes the effect of age on wage distribution (Riley 1987). Therefore, one approach to studying intracohort patterns—an approach typically employed in research taking a demographic perspective—is to construct a synthetic cohort, track the distribution of wages at different ages, and summarize an age profile of wage inequality (Crystal and Shea 1990; Lam and Levison 1992; Danziger and Gottschalk 1993; Crystal and Waehrer 1996; O'Rand 1996; Lemieux 2006). Although the "age profile approach" describes the way the aggregate level of inequality varies with age, it does not address how this aggregate pattern is affected by the varying age-to-age wage trajectories of individuals within the group (Halpern-Manners, Warren, and Brand 2009). Thus, the age profile approach is inadequate for identifying the microlevel mechanisms that generate the macrolevel wage inequality.

This analysis takes the position that intracohort wage inequality should be studied from its microlevel basis: the life course trajectory. This basis assumes that a person's life unfolds through a succession of intercorrelated life stages (Mayer 2004, 2009; Gottschalk and Moffitt 1994; Western et al. 2012) that, when linked together, form a life course trajectory. As applied here, a life course trajectory depicts not only wages at each stage in an individual's life but also the trajectory interconnecting these stages in temporal order. When aggregated, the trajectories of all individuals in a cohort determine the development of intracohort inequality over their lifetimes.

To date, two major theoretical perspectives underpin research investigating the wage inequality–generating process across the life course. The first is the *permanent income hypothesis*, which is an economic theory that presumes that individuals rationally adjust their levels of consumption across the life course on the basis of changes in personal income/wealth. This line of research improves on the static model of wage attainment by extending the time horizon across the life course (Friedman 1957; Houthakker 1958). Yet, it relies on the assumption that individuals can fully anticipate and adjust consumption patterns to their future income. This assumption may hold true in extremely stable societies (DiPrete 2002), but it is highly unrealistic for modern societies in which unpredictable variability in life course wage attainment is the norm (DiPrete and McManus 1996; Gottschalk and Danziger 2005; Kalleberg 2009; Mouw and Kalleberg 2010*a*; Western et al. 2012).

The second theoretical perspective, the *life course perspective*, embeds the process of wage attainment in the social context, assuming that wages are subject to influences and uncertainties from various domains of social life (Elder 1985; Shanahan 2000; Elder, Johnson, and Crosnoe 2003; Wu 2003; Mayer 2009). This perspective recognizes the influence of interrelated life conditions such as health status, psychological traits (Sampson and Laub 1990; Wheaton 1990; Shanahan 2000), and socioeconomic status (DiPrete 2002; Elman and O'Rand 2004) situated in a variety of life events such as marital transitions (Williams and Umberson 2004), childbearing (Budig and England 2001; Correll, Benard, and Paik 2007), military service (Sampson and Laub 1996; MacLean and Elder 2007), job mobility (Wegener 1991; Rosenfeld 1992), and geographic migration (Hagan, MacMillan, and Wheaton 1996). Together, these conditions and events determine a person's social status trajectory through life. The life course perspective suggests that the framework I establish for modeling the life course wage trajectory should embody two key aspects. First, because wages are likely to depend on the person's experience in a multitude of life domains, some of which will be unpredictable, the framework should incorporate unanticipated variability in wage attainment. Second, given the wide scope and diversity of life domains that may affect each person's wage attainment, the framework should treat individuals' life course trajectories as fundamentally heterogeneous.

Although the life course perspective supports the microlevel foundations of investigating wage inequality, research in this area still suffers from several limitations. First, few studies have shed light on intracohort inequality in earnings and economic well-being. Notable exceptions include work by Crystal and Shea (1990) and Crystal and Waehrer (1996), which illustrate the importance of age patterns in economic inequality. However, most research in this field focuses on the observed pattern of aggregated inequality, failing to uncover the microlevel mechanisms generating the macrolevel inequality. Mentions of such micro-macro links exist; for example, in discussing the variance-covariance structure of the multilevel growth curve models, Raudenbush (2005, p. 149) remarks that "the variance of the observations is a function of age (or time), which is sensible, because individuals are presumed to grow at different rates." Yet, I know of no formal framework for systematically studying the consequences of such variation in life course trajectories.

Second, even when prior work has explored the mechanisms for intracohort patterns of wage inequality over time, it has focused almost exclusively on the wage gaps between cohort groups, with groups usually defined as people sharing the same observed social attributes, such as gender, race, level of education, and criminal background (Western 2002; Tomaskovic-Devey, Thomas, and Johnson 2005; Willson, Shuey, and Elder 2007; Fernandez-Mateo 2009). For example, Fernandez-Mateo (2009) used supply- and demand-side factors to explain the gender difference in the rate of wage growth over experience or tenure. Tomaskovic-Devey et al. (2005) conceptualized wage attainment over a person's career as a dynamic process of human capital accumulation embedded in the interactions between individual workers, colleagues, employers, and the workplace environment and used this conceptualization to explain the growth of racial inequality over the life course. Western (2002) examined the impact of imprisonment as a turning point in the life course and found that imprisonment reduces the rate of subsequent wage growth by about 30%. Accompanying the empirical interests in group-based trajectory analyses are some recent methodological works that proposed strategies for categorizing individual trajectories by a finite set of discrete trajectory groups (Nagin 1999, 2009; Nagin and Tremblay 2005). Yet, the almost exclusive focus of research on between-group differences has left out the question of how much inequality remains within these groups as well the relative share of between- and within-group trajectory variations. This analysis broadens existing work on this subject by incorporating between-group, within-group, and total cohort inequality into a comprehensive framework.

THREE ESSENTIAL PROPERTIES OF THE LCT FRAMEWORK

Next I turn to defining the essential properties of the LCT framework on which to develop investigations of intracohort patterns of wage inequality. As mentioned above, I posit that the LCT framework should account for three essential properties: (1) random variability, (2) trajectory heterogeneity, and (3) cumulative advantage. Below I explain why these properties are essential to the LCT framework and draw three hypotheses about the implications of the microlevel mechanisms for the intracohort pattern of wage inequality.

Random Variability Property

Because the life course perspective assumes the interactions of multiple life domains, some of which are not fully anticipated, wages over the lifetime are expected to fluctuate in response to unplanned conditions or events (DiPrete 2002; Gottschalk and Moffitt 2009; Western et al. 2012). Transitory events, such as receiving a year-end bonus or taking a short sick leave, may affect wages only during the time they occur. Other fluctuations, such as receiving a promotion or being fired, may have lasting effects on future wage attainment given their potential impact on human capital accumulation and social status (Rosenbaum 1979; Heckman and Borjas 1980; DiPrete 1981; Gangl 2006; Mouw and Kalleberg 2010*a*). Empirical work has directly assessed the significance of random variability in wage attainment. Gangl (2005), who estimated the contributions of different variance components of income using data from 12 countries, found that the United States ranks high in "transitory variance in wage," constituting 20.8% of the total variance of log income in the country. Recently, Western et al. (2012) reviewed related empirical research and concluded that, over recent decades, economic volatility and insecurity have increased significantly in the United States. Thus I propose that the following property:

PROPERTY 1 (random variability property).—*The LCT framework should contain a random component to capture the random variability in wage attainment.*

Not only is random variability an important part of total wage inequality, but the accumulation of random variability also may act to increase wage inequality over the life course. When unanticipated residual wage fluctuations—either setbacks or windfalls—have lasting effects on individuals' earnings, the effects of seemingly transitory wage shocks accumulate over their lifetimes, inducing greater intracohort wage inequality (Gangl 2005; Gottschalk and Moffitt 1994). On the basis of this argument, I raise the following hypothesis about the connection between random variability and total intracohort inequality:

Hypothesis 1.—*Intracohort inequality will increase over the life course as a result of the accumulation of random variability over time.*

Trajectory Heterogeneity Property

The LCT framework property of trajectory heterogeneity relies on two notions of wage, which I define as *baseline wage* and *wage trajectory*. Baseline wage refers to the wage earned at the beginning of a person's career and can be seen as the starting point of the person's wage attainment process. Wage trajectory refers to the pattern by which a person's level of wage develops from the baseline wage across the life course. While a sizable body of literature has evaluated heterogeneity in individuals' baseline wages, sociologists have only begun to uncover heterogeneity in individuals' wage trajectories.

Wage trajectory can vary by person for several reasons. First, wage variance is inherent in the canonical human capital theory of wage determination, which posits that individuals acquire human capital through labor market experience, which in turn increases wages over time, as the market yields positive economic returns on human capital (Schultz 1961; Ben-Porath 1967; Mincer 1974; Becker 1994; Heckman, Lochner, and Todd 2006). However, rates of human capital accumulation vary by labor market experience as do market returns. Simply put, different kinds of jobs yield different advantages in terms of amassing human capital and market rewards—differences reflected in wage trajectory heterogeneity (Mincer 1996; Heckman et al. 2006).

Heterogeneity in wage trajectories is also embedded in family, work, and organizational contexts. Individual experiences in nonmarket domains of life, such as marital transitions, childbearing, and coresiding with other family members, may spill over to the work domain, affecting wage trajectories. For example, working mothers may give up jobs with faster wage growth in exchange for jobs with better work-family compatibility, resulting in a diverging gender gap among married couples with children over their life course. In addition, trajectories are affected by structural and organizational factors, such as employment relations (Kalleberg 2009), organizational settings (Baron 1984), and occupational reward systems (Grodsky and Pager 2001; Carbonaro 2007; Weeden and Grusky 2012). On the basis of these ideas, I propose the following property:

Property 2 (trajectory heterogeneity property).—*The LCT framework should allow for heterogeneity in individuals' wage trajectories.*

While some earlier works have alluded to the idea of trajectory heterogeneity in wage attainment, few of them have explicitly discussed its implications for the intracohort pattern of wage inequality. Here I argue that the heterogeneity in wage trajectories will cause wage inequality within a cohort of individuals to increase over the life course.[3] Panel *A* of figure 1 illustrates this phenomenon.[4] Although persons A, B, and C have little wage gap when starting their job careers, their wages grow at different rates, indicated by the slopes of the lines, and over 20 years of working, their variable trajectories have put them further and further apart—increasing intracohort wage inequality. Had A, B, and C maintained parallel wage trajectories, their relative wages would have been constant over time, and intracohort wage inequality would have remained unchanged. This leads me to the following hypothesis:

HYPOTHESIS 2.—*Intracohort inequality will increase over the life course as a result of the heterogeneity in the life course wage trajectories.*

Cumulative Advantage Property

While the trajectory heterogeneity property emphasizes between-person differences in wage trajectories, the third essential property of the LCT framework emphasizes the positive dependence of an individual's wage growth rate on his or her baseline wage. That is, not only do individuals have different wage trajectories based on a range of job, market, personal, and structural factors discussed above, but those with higher baseline wages may experience faster rates of wage growth, which leads to the divergence of wage trajectories over time. In prior literature, this positive association has been commonly referred to as "cumulative advantage" or, as Merton (1968, p. 62) put it, "the rich get richer at a rate that makes the poor become relatively poorer."[5] Recently, a number of sociological studies have invoked cumulative advantage in explaining the increase of intracohort inequality on dimensions such as wage, living conditions, and physical well-being over the life course (e.g., Cole 1979; Rao 1980; DiPrete 1981; Rosen 1981; Allison et al. 1982; Dannefer 1987; Crystal and Shea 1990; Frank and Cook 1995; O'Rand 1996; Ross and Wu 1996; Adler 2001; Dan-

[3] The link between trajectory heterogeneity and inequality has also been noticed by earlier studies: e.g., by devising a formal model of the trajectory of scientific productivity, Allison, Long, and Krauze (1982, p. 623) showed mathematically that if we adopt a scale-invariant measure of inequality, "a homogeneous rate of accumulation would not lead to increasing inequality but a heterogeneous rate would produce increasing inequality."

[4] Here, fig. 1 provides a schematic illustration, which aims to exemplify the general implications of this specific mechanism yet does not necessarily accord with every characteristic of any particular case.

[5] The earliest scholarly discussion of the cumulative advantage dates back to the "Matthew effect" in the scientific career coined by Merton (1968). The Matthew effect describes the process in which the scientists who have received scientific recognition at an early stage of their career are more likely to acquire more resources and gain greater recognition in subsequent years. However, Merton did not explicitly draw the distinction between between-group and within-group cumulative advantage.

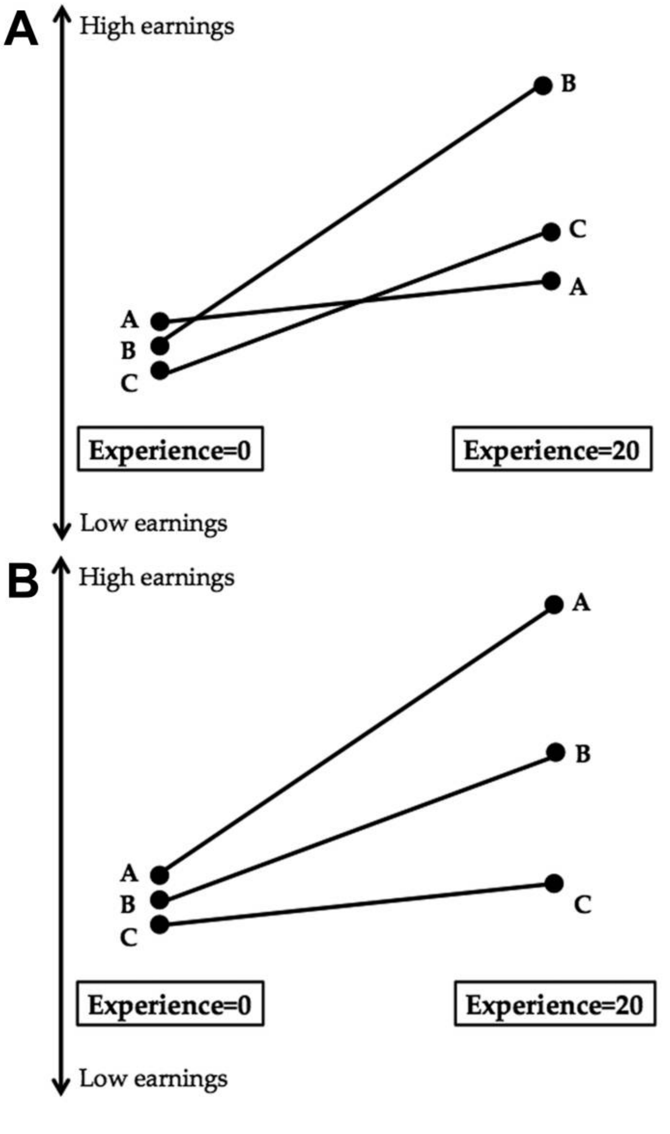

FIG. 1.—Schematic demonstration of the contributions of trajectory heterogeneity and cumulative advantage to the intracohort pattern of wage inequality. *A*, Illustration of trajectory heterogeneity. *B*, Illustration of cumulative advantage.

nefer 2003; Elman and O'Rand 2004; DiPrete and Eirich 2006). However, as several scholars have pointed out, this term has been used quite casually and without a clear definition or conceptualization (DiPrete and Eirich 2006; Willson et al. 2007). After conducting an extensive review of recent works on cumulative advantage as an inequality-generating process, DiPrete and Eirich (2006) called for future works to theorize this concept more precisely and distinguish between its various forms in an effort to generate "a deeper understanding for the reasons why trajectories diverge at both the group and the individual level of observation" (p. 292).

Cumulative advantage is a complex social process that may involve the simultaneous operation of numerous mechanisms on different levels. And it is beyond the scope of this analysis to discuss these comprehensively. Still, one direction for advancing our understandings of cumulative advantage is to break down this concept into more specific components. In my LCT framework, I decompose cumulative advantage into between-group and within-group cumulative advantage.

Between-group cumulative advantage refers to the process through which the wage advantage of one social group over another social group at an early life stage magnifies over the life course.[6] Prior works have documented evidence of between-group cumulative advantage, with group defined by gender (Reskin 1978; Tomaskovic-Devey 1993; Noonan, Corcoran, and Courant 2005; Fernandez-Mateo 2009), race (Tomaskovic-Devey et al. 2005; Shuey and Willson 2008; Walsemann, Geronimus, and Gee 2008; Kim and Miech 2009), and level of educational attainment (Ross and Wu 1996; Elman and O'Rand 2004; DiPrete and Eirich 2006).[7]

Within-group cumulative advantage refers to the amplification of wage advantages among individuals sharing the same group attributes. For example, as recognized by sociological studies of scientific careers, among scientists sharing the same observed individual attributes, those with greater success at the start of their careers tend to have faster rates of upward career mobility (Merton 1968; Cole and Cole 1973; Allison 1980; Xie 2014). This implies that even among individuals who are similar with regard to group membership, those who receive a higher wage in their first job may experience higher wage growth in the future. Empirically, if the positive association between baseline wage and wage growth rate persists after controlling for observed/social group membership, within-group cumulative advantage is at work.

The question of whether cumulative advantage exists between or within social groups has not yet been systematically examined. While findings from recent studies tend to favor the mechanism of cumulative advantage (Lynch 2003), other literature has discussed the possibility of the "age-as-leveler" phenomenon, in which outcome advantages associated with social

[6] Here, "social group" refers to the collection of individuals who share a common social attribute recognizable by others.

[7] I will introduce measures for specific group indicators in my empirical analyses.

groups diminish, rather than magnify, over age (Krieger and Fee 1994; Elo and Preston 1996). It is possible that cumulative advantage exists between, but not within, social groups or that it exists between some groups but not others. To test these possibilities, the following property is necessary:

PROPERTY 3 (cumulative advantage property).—*The LCT framework should reflect both the between-group and within-group cumulative advantage in wage attainment.*

Panel *B* of figure 1 illustrates the mechanism of cumulative advantage in the growth of wage inequality over the life course. Persons A, B, and C have entered the labor market with different baseline wages and each experiences wage growth that reflects this hierarchy. Thus, person A has the steepest wage trajectory and person C has the flattest, with person B in the middle. These differences in growth rates mean that the initial wage inequality amplifies over the 20 years of labor market experience.[8] On the basis of this idea, I propose the following hypothesis:

HYPOTHESIS 3.—*Intracohort inequality will increase over the life course as a result of the mechanism of cumulative advantage.*

MATHEMATICAL FORMALIZATION OF THE LCT FRAMEWORK

While much has been conjectured about mechanisms underlying intracohort wage inequality, a rigorous and logical formalization remains missing. Without such formalization, the researcher is often at the risk of mistakenly interpreting the effect of one mechanism as that of another or failing to distinguish the influences of two distinct mechanisms. Here I formalize the LCT framework into a mathematical model, showing how the model can satisfy the three essential properties of the LCT framework and yield results consistent with the three hypotheses.

Like all mathematical models of social processes, the LCT model relies on some simplifying assumptions. Thus, the model is designed for the general case and may not work for every particular case in real life. I have kept the model as parsimonious as possible to the extent that these simplifying assumptions are inconsequential to the main conclusions drawn from the model. Possible extensions of the mathematical formalization are discussed in either the main text or the footnotes, and I assess the sensitivity of my conclusions to alterations of the model assumptions in auxiliary analysis. Appendix table A1 summarizes four key assumptions of the framework and discusses alternative specifications.

[8] For the sake of demonstration, the schematic illustration described here does not differentiate between "between-group cumulative advantage" and "within-group cumulative advantage."

Model Setup

In canonical life course research, biological age is usually considered the primary dimension along which temporal change occurs. Yet, in a broader sense, the life course also involves other temporal dimensions, such as work experience, career progress, length of marriage, and the duration of exposure to certain environments (Rosenfeld 1992; Western 2002; Wu 2003). Because wage is an indicator of economic rewards earned through activities in the labor market, this analysis considers years of labor market experience as a better link to the trajectory of wage attainment than biological age. Accordingly, the mathematical formalization of the LCT framework will describe wage trajectory along the axis of labor market experience. I use t to denote the number of years an individual has spent in the labor market, with t equal to zero at market entry. As a simplification, I assume that once a person has entered the labor market, the person remains in the labor market until retirement and that years of experience accumulate regardless of how many hours or weeks the individual spent working in year $t - 1$.[9] The variable Y_{it} denotes the wage for person i at t years in the labor market, Y_{i0} denotes the beginning/baseline wage, and γ_i denotes the person-specific, time-invariant growth rate from $t - 1$ to t. I assume that Y_{it} is generated by the following process:

$$\begin{aligned} Y_{it} &= (1 + \gamma_i) \cdot Y_{i,t-1} \\ &= (1 + \gamma_i)^2 \cdot Y_{i,t-2} \\ &= (1 + \gamma_i)^t \cdot Y_{i0}. \end{aligned} \tag{1}$$

Simply speaking, Y_{it} grows exponentially over t as a function of the person's wage at the previous period $Y_{i,t-1}$ and the fraction of the increment captured by γ_i. This exponential growth process is similar to the process described by DiPrete and Eirich (2006) as a "strict cumulative advantage"

[9] To be sure, this assumption may not always hold true in real life. For instance, it is possible that a person enters the labor market, then drops out of the labor force or works a minimal amount of time for some years, and later comes back to the labor market. Yet, the model can be altered in proper ways to address these special cases. One simple method is to treat the years in which a person stays out of the labor market as "missing" observations and not count these years in calculating t. Yet, it is also possible to reconcile this issue by specifying a different (which can even be zero or negative) growth rate of wage for the years in which the person has stayed out of the labor market. For example, we could specify $Y_{it} = (1 + \gamma_i) \cdot Y_{i(t-1)}$ if the person remains in the labor market in year $t - 1$ and let $Y_{it} = (1 + \gamma_i') \cdot Y_{i(t-1)}$ if the person dropped out of the labor market for a significant amount of time in year $t - 1$.

model, which is analogous to the process of "wealth accumulation through the mechanism of compound interest" (p. 272).[10] This model represents the simplest form of cumulative advantage. The emphasis of this article, however, is between- and within-group cumulative advantage, which I will define and discuss in detail later.

Following the standard practice in modeling wage determination adopted by the human capital model (Heckman, Lochner, and Todd 2003), I define *log wage* as the key outcome variable. Accordingly, I take the logarithm of both sides of equation (1), which yields

$$\ln Y_{it} = t \cdot \ln(1 + \gamma_i) + \ln Y_{i0}. \tag{2a}$$

The log transformation from equation (1) to equation (2a) is particularly helpful for further development of the model because it transforms the wage equation from the multiplicative form to an additive equation with separable components.

Next, to incorporate the random variability property, I add a component to equation (2a) to capture the random variability in individual wage. Denoted by e, this random component is independent of any observation of Y and γ and transforms the deterministic form of equation (2a) into the nondeterministic form:

$$\ln Y_{it} = t \cdot \ln(1 + \gamma_i) + \ln Y_{i0} + e_{it}. \tag{2b}$$

Also, for the *random variability property* to exist, the random component e should take up a nonzero variance, as I formally state in the following condition:

CONDITION 1.—$\mathrm{Var}(e) > 0$.

That is, condition 1 ensures that the random variability property is satisfied.

For the sake of parsimony, I rewrite the logarithm of wage in equation (2b) as a linear combination of three components: a linear function of labor market experience, a person-specific fixed effect, and a random component, as below:

$$\ln Y_{it} = \theta_i \cdot t + \lambda_i + e_{it}, \tag{3}$$

where $\theta_i = \ln(1 + \gamma_i)$ and $\lambda_i = \ln Y_{i0}$.

The three components in equation (3) have intuitive interpretations: the slope on t, θ_i, is a function of γ_i; thus, it captures the person-specific wage

[10] To explain, in the language of wealth or the asset accumulation process, the baseline wage Y_{i0} can be seen as the "principal" or "initial investment," γ_i as the "interest rate," and Y_{it} as the value of assets at time t.

growth rate. The person-specific intercept, λ_i, is the logarithm of baseline wage Y_{i0}; thus, it captures the person-specific baseline wage. Finally, e_{it} captures the random variability in wage.[11]

It is important to note that several key elements in the setup of this model are closely related to three classes of models developed by previous works. First, as shown in equation (1), the basic setup of my model can be seen as a discrete case of the well-known Yule process of exponential growth. The Yule process assumes that $Y_{it} = Y_{i0}e^{\gamma_i t}$, so that the increment in Y at a given time point depends on the accomplishment at this time point up to a scalar of γ_i (i.e., $dY_{it}/dt = \gamma_i Y_{it}$). Similarly, from equation (1), we can write the increment in Y from $t - 1$ to t as a function of $Y_{i,t-1}$ and γ_i: $Y_{it} - Y_{i,t-1} = \gamma_i Y_{i,t-1}$. As such, my model and the Yule process both stem from a basic setup in which achievement at the current period affects the increment in achievement in the next period.

Second, equation (1) relates to the contagious Poisson process as proposed by Allison et al. (1982) to model the process of a scientific career. Their study models the propensity to publish a scientific paper at time t, denoted by $P(t)$, as a linear function of the number of papers already published at time t (denoted by $X(t)$). That is, they assume that $P(t) = \alpha + \beta X(t)$. Essentially, the parameter γ in my model and the parameter β in their model have similar interpretations, in that they both characterize the degree to which the amount of future increment depends on current achievement. Moreover, both my model and their model are flexible enough to allow for the between-person variation in these two parameters; in other words, both models allow for the heterogeneity in wage trajectories. Also, both models emphasize the idea that the inclusion of a random component is essential to characterizing a social process.[12]

Third, my model can be viewed as an extended application of Mincer's (1974) human capital equation for wage determination. In the human capital equation, workers accumulate human capital through work experiences, and thus their wage will positively depend on the years of labor market experience. Formally, the human capital equation expresses the expectation of log wage as

$$E(\ln Y|s_i, x_i) = \alpha_i + \rho_{si}s_i + \beta_{0i}x_i + \beta_{1i}x_i^2,$$

[11] While modeling the specific forms of the random component e_{it} is beyond the scope of this article, the economic literature on the income process offered some statistical strategies for modeling random variability (e.g., Gottschalk and Moffitt 1994; Auxiliary analyses to be presented later will further explain the variations in the random component.

[12] Allison et al. (1982, p. 619) pointed out that one crucially important element of the scientific career process is that "the occurrence of publications or citations is at least partially governed by random processes."

where α_i represents the intercept, s_i indicates formal schooling, x_i indicates experience, and ρ_{is}, β_{0i}, and β_{1i} represent the return on schooling, experience, and quadratic experience, respectively (Mincer 1996; Heckman et al. 2006). As such, the β_{0i} in this human capital equation has an interpretation similar to that of θ_i in my model because they both capture the speed at which wage grows over years of experience. Also, by having the subscript i in the speed-of-wage-growth parameter, both models can capture the heterogeneity in the rate of wage growth over the life course.

Although my formalization allows the wage growth rate to vary by person (represented by the subscript i in θ), it does not capture the variations of wage growth rate by time, as there is no subscript t in θ. I impose such a simplification so as to keep this article's main focus on the significance, rather than the functional form, of the between-person variation in wage growth rate. In future research, however, several parameterizations can be adopted to account for the temporal variation of θ. Here, I briefly propose two examples. The first is to specify θ_{it} using a stepwise spline function, which captures the differences in the wage growth rate across different stages of life. For example, suppose that wage growth rate equals θ_{i1} for the earlier period between t_1 and t_2 and changes to θ_{i2} for the later period between t_2 and t_3. Then we can express θ_{it} as $\theta_{it} = \theta_{i1}$ if $t_1 \le t \le t_2$ and $\theta_{it} = \theta_{i2}$ if $t_2 \le t \le t_3$. In this parameterization, θ_{i1} and θ_{i2} capture the individual's wage growth rate at the two different time periods. The second form of parameterization is to employ a polynomial function to approximate the temporal variation of wage growth rate. For example, we can specify θ_{it} as a polynomial of up to the power of p:

$$\theta_{it} = \alpha_{0i} + \alpha_{1i} \cdot t + \alpha_{2i} \cdot t^2 + \alpha_{3i} \cdot t^3 + \cdots + \alpha_{pi} \cdot t^p.$$

In this parameterization, α_{0i} captures the time-invariant part of the wage growth rate, and α_{1i}, α_{2i}, . . . , α_{pi} capture the dependence of the wage growth rate on time t up to a given power (p).

Deriving the Intracohort Pattern of Wage Inequality

Next, I use the microlevel wage attainment process specified by equation (3) to derive the macrolevel intracohort pattern of wage inequality. I choose the variance of log wage at t, denoted by Var $(\ln Y_t)$, as the indicator of wage inequality for individuals with t years of labor market experience. This indicator has three particular features that fit well with the purpose of this study. First, it is scale invariant, meaning that if the wage for everyone at every time point increases by the same factor, the variance of log wage will not change.[13] Hence, the observed and predicted changes in this measure of inequality are free from any alternation in the scale of the metric measuring wage (Faia 1975; Allison et al. 1982).[14] Second, given the generally accepted notion of diminishing marginal utility from monetary income—that is, the notion that the marginal benefit associated with one unit of income decreases with income level—the logarithm of wage is particularly desirable as an indicator of the actual individual well-being because its sensitivity to any fixed amount of monetary transfer decreases as absolute wage level increases (Allison 1978; Hedderson and Harris 1985). Third, equation (3) shows that log wage ($\ln Y_t$) can be expressed as the linear combination of separable components; therefore, its variance can be conveniently written as the sum of variances and covariances of these components, as follows:

$$\mathrm{Var}_t = \mathrm{Var}\,(\ln Y_t) = \mathrm{Var}\,(\lambda) + t^2 \cdot \mathrm{Var}\,(\theta) + 2t \cdot \mathrm{Cov}\,(\lambda,\, \theta) + \mathrm{Var}(e_t). \quad (4)$$

According to equation (4), the total wage inequality at time t can be written as the summation of four variance components: $V1$, $V2$, $V3$, and $V4$.[15] The first component $V1$ ($\mathrm{Var}(\lambda)$) captures the variance in baseline wage, and because baseline wages do not change over time, this variance component does not contribute to the change of wage inequality over t. The last component $V4$ ($\mathrm{Var}(e_t)$) captures the part of wage inequality due to the random variability in wage attainment. Under condition 1, this random variability will have positive variance, and thus $V4$ will be positive. Further, to the extent that random variability accumulates over the life course, $V4$ will increase with t, and the overall wage inequality will also increase. Therefore, hypothesis 1 is supported.

It takes some further calculations to show that the two variance components in the middle, $V2$ ($t^2 \cdot \mathrm{Var}(\theta)$) and $V3$ ($2t \cdot \mathrm{Cov}(\lambda, \theta)$), correspond to the trajectory heterogeneity property and cumulative advantage prop-

[13] In laying out the axiom of scale invariance as a key principle for measuring inequality, Schwartz and Winship (1980, p.7) explained that under scale invariance, "the size of the pie to be divided has no bearing on the degree of inequality—it is only the relative share each person receives that is important in determining inequality."

[14] In fact, as Faia (1975), Allison et al. (1982), and DiPrete and Eirich (2006) have pointed out, although the compounding process in eq. (1) automatically implies the increase in wage inequality over t, it does not, by itself, necessarily lead to the increase in the scale-invariant measures of inequality. This article shares the same concern with these authors and will tease out the mechanisms that give rise to the changes in the scale-invariant measure of wage inequality over the life course.

[15] Note that in eq. (4), there is no term of the covariance between e_{it} and other variables because the model assumes that the random component is independent of the other components.

erty, respectively. The second component of wage inequality, $V2$, corresponds to the trajectory heterogeneity property. To see this, note that $V2$ depends on the variance of the person-specific rate of wage growth, $\mathrm{Var}(\theta)$. Since individuals follow heterogeneous wage trajectories over life, and thus will experience varying levels of wage growth rate, we therefore have the following condition:

CONDITION 2.—$\mathrm{Var}(\theta) > 0$.

Condition 2 ensures that the model satisfies the requirement of the trajectory heterogeneity property (i.e., property 2). Further, when $\mathrm{Var}(\theta) > 0$, $V2$ $(= t^2 \cdot \mathrm{Var}(\theta))$ will increase with t. Since $V2$ is a component of the total intracohort wage inequality, this means that when condition 2 is satisfied, total wage inequality among the cohort of individuals will increase over their lives, a conclusion consistent with hypothesis 2.

The third component of wage inequality, $V3$, is determined by the product of t and $\mathrm{Cov}(\lambda, \theta)$. This component can be further decomposed into the between-group and within-group components of the cumulative advantage property. To illustrate, I introduce an m-dimensional vector of covariates, S, to represent the individual's time-invariant social group measured on m different social dimensions. Then, by the law of total covariance, I decompose the covariance between λ and θ into the part due to S (between-group) and the part not due to S (within-group):[16]

$$\mathrm{Cov}\,(\lambda, \theta) = \mathrm{Cov}\,(E(\lambda|S), E(\theta|S)) + E(\mathrm{Cov}(\lambda, \theta|S)). \tag{5}$$

In the first component of equation (5), $E(\lambda|S)$ represents the expectation of the baseline wage conditional on the individual's social groups, and $E(\theta|S)$ represents the expectation of the wage growth rate conditional on the individual's social groups. Therefore, the covariance between these two quantities, $\mathrm{Cov}(E(\lambda|S),\ E(\theta|S))$, represents the association between the baseline wage and the wage growth rate explained by social groups, that is, the between-group component of cumulative advantage. For the between-group component of the cumulative advantage property to exist, there should be a positive between-group association between the baseline growth rate and the wage growth rate. Thus, the covariance between $E(\lambda|S)$ and $E(\theta|S)$ should be positive:

CONDITION 3*a*.—$\mathrm{Cov}(E(\lambda|S),\ E(\theta|S)) > 0$.

The second part in equation (5), $E(\mathrm{Cov}(\lambda, \theta|S))$, is the covariance between λ and θ conditional on S, so it represents the association between the

[16] The law of total covariance is a mathematical theorem that states that for three random variables, X, Y, and Z, on the same probability space with the covariance of X and Y being finite, we have $\mathrm{Cov}\,(X, Y) = E(\mathrm{Cov}\,(X, Y|Z)) + \mathrm{Cov}(E(X|Z), E(Y|X))$.

baseline wage and the wage growth rate within these social groups, that is, the within-group component of cumulative advantage. In order to satisfy the within-group component of the cumulative advantage property, this association should be positive:

CONDITION 3*b*.—$E(\mathrm{Cov}(\lambda, \theta|S)) > 0$.

To sum up the above discussion, condition 3*a* ensures that cumulative advantage exists between observed social groups, and condition 3*b* ensures that cumulative advantage exists within observed social groups.

Given the expression in equation (5), we can rewrite $V3$ in equation (4) as a linear combination of two components ($V3a$ and $V3b$):

$$V3 = 2t \cdot \mathrm{Cov}\,(\lambda, \theta) = 2t \cdot \mathrm{Cov}(E(\lambda|S), E(\theta|S)) + 2t \cdot E(\mathrm{Cov}(\lambda, \theta|S)). \tag{6}$$

Equation (6) shows that under condition 3*a* and condition 3*b*, the slopes on t in $V3a$ (the first term on the right-hand side) and $V3b$ (the second term) are positive. Thus, both components will increase with t, and so will the total wage inequality—a prediction that is consistent with hypothesis 3.

In addition to confirming our theoretical hypotheses, the mathematical formalization also helps clarify the relations and distinctions between different components of total wage inequality. First, while trajectory heterogeneity and cumulative advantage both affect total wage inequality by acting on the variation in wage growth rate, there exists an important distinction between these two mechanisms. As equation (4) shows, they act on different elements of this variation: the contribution of trajectory heterogeneity works through affecting the degree of between-person variation in wage growth rate regardless of where this variation comes from, while the contribution of cumulative advantage works through affecting the intensity of dependence of the wage growth rate on the baseline wage. Hence, even if there is no association between the baseline wage and the wage growth rate—that is, the case in which $V3$ equals zero—the heterogeneity in the wage growth rate, by itself, could still cause total wage inequality to increase over the life course as long as the variance of θ is positive. Second, equation (4) suggests that mathematically, trajectory heterogeneity causes total wage inequality to increase by affecting t^2, whereas cumulative advantage causes total wage inequality to increase by affecting $2t$. When t takes a value of two or larger, t^2 will increase at a faster rate than $2t$ does. Therefore, one could expect the contribution of trajectory heterogeneity to the growth of total inequality to be larger than that of cumulative advantage—a result that will be confirmed by my later empirical analyses.

Up to this point, I have shown that under conditions 1, 2, 3*a*, and 3*b*, the mathematical formalization of the LCT framework satisfies the three essential properties of the LCT framework and yields the same predictions as those given in hypotheses 1, 2, and 3. For a succinct illustration, I summarize the three essential properties, their corresponding hypotheses, and the corresponding conditions in the mathematical formalization in table 1. Throughout this article, table 1 can be kept as a useful reference for comprehending the connections between theoretical, mathematical, and empirical parts of the LCT framework.

APPLICATION OF THE LCT FRAMEWORK: THE INTRACOHORT PATTERN OF WAGE INEQUALITY IN THE UNITED STATES

The scope of the LCT framework extends beyond the formalization of an analytical construct. Next, I apply the LCT framework to a nationally representative longitudinal data set that follows a cohort of individuals in the United States through their life experiences. While I realize that the empirical results should be interpreted as specific to this specific cohort in the specific historical period, the empirical analyses and findings suggest that with appropriate data, the LCT framework has the promise of being utilized by future research to examine and compare the intracohort pattern of wage inequality in different social contexts.

The application of the LCT framework proceeds with three parts. In the main analysis, I (1) test for the significance of the three essential properties of the LCT framework in reality and (2) assess their contributions to the observed intracohort pattern of wage inequality in the United States. Then, I will conduct two rounds of auxiliary analyses: the first allows the person-specific wage growth rate to vary across different life stages, and the second introduces controls for a set of time-varying indicators of work experience, occupation, and family-domain life transitions. Finally, I discuss the limitations of my analyses and suggest potential directions for future extensions.

Data and Sample Restriction

To empirically examine the underlying mechanisms in individuals' life course trajectories, a longitudinal data set that links repeated observations for each individual across a span of his or her life course is needed. The National Longitudinal Survey of Youth 1979 (NLSY79) data suit this purpose well in that they follow a nationally representative sample of 12,686 young people in the United States who were 14–22 years old when they were first surveyed in 1979. That is, this data set covers a sample that is representative of the cohort of population born largely between 1957 and 1965. These individuals were interviewed annually through 1994 and on a biennial basis thereafter. The currently available NLSY79 data provide useful information about

TABLE 1

SUMMARY OF THE ESSENTIAL PROPERTIES, CORRESPONDING HYPOTHESES, CONDITIONS IN THE MATHEMATICAL FORMALIZATION, ELEMENTS IN THE MULTILEVEL GROWTH CURVE MODEL, AND THE RESULTS FROM EMPIRICAL ANALYSES OF THE LCT FRAMEWORK

Essential Property	Corresponding Hypothesis	Condition in Mathematical Formalization	Element in the Multilevel Growth Curve Model	Supported by Data?
Random variability property	Intracohort inequality will increase over the life course as a result of the accumulation of random variability	$\mathrm{Var}(e) > 0$	$\mathrm{Var}(e) > 0$	Yes
Trajectory heterogeneity property	Intracohort inequality will increase over the life course as a result of trajectory heterogeneity	$\mathrm{Var}(\theta) > 0$	$\mathrm{Var}(\beta_1) > 0$	Yes
Cumulative advantage property	Intracohort inequality will increase over the life course as a result of cumulative advantage	Between-group, $\mathrm{Cov}(E(\lambda\|S), E(\theta\|S)) > 0$ Within group, $E(\mathrm{Cov}(\lambda, \theta\|S)) > 0$	The pairs of γ_{01} and γ_{11}, γ_0 and γ_{12}, γ_0 and γ_{13} are significant and have the same signs within each pair	Yes
		Within-group: $E(\mathrm{Cov}(\lambda, \theta\|S)) > 0$	$\mathrm{Cov}(u_1, u_0) > 0$	No

the year-to-year wage trajectories for these individuals from the beginning of their career to their mid and late career.[17]

The key indicator of the life course in this study, as I discussed earlier, is the years of labor market experience. I construct a variable called "potential experience" to approximate the years that an individual has spent in the labor market after finishing formal schooling. This variable is calculated as age minus 18 for those with high school education or less, age minus 22 for those with some college education but less than four years, and age minus 25 for those with at least four years of college education.[18]

Owing to the heterogeneity in the NLSY79 cohort's birth year and the heterogeneity in the respondent's age of labor market entry, in the currently available NLSY79 data, some respondents have longer wage records than others do. The estimated wage inequality for those with longer years of experience may overrepresent those with longer records available and underrepresent those with shorter records. Thus, to the extent that these individuals differ systematically in wage attainment, this over- and underrepresentativeness could cause substantial bias to the estimation of wage inequality. For this reason, I choose to restrict my analytic sample to observations between the individuals' entrance into the labor market (i.e., zero years of potential experience) and their midcareer (i.e., 20 years of potential experience). This restriction will reduce the above problem because even for those in the youngest NLSY79 cohort (born in 1965) who have not entered the labor market until age 25 (e.g., around year 1990), their first 20 years of potential experience have all been covered by the currently available NLSY79 data. After sample restriction, my analytic sample comes to a total of 133,121 person-year observations.[19] All data analyses are weighted.

[17] My study favors the NLSY79 data over other data sets for several reasons. First, while other nationally representative longitudinal data sets, such as the Panel Study of Income Dynamics, do exist, most of them cover individuals who were born in a wide range of years. As a result, the number of respondents within a narrowly defined birth-year range (i.e., individuals from the same cohort) is relatively small compared to the NLSY79 data. Second, while some more recent data, such as the NLSY97 data, also follow individuals born within a narrow range of years over their career experiences, the respondents are still too young and are only at the beginning stages of their careers. Thus the NLSY79 data are also preferred over such recent data sets.

[18] Recall that as explained earlier, my choice of labor market experience rather than biological age as the key dimension of the life course process is based on the better fit between labor market experience and my purpose of modeling the wage attainment process. I also experimented with biological age as the dimension of the life course process. The results were consistent with those from using potential experience and are thus omitted from the article.

[19] Certainly, even within this restricted time period, missing data on some variables and nonresponses are still likely in longitudinal surveys. Individual wages are coded as missing if the respondents were not working at the time of the interview.

Measures

I use the logarithm of hourly wage of the individual's current or most recent job, which is adjusted to 1999 dollars by the Consumer Price Index, as the key outcome variable. I prefer log hourly wage over annual earnings or family income because, unlike the other two, hourly wage measures the economic return that the individual receives for one hour of labor that he or she provides; thus, it is not affected by the total hours worked by the individual or other family members.[20] Consistent with my mathematical formalization, I measure wage inequality as the variance of log hourly wage. The individual's wage will be coded as missing if he or she is not working at the time of the interview. Fortunately, the multilevel growth curve model to be employed by this study, which I will introduce later, is flexible with missing data and unbalanced observations (Curran, Obeidat, and Losardo 2010).[21] Meanwhile, it is possible that individuals choose to work at multiple jobs. However, as several earlier works suggested, the decision to work multiple jobs depends on the business cycle or macroeconomic conditions; therefore, the reported wage from the primary job may be more reliable than that from secondary jobs (Partridge 2002; Amuedo-Dorantes and Kimmel 2009). Hence, in cases in which an individual is concurrently working at more than one job, only hourly wage from the individual's primary job will be used.[22]

Next, I introduce my measures for individuals' social group attributes. While my specification of "social groups" in the theoretical and mathematical parts of the LCT framework can be applied to any type of person-specific and time-invariant group indicators, it is not possible to exhaust all potential indicators in the empirical analysis. I choose to focus on three indicators of the individual's social group that sociologists have long believed to be most central to the stratification system: gender, race, and educational attainment.

First, gender is an important social attribute that separates individuals into groups of different earnings positions (Reskin 1978; Tomaskovic-Devey and Skaggs 2002; DiPrete and Eirich 2006). Despite the recent social movements toward promoting gender wage equality in America, males still earn signif-

[20] There are, of course, some limitations to the measure of hourly wage in capturing inequality among individuals. I will discuss more on its limitations in later sections.

[21] Yet, I will discuss and assess the sensitivity of my conclusions with regard to the missing wage information by imputing these values later.

[22] Given the relatively minimal proportion of individuals working at multiple jobs compared to those who are working at only one job, this simplification would have only a moderate impact on estimating the individual's wage level. For example, according to statistics from earlier works using the NLSY79 data, Amuedo-Dorantes and Kimmel (2009, table 1) showed that in the year 2000, about 50% of men were working, yet only 7% of men are working at multiple jobs.

icantly higher wages than females of similar qualifications, and this gender inequality has been found to magnify over the life course. Tomaskovic-Devey and Skaggs (2002) argued that the gender wage gap can emerge and intensify over people's careers as a result of the social closure process in the workplace that excludes female workers from on-the-job training and productivity-enhancing workplace networks. Fernandez-Mateo (2009) showed that even in the case of contract employment, where women's disadvantage in workplace resources and firm-specific skills is expected to affect their wage only minimally, men still experience substantially faster wage growth than women. In addition, life events in the family domains such as marriage and childbearing often promote wage growth for men yet limit wage growth for women (Budig and England 2001; Noonan et al. 2005; Correll et al. 2007). Therefore, women might incur further wage disadvantage to men when they get married or become parents at later stages of their lives.

Second, race is another dimension of social attributes along which cumulative advantage may occur (Tomaskovic-Devey et al. 2005; Shuey and Willson 2008; Walsemann et al. 2008; Kim and Miech 2009). Racial minorities incur baseline as well as cumulative disadvantage in their career process. Tomaskovic-Devey et al. (2005) showed that blacks and Hispanics have flatter wage trajectories relative to whites and argued that this race-based cumulative advantage is likely due to the discrimination against racial minorities through monopolistic social closure in the workplace and the devaluation of racial minorities' human capital over their careers (see also Tomaskovic-Devey 1993; Burt 1997; Royster 2003). My analyses examine the difference in the baseline wage as well as the wage growth rate between whites, blacks, and Hispanics.[23]

Third, cumulative advantage in wage could occur between groups of different levels of educational attainment (Elman and O'Rand 2004; DiPrete and Eirich 2006). Because people with higher educational attainment are usually believed to have a greater stock of human capital, they likely receive higher wages at their entrance into the labor market. Furthermore, in the dynamics within the workplace, higher educational attainment usually indicates a higher status for the worker, which could signal lower uncertainty in the quality of job performance, enhance the visibility of a worker among his or her colleagues in the organization (Gould 2002), promote the worker's exposure to additional organizational resources (DiPrete and Eirich 2006), and lift the worker's confidence and motivation in work (Nease, Mudgett, and Quiñones 1999; Tay, Ang, and Van Dyne 2006). All these factors can lead to a faster rate of wage growth, resulting in the life course magnification of wage advantage of more highly educated in-

[23] In NLSY79 data, nonblacks and non-Hispanics are coded as white.

dividuals. In my analyses, I categorize educational attainment into three levels: high school or less, some college but less than four years, and at least four years of college.[24]

Certainly, while the three dimensions of social groups described above are the most fundamental ones identified in the long tradition of sociological literature, I do recognize that omitting other dimensions of social groups constitutes an important limitation of my analyses. Indicators of these other dimensions of social groups require more sophisticated considerations that should be informed by both theoretical and empirical knowledge, which are beyond the scope of this study. I believe that the initial attempt in this article to distinguish between between-group and within-group components of cumulative advantage based on the above three dimensions of social groups could lay the foundations for future works following this line of inquiry.

Table 2 gives the weighted sample distribution of time-invariant variables including gender, race, and educational attainment (panel A), the means and standard deviations of log hourly wage by demographic groups (panel B), and those by years of potential experience (panel C). Two patterns are worth noting from the descriptive statistics. First, consistent with findings from earlier studies, average wages differ among individuals belonging to different gender, race, and educational attainment groups: on average, the mean hourly wage for men is higher than that for women by about 30% ($\approx e^{2.48-2.22} - 1$). Among the three racial groups, whites earn the highest hourly wage, followed by Hispanics, and blacks earn the lowest. Average wage also increases with the level of educational attainment: people with at least four years of college earn the highest, followed by those with some college but less than four years, and people with high school or lower educational attainment earn the lowest, on average. Second, the distribution of wages by groups of potential experience accords with stylized facts documented by earlier works that average wage, as well as wage dispersion, increases with age (Dannefer 1987; Easterlin, Macunovich, and Crimmins 1993). Specifically, the variance of log hourly wage increases by about 130% from 0.32 ($= 0.57^2$) for the group with zero to five years of potential experience to 0.74 ($= 0.86^2$) for the group with 16–20 years of potential experience.

[24] To be sure, individuals could differ from one another in terms of a finer-grained measure of educational attainment, such as years of schooling. However, I prefer the categorical measure of educational attainment because in the workplace, individuals are usually differentiated from each other not necessarily on the exact number of years of schooling they have completed but, more likely, on observed educational degrees, such as high school or college.

TABLE 2
Descriptive Statistics of the NLSY79 Sample Used in the Empirical Analysis

	A. Time-Invariant Variables	
	%	
Gender:		
Male	50.84	
Female	49.16	
Race:		
White	79.82	
Hispanic	6.31	
Black	13.87	
Educational attainment:		
High school or less	58.35	
Some college but less than four years	21.74	
At least four years of college	19.91	
	B. Log Hourly Wage by Demographic Characteristics	
	Mean Log Hourly Wage	SD Log Hourly Wage
By gender:		
Male	2.48	.68
Female	2.22	.70
By race:		
White	2.38	.71
Hispanic	2.30	.68
Black	2.20	.64
By educational attainment:		
High school or less	2.24	.61
Some college but less than four years	2.40	.69
At least four years of college	2.59	.85
	C. Log Hourly Wage by Potential Experience	
0–5 years	2.26	.57
6–10 years	2.39	.64
11–15 years	2.45	.69
16–20 years	2.52	.86

Note.—Data are from the National Longitudinal Survey of Youth 1979–2010, Bureau of Labor Statistics. All sample statistics are weighted.

Statistical Strategy

My core empirical analyses employ the multilevel growth curve model to predict log hourly wage for person i with t years of potential experience. The multilevel growth curve model is a statistical tool that allows the researcher to describe the patterns of variability in the individual trajectory. Thus, with appropriate modification, this model can be applied to studying the microlevel foundations of the varying extents of inequality over the life course.[25] The multilevel growth curve model fits well with the purpose of this study in two respects. First, the method of maximum likelihood estimation adopted by this model is flexible with partially missing data and the unequally spaced time points of observations (Curran et al. 2010), which are common in the wage-related variables in the NLSY79 data.[26] Second, rather than limiting its attention to a finite set of discrete, typological trajectory groups, the multilevel growth curve model allows for between-group trajectory differentials as well as variation across individuals' trajectories within observed social groups (Bryk and Raudenbush 1987; Raudenbush 2005). With appropriate specifications, the model can be utilized to distinguish between the between- and within-group components of cumulative advantage.[27]

My implementation of the multilevel growth curve model involves two levels. The level 1 model is organized around the person-year observations, and the level 2 model is organized around the individuals. In level 1, I predict log hourly wage for person i with t years of potential experience, denoted by W_{it}, by the following equation:

$$W_{it} = \beta_{0i} + \beta_{1i} \cdot t + \beta_2 \cdot t^2 + e_{it}. \tag{7}$$

In equation (7), β_{0i} represents the person-specific random intercept, and β_{1i} represents the person-specific random slope on t. With regard to the LCT framework, these two parameters have meaningful interpretations: β_{0i} can be interpreted as the person-specific *baseline wage*, and β_{1i} can be interpreted as the person-specific *wage growth rate*. The coefficient β_2 captures the effect of the squared term of years of experience. While in reality it is possible that β_2 varies by person, for the sake of parsimony, my main analysis assumes that this coefficient is the same for everyone.[28] Yet, in

[25] For an example of multilevel growth curve models in studying cumulative health inequality, see the work by Willson et al. (2007).

[26] An important assumption underlying the treatment of missing data by the multilevel growth curve model is that missing observations are missing at random (Little and Rubin 1989; Lynch 2003). That is, the likelihood of missing observations should not be systematically associated with other variables in the model. The possibility of violation of this assumption, of course, may exist in the real world. Later discussions will deal with the potential implications of such violations.

[27] An alternative method for analyzing longitudinal data is the fixed-effect model. In fact, a number of prior works have employed the fixed-effect model to study wage trajectories over the life course (e.g., Western 2002; Tomaskovic-Devey et al. 2005). This article chooses to adopt the random-effect setting in the multilevel growth curve model rather than the fixed-effect model because the former allows me to explicitly estimate the level of variation in the population distribution of the random slope on years of experience.

[28] This simplification has also been adopted by earlier studies using the multilevel growth curve model to study inequality (e.g., Xie and Hannum 1996; Kim and Sakamoto 2008*a*).

preliminary analyses omitted from the article, I assessed the possible variation of β_2 by social groups, and the results are consistent with those assuming a fixed β_2.[29] Finally, the residual term e_{it} represents the unexplained random variability of wage for person i at time t.

In level 2, I predict the person-specific random intercept β_{0i} and random slope β_{1i} using three covariates, S_1, S_2, and S_3, which indicate three dimensions of the individual's social groups: S_1 represents gender, S_2 represents race, and S_3 represents the level of educational attainment. The level 2 model is expressed by the following two equations:

$$\beta_{0i} = \gamma_{00} + \gamma_{01}S_{1i} + \gamma_{02}S_{2i} + \gamma_{03}S_{3i} + u_{0i}, \tag{8}$$

$$\beta_{1i} = \gamma_{10} + \gamma_{11}S_{1i} + \gamma_{12}S_{2i} + \gamma_{13}S_{3i} + u_{1i}. \tag{9}$$

Equation (8) specifies the person-specific baseline wage. The variable γ_{00} represents the constant part of the baseline wage that is universal across persons and years of experience, and γ_{01}, γ_{02}, and γ_{03} represent the effects of gender, race, and educational attainment on the baseline wage, respectively. The residual in the baseline wage, u_{0i}, is the person-specific random component in the baseline wage capturing the unobserved individual heterogeneity that is not explained by the indicators of the person's observed social groups. Equation (9) specifies the person-specific wage growth rate. The variable γ_{10} represents the constant part of the growth rate of log hourly wage over t, and γ_{11}, γ_{12}, and γ_{13} represent effects of gender, race, and educational attainment on the wage growth rate. The residual, u_{1i}, captures the random component in the wage growth rate that is not explained by the three indicators of observed social groups. I assume u_0 and u_1 to have zero mean and allow the correlation between these two unobserved residuals to be nonzero.

Note that my main analyses here assume that the wage growth rate varies by person yet does not change over time. To assess the robustness of my conclusions with regard to this assumption, later auxiliary analyses will introduce the temporal variation in the wage growth rate to the model. In addition, the main analyses do not control for work experience and family-domain life events in predicting wage. These time-varying variables may have mediated the effects of gender, race, and educational attainment on the baseline wage and the wage growth rate, or they may have contributed to some of the residual variations in wage. Later auxiliary analyses will

[29] With regard to between-group differences, in this preliminary analysis, I found no significant differences in β_2 by gender or race. The only significant difference occurs between individuals with different levels of educational attainment: people with higher educational attainment tend to experience a larger negative effect on the squared years of potential experience.

examine whether controlling for these time-varying variables explains away some of the variations left unexplained by the main analyses.

Specified by equations (7)–(9), the key elements in this multilevel growth curve model correspond directly to the essential properties in the LCT framework introduced earlier:

1. In equation (7), the residual e represents the random component in wage. If $\mathrm{Var}(e) > 0$, the random variability property will be supported.
2. In equation (9), the between-person variation in β_1 reflects the individual heterogeneity in wage trajectories. If $\mathrm{Var}(\beta_1) > 0$, the trajectory heterogeneity property will be supported.
3. If between-group cumulative advantage exists in reality, indicators of a person's social groups should affect β_0 and β_1 in the same direction. Thus, if the pairs of coefficients in β_0 and β_1 corresponding to the same covariate (i.e., γ_{01} and γ_{11}, γ_{02} and γ_{12}, γ_{03} and γ_{13}) are all significantly different from zero and have the same signs within each pair, this means that groups with higher baseline wages experience a faster wage growth rate, and thus the between-group component of the cumulative advantage property will be supported.
4. For within-group cumulative advantage to exist in reality, the residual components in β_{0i} and β_{1i} should associate positively. Thus, if $\mathrm{Cov}(u_0, u_1) > 0$, this means that within these groups, those with higher baseline wages tend to have a higher wage growth rate, and the within-group component of the cumulative advantage property will be supported.

For the clarity of demonstration, I summarize the elements in the multilevel growth curve model and their correspondence with the essential properties in table 1. As such, the theoretical components of the LCT framework are linked to the statistical strategy. Establishing this link is crucial for the empirical application of the LCT framework.

Testing for the Significance of Three Essential Properties of the LCT Framework

The first round of empirical analyses employs the multilevel growth curve models introduced earlier to test for the significance of three essential properties of the LCT framework. Table 3 gives the results from two multilevel growth curve models predicting log hourly wage. First, does trajectory heterogeneity exist in reality? Model 1 allows individual characteristics to affect only the baseline wage. Consistent with the patterns from the descriptive statistics, an individual's group attributes are significantly associated with his or her baseline wage: males tend to earn a higher

TABLE 3
ESTIMATED COEFFICIENTS FROM MULTILEVEL GROWTH CURVE MODELS PREDICTING LOG HOURLY WAGE

	Model 1	Model 2
Coefficients predicting baseline wage (β_0):		
Constant intercept (γ_{00})	1.952***	1.926***
	(.011)	(.013)
Gender (γ_{01}) (reference: male):		
Female	−.252***	−.205***
	(.011)	(.015)
Race (γ_{02}) (reference: white):		
Hispanic	−.011	.007
	(.013)	(.017)
Black	−.118***	−.083***
	(.013)	(.019)
Educational attainment (γ_{03}) (reference: high school or less):		
Some college but less than four years	.331***	.302***
	(.012)	(.016)
At least four years of college	.734***	.723***
	(.017)	(.018)
Coefficients predicting wage growth rate β_1:		
Constant slope (γ_{10})	.052***	.058***
	(.002)	(.002)
Gender (γ_{11}) (reference: male):		
Female		−.010***
		(.002)
Race (γ_{12}) (reference: white):		
Hispanic		−.004
		(.002)
Black		−.008**
		(.002)
Educational attainment (γ_{13}) (reference: high school or less):		
Some college but less than four years		.006*
		(.003)
At least four years of college		.002
		(.004)
Other coefficient:		
Squared experience (β_2)	−.002***	−.002***
	(.000)	(.000)
Variance components:		
var(u_0)	.637***	.636***
	(.082)	(.081)
var(u_1)	.014***	.014***
	(.001)	(.001)
cov(u_0, u_1)	−.065***	−.065***
	(.007)	(.007)
var(e)	.165***	.165***
	(.004)	(.004)

NOTE.—Data are from the National Longitudinal Survey of Youth 1979–2010, Bureau of Labor Statistics. The number of individuals is 12,099; the number of person-year observations is 133,121. Robust SEs are in parentheses. All analyses are weighted.

* $P < .05$.

** $P < .01$.

*** $P < .001$.

baseline wage than females; whites earn the highest among the three racial groups, followed by Hispanics and then blacks; the baseline wage tends to be the highest for people with at least four years of college education, followed by those who had less than four years of college and then those with only a high school diploma or less. Model 1 assumes that a person's wage growth rate β_{1i} is solely determined by two factors: a constant slope (γ_{10}) and a person-specific random effect (u_{1i}) on the wage growth rate. That is, model 1 allows the wage growth rate to vary by person yet does not allow it to depend systematically on indicators of their measured characteristics.[30] As table 3 shows, the coefficient on years of potential experience is significantly positive (0.052) and the coefficient on squared experience is significantly negative (−0.002), indicating that the rate of wage growth decreases with years of potential experience. The variance of the person-specific wage growth rate is 0.014 and is significantly larger than zero. Recall that earlier I illustrated that the condition $\mathrm{Var}(\beta_1) > 0$ implies that there exists substantial heterogeneity in wage trajectories; therefore, the trajectory heterogeneity property is supported.

Next, does cumulative advantage exist in reality? To test this, I further allow the wage growth rate to depend on indicators of social groups in model 2. I will discuss the results for between-group and within-group cumulative advantage separately. As shown earlier, the significance of between-group cumulative advantage can be tested by checking whether groups with higher baseline wages tend to experience higher wage growth rates—that is, by checking whether the three pairs of coefficients, γ_{01} and γ_{11}, γ_{02} and γ_{12}, and γ_{03} and γ_{13}, are statistically significant and have the same signs within each pair. The results in model 2 support the significance of cumulative advantage associated with all three indicators of social groups: first, being female is significantly associated with a lower baseline wage as well as a slower wage growth rate. This finding contrasts with the conclusion in some earlier works that the disadvantage in wages for females remains unchanged or even diminishes over their life courses (e.g., Bielby and Bielby 1992). Instead, this finding suggests that gender inequality should be considered in light of a life course cumulative advantage process (Tomaskovic-Devey and Skaggs 2002). Second, in accord with the findings of Tomaskovic-Devey et al. (2005), race is also found to be a significant dimension along which cumulative advantage occurs. While there is no significant difference between whites and Hispanics in the sample, the results show that compared to whites, blacks earn significantly lower baseline wages and experience significantly slower wage growth rates. Third, in-

[30] In other words, this model assumes that the variance in β_1 is entirely due to the variance in u_1.

dividuals with higher educational attainment, especially those with an educational attainment beyond high school, not only receive higher wages at the beginning of their career process but also experience faster wage growth rates over their lives.

For a graphic illustration of the between-group cumulative advantage, figure 2 displays the predicted life course trajectories of average wage by gender, race, and educational groups based on the estimation of model 2. In each panel, I contrast the life course trajectories of individuals from social groups that have been found to differ significantly in baseline wages as well as wage growth rates: males versus females, whites versus blacks, and people with high school or less educational attainment versus those with some college but less than four years. Consistent with the schematic illustration of cumulative advantage in the earlier presented panel *B* of figure 1, the curves show that individuals belonging to social groups with higher baseline wages tend to experience steeper wage trajectories, leading to the divergence of their wage trajectories over the life course.

The test for within-group cumulative advantage, however, tells a different story. In model 2, the covariance between the two residual terms, u_0 and u_1, is negative, which suggests that conditional on gender, race, and educational attainment, the residual in the baseline wage associates negatively with the residual in the wage growth rate. This means that among individuals who share the same group-level attributes on the three measured dimensions, those with higher wages at the beginning tend to have a lower wage growth rate, and those who started out at a lower baseline wage tend to "catch up" gradually over the life course. The fact that wage trajectories within groups tend to converge over the life course means that the within-group component of cumulative advantage is not supported by my analyses. Exploring the specific processes underlying such convergence in wage trajectories within groups is beyond the scope of this study. Yet, some conjectures could be raised. First, this phenomenon may imply that the labor market provides "compensation" for jobs that offer lower starting wages by offering improved prospects of wage growth in the future, so that job seekers choosing among different jobs face a "trade-off" between a higher wage at the beginning and a faster rate of wage growth (Rosen 1986). Second, from the perspective of the individual's work attitude, it is also possible that among individuals with similar observed characteristics, those who earn lower wages at the beginning are better motivated to work harder and achieve faster wage growth in the future than those with higher starting wages. Third, it is not uncommon for young workers, especially those with higher skills, to "test the water" by "job shopping" in their early years to learn about their true abilities and preferences, or simply to work in a low-skill job such as taxi driving or doing community service, before they shift into a "true" career job (Johnson 1978; Borjas and Rosen 2012). As such, the

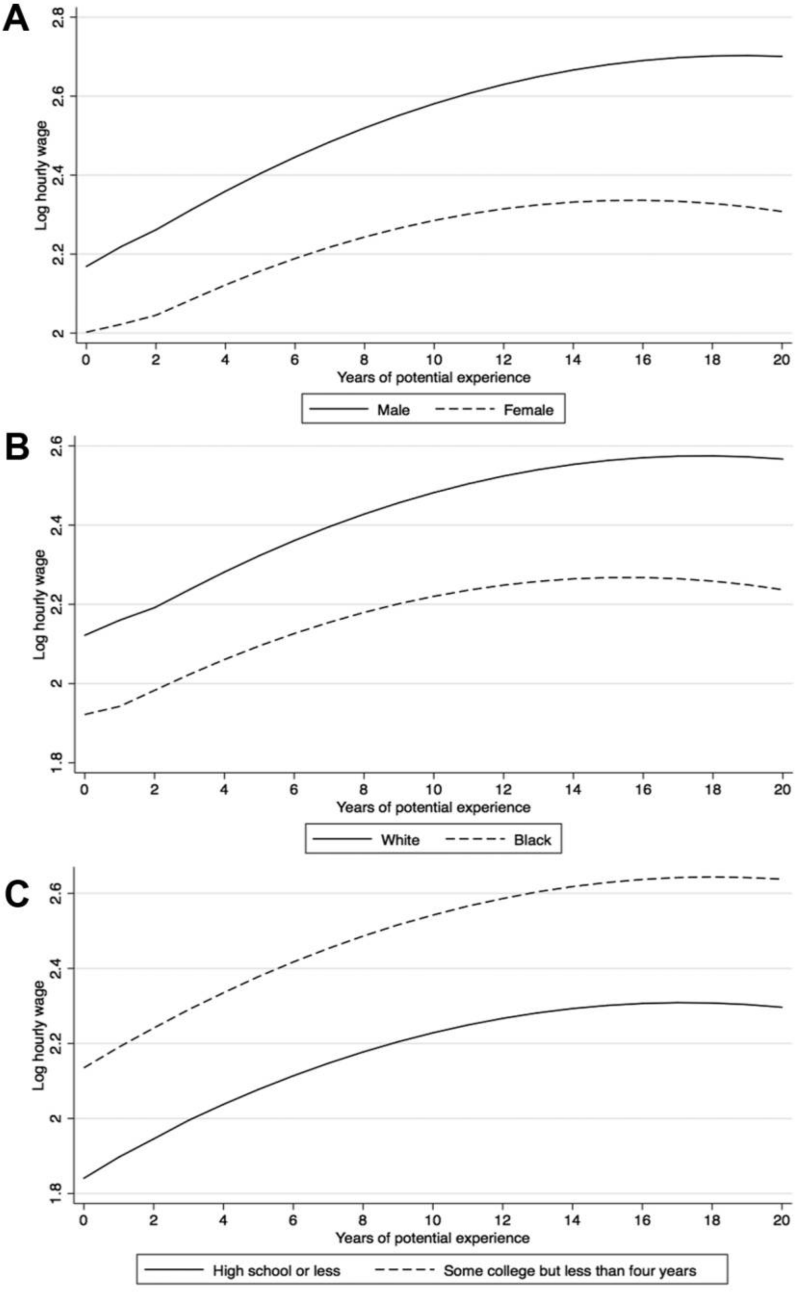

FIG. 2.—Predicted average log hourly wage by years of potential experience, by gender, race, and educational groups. Data are from the National Longitudinal Survey of Youth 1979–2010, Bureau of Labor Statistics.

within-group "catch-up" in wage attainment may in part be the manifestation of these people moving from career-atypical jobs to true career jobs over time.[31] Fourth, one defining feature of the recent rise in economic inequality in the United States is the divergence of the income of the superrich (e.g., the top 1%) from the income of the majority of wage earners (McCall and Percheski 2010; Volscho and Kelly 2012; Piketty 2014), which is likely driven by the top income earners' cumulative advantage in obtaining higher earnings. The superrich make up a small portion of the population and are difficult to capture with survey data, especially given NLSY79 data's oversampling of low-wage individuals. If the analyses are applied to a larger sample of top income earners, however, it is possible that within-group cumulative advantage will be observed for this specific share of the population.

Finally, does the random variability property exist in reality? The results suggest yes. In model 1 and model 2, the residual takes a significantly positive variance of 0.165, which equals about one-fourth of the variance in individuals' random intercept. Hence, random variability takes up a substantial portion of total wage inequality and the random variability property is supported.

The last column of table 1 summarizes the findings by stating whether the proposed properties are supported (marked yes) or not (marked no) by the data. Both the random variability property and the trajectory heterogeneity property are supported by the data, while the findings for the cumulative advantage property are mixed: cumulative advantage exists between groups defined by gender, race, and educational attainment but does not exist within these groups.

Assessing the Contributions of Three Mechanisms to the Observed Growth of Intracohort Wage Inequality

Given the significance of the random variability property, the trajectory heterogeneity property, and the between-group cumulative advantage property in life course wage attainment revealed by the above analysis, I now go on to assess the contributions of these mechanisms to the growth of total intracohort wage inequality by implementing the following four-step simulation procedure.[32]

[31] This could be tested by excluding the beginning few years of potential experience or by a detailed examination about the occupational mismatch at these individuals' first few jobs.

[32] According to my earlier analyses, only between-group cumulative advantage is supported by data, while within-group cumulative advantage is not. Thus, the assessment of the contribution of cumulative advantage to the change in total intracohort wage inequality will focus only on the between-group component.

Step 1. I use the estimated coefficients (each denoted by the true coefficient with a hat) from model 2 to predict log hourly wage for person i with t years of potential experience, that is,

$$\widehat{W_{it}} = \widehat{\beta_{0i}} + \widehat{\beta_{1i}} \cdot t + \widehat{\beta_2} \cdot t^2,$$

where $\widehat{\beta_{0i}}$, $\widehat{\beta_{1i}}$, and $\widehat{\beta_2}$ are calculated by equations (8) and (9).

Step 2. I calculate wage inequality among this cohort of individuals at each year of potential experience using the variance of log hourly wage predicted from step 1. I denote the variance of log hourly wage at t years of potential experience by $\mathrm{Var}(\widehat{W_t})$. Since $\mathrm{Var}(\widehat{W_t})$ is estimated from the full model (model 2), it represents the predicted wage inequality assuming that both trajectory heterogeneity and between-group cumulative advantage are at work; therefore, I term it "TH + BCA."

Step 3. Similarly to step 1, I conduct another round of prediction of log hourly wage. Yet, I manipulate the wage attainment process by "shutting down" the mechanism of between-group cumulative advantage while preserving the heterogeneity in wage trajectories. That is, I simulate the counterfactual of wage trajectories under the assumption that only trajectory heterogeneity is at work but between-group cumulative advantage is not. To do so, I generate log hourly wage by

$$\widehat{W_{it}^*} = \widehat{\beta_{0i}} + \widehat{\beta_{1i}^*} \cdot t + \widehat{\beta_2} \cdot t^2,$$

where I generate values of $\widehat{\beta_1^*}$ so that $\mathrm{Var}\,(\widehat{\beta_1^*}) = \mathrm{Var}(\widehat{\beta_1})$ under the restriction that β_1^* is uncorrelated with S_1, S_2, or S_3. Details about the technical procedure for constructing the counterfactual wage trajectories are presented in appendix B.

Step 4. Similarly to step 2, I calculate wage inequality using the log hourly wage at each year of potential experience predicted from step 3, which forms the trajectory of $\mathrm{Var}(\widehat{W_t^*})$. Because $\mathrm{Var}(\widehat{W_t^*})$ represents the predicted wage inequality under the assumption that only trajectory heterogeneity is at work but between-group cumulative advantage is not, I term it "TH."

Through the above four steps, I have obtained two sequences of predicted intracohort wage inequality: TH and TH + BCA.[33] These two sequences of predictions then help me to discern the contributions of trajectory heterogeneity and between-group cumulative advantage to the

[33] Note that the other components in the wage determination equation either affect only the time-invariant baseline wage (e.g., determinants for β_{0i}) or affect the level of wage equally for everybody (e.g., $\beta_2 \cdot t^2$), so they will not bring about any change in between-person wage inequality.

total intracohort pattern of wage inequality: if TH increases with t, this means that the mechanism of trajectory heterogeneity will contribute to the increase in wage inequality—a finding that supports hypothesis 2; if TH + BCA increases with t at a faster rate than TH, this means that adding the mechanism of between-group cumulative advantage will further accelerate the growth of wage inequality over the life course—a finding that supports hypothesis 3; if, after controlling for both TH and BCA, there still exists an extra increase in wage inequality that is not explained, this implies that the accumulation of random variability has contributed to the growth of intracohort wage inequality—a finding that supports hypothesis 1.

As an important last step, I adjust the observed and predicted intracohort wage inequality by the historical trend of wage inequality in the macroeconomy. This adjustment is necessary because given the well-documented surge of wage inequality in the United States during the observation window (i.e., from 1979 to 2010) of the NLSY79 cohort (Lemieux 2006; Autor, Katz, and Kearney 2008; McCall and Percheski 2010), it is possible that the increase in wage inequality among the NLSY79 respondents over the observed period is driven entirely by the economywide increase in wage inequality rather than by the discussed mechanisms underlying individuals' life course trajectories. Hence, the purpose of this adjustment is to rule out the confounding effect of the changing macroeconomy on the growth of intracohort wage inequality across the observed period. This adjustment is implemented as a standardization process similar to the better-known adjustment process for the Consumer Price Index, except that my adjustment factor is the level of wage inequality instead of the price index. First, I estimate the year-specific index for wage inequality in the American macroeconomy using the Current Population Survey, which provides large-sample nationally representative estimates of American wage inequality for each calendar year. Then, I match this index to each individual observation on the basis of the year in which wage information was recorded. Finally, I use the matched indexes to convert the wage inequalities measured for the NLSY79 cohort at different years to the comparable level of wage inequality at year 2000.[34] The detailed procedure of this adjustment is presented in appendix C.

Figure 3 plots the observed and predicted inequality in log hourly wage by years of labor market experience. The solid curve indicates the ob-

[34] Because wage inequality is calculated by individuals' years of potential experience, it is likely that individual observations for each year of potential experience are recorded at different calendar years. In this case, I will take the average of the adjustment factor of wage inequality across the individual observations recorded at different calendar years and construct the average adjustment factor in my calculation of adjusted wage inequality.

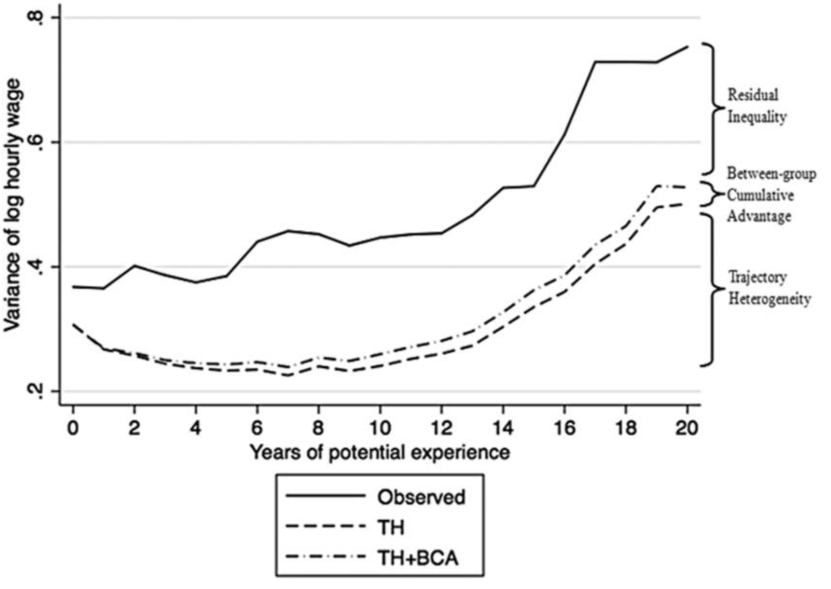

FIG. 3.—Observed and predicted variance of log hourly wage by years of potential experience. Data are from the National Longitudinal Survey of Youth 1979–2010, Bureau of Labor Statistics. Observed inequality is the variance of log hourly wage of the sample, TH is the variance of the predicted wage under the assumption that only trajectory heterogeneity is at work, and TH + BCA is the variance of the predicted wage under the assumption that both trajectory heterogeneity and between-group cumulative advantage are at work.

served wage inequality—measured by the variance of log hourly wage—among NLSY79 respondents from zero to 20 years of potential experience. During this period, the observed intracohort wage inequality—by the measure of variance of log hourly wage—has more than doubled from about 0.368 to 0.753. Thus, the general pattern suggests that the life course works as a differentiation process through which individuals become increasingly differentiated from each other in terms of wage. The lowest curve (dashed) in this figure is the TH curve, which gives the predicted variance of log hourly wage by years of potential experience under the assumption that only trajectory heterogeneity is at work while between-group cumulative advantage is not. The upward slope of this curve indicates that the mechanism of trajectory heterogeneity causes intracohort wage inequality to increase over the life course—a result that supports hypothesis 2.

The dashed-dotted curve, which is located above the TH curve, is the TH + BCA curve. It gives the predicted variance of log hourly wage by potential experience under the assumption that both trajectory heterogeneity and between-group cumulative advantage are at work (i.e., TH + BCA). Intracohort wage inequality increases at a faster speed under TH +

BCA than it does under TH, which suggests that introducing the mechanism of between-group cumulative advantage based on gender, race, and educational attainment further accelerates the increase in intracohort wage inequality over the life course. This result is consistent with the prediction from hypothesis 3 that intracohort wage inequality increases over the life course because of the mechanism of between-group cumulative advantage.

Meanwhile, the gap between the observed inequality and the TH + BCA curve represents the residual variance in wage that is not explained by the model. Therefore, it measures the magnitude of the random variability in wage inequality. The figure shows that over the 20 years of the life course, the magnitude of random variability has grown gradually. Hence, this finding supports hypothesis 1. In relation to my earlier discussion, this result is consistent with arguments from some earlier works that individuals carry wage fluctuations at the early life stages to later life stages, which results in the accumulation of random variability over the life course.

Finally, to what extent does each mechanism contribute to the total increase in intracohort wage inequality? To quantify the contributions of the three mechanisms respectively, I first illustrate that their contributions to total wage inequality are separable. The illustration is quite straightforward: recall that in equation (4), I have decomposed the variance in log wage into the summation of four additive and separable components: $V1$, $V2$, $V3$, and $V4$. Therefore, the change in Var_t over the life course, denoted by $\Delta\,\mathrm{Var}_t$, can be decomposed as below:

$$\Delta\,\mathrm{Var}_t = \Delta V1 + \Delta V2 + \Delta V3 + \Delta V4. \tag{10}$$

Equation (10) suggests that the change in total intracohort wage inequality can be separated into the changes in the four separable variance components of the total wage inequality. As illustrated earlier, random variability, trajectory heterogeneity, and cumulative advantage contribute to total inequality through $V4$, $V2$, and $V3$, respectively; therefore, their contributions to the growth of total wage inequality over time will be separately measured by $\Delta V4$, $\Delta V2$, and $\Delta V3$. Table 4 demonstrates, with each row, the intracohort wage inequality (1) in the observed sample, (2) under TH, (3) under TH + BCA, and (4) in the residual. The first and second columns give the level of wage inequality measured at the entrance and twentieth year of labor market experience, respectively. The third column calculates the change in wage inequality between these two points in life. The last column expresses this change as the percentage of the observed change in total wage inequality. As the last column indicates, the mechanism of trajectory heterogeneity alone explains 50.39% of the total increase in wage inequality. Introducing the mechanism of cumulative

TABLE 4
CONTRIBUTIONS OF TRAJECTORY HETEROGENEITY, BETWEEN-GROUP CUMULATIVE ADVANTAGE, AND RESIDUAL INEQUALITY TO THE OBSERVED INTRACOHORT GROWTH OF WAGE INEQUALITY

Prediction Specifications	$t = 0$	$t = 20$	Δ_{Var}	% of Δ_{Var} Explained
Observed inequality . . .	.368	.753	.385	100.00%
TH	.307	.501	.194	50.39%
TH + BCA	.307	.528	.221	57.40%
Residual inequality . . .	.061	.225	.164	42.60%

NOTE.—Data are from the National Longitudinal Survey of Youth 1979–2010, Bureau of Labor Statistics. The columns of $t = 0$ and $t = 20$ indicate the variance of log hourly wage among this cohort at zero and 20 years of labor market experience respectively; Δ_{Var} is the change in variance of log hourly wage between zero and 20 years of experience. All the variances are adjusted for the trend of wage inequality in the macroeconomy at the time when they are measured. Observed inequality is the variance of log hourly wage of the sample, TH is the variance of the predicted wage under the assumption that only trajectory heterogeneity is at work, and TH + BCA is the variance of the predicted wage under the assumption that both trajectory heterogeneity and between-group cumulative advantage are at work. The marginal contribution of BCA to total wage inequality can be calculated as 57.40% − 50.39% = 7.01%.

advantage based on gender, race, and educational attainment explains an extra 7.01% (= 57.40% − 50.39%) of the total increase in wage inequality. In total, the combination of these two mechanisms explains more than half (57.40%) of the total increase in wage inequality. The empirical finding of a much larger effect of trajectory heterogeneity than cumulative advantage accords with my earlier expectations informed by the mathematical formalization.[35]

The rest of the increase in wage inequality, taking up 42.60% of the observed growth of wage inequality over the cohort's life course, is due to the increase in residual inequality. It reflects the increase in the random variability that is left unexplained by the observed variables incorporated in this model. The findings suggest that at least for the first 20 years of labor market experience of this specific NLSY79 cohort, a substantial share of total growth of wage inequality over their lives is attributable to the growth of random variability. In a broader sense, this finding is consistent with, and provides new evidence for, the recent findings in the stratification literature that earnings attainment in American society in the post-

[35] Yet, the relatively small size of the quantitative contribution of between-group cumulative advantage should not be taken as an indication of the nonsignificance of this mechanism. In fact, the significant effects of individuals' group attributes on both the baseline wage and the wage growth rate provide evidence that gender, race, and educational attainment have played salient roles in the long-term stratification of individuals over their life courses.

1980 era is marked by substantial earnings volatility and economic insecurity (Gottschalk and Moffitt 1994; Western et al. 2012).

AUXILIARY ANALYSES

As mentioned earlier, the LCT framework is designed for studying the intracohort pattern of inequality in general and thus may not exactly fit every particular situation in reality. Yet, fortunately, the richness of measures in the NLSY79 data allows me to empirically assess the potential implications of relaxing some of the key assumptions in the model. Next, I present results from two auxiliary analyses. The first relaxes the assumption of the time invariance of the wage growth rate for an individual, and the second introduces controls for time-varying indicators of work and family domain experiences.

Introducing the Temporal Variation of the Wage Growth Rate

Recall that the main analyses impose the simplifying assumption that the rate of wage growth—represented by β_{1i}—is constant over t. In reality, however, it is possible that the rate of wage growth changes over the life course for the same person. To account for this possibility, I introduce the temporal variation of the wage growth rate to the multilevel growth curve model by replacing the linear function of potential experience with a piecewise linear function (i.e., a spline function). The spline function contains two knots, one at six years of potential experience and the other at 13 years of potential experience, to separate the time period between zero and 20 years of potential experience into three parts. I define t_1, t_2, and t_3 as below:

$$t_1 = \begin{cases} t & \text{if } t \in [0,\ 6] \\ 6 & \text{if } t \in [7,\ 20] \end{cases},$$

$$t_2 = \begin{cases} 0 & \text{if } t \in [0,\ 6] \\ t - 6 & \text{if } t \in [7,\ 13] \\ 7 & \text{if } t \in [14,\ 20] \end{cases}, \tag{11}$$

$$t_3 = \begin{cases} 0 & \text{if } t \in [0,\ 13] \\ t - 13 & \text{if } t \in [14,\ 20] \end{cases}.$$

With t_1, t_2, and t_3 defined as above, I rewrite equation (7) into the piecewise linear form:

$$W_{it} = \beta_{0i} + \beta^1_{1i} \cdot t_1 + \beta^2_{1i} \cdot t_2 + \beta^3_{1i} \cdot t_3 + e_{it}, \tag{12}$$

where β_{0i} is specified in the same way as in equation (8), and each $\beta^j_{1\text{i}}$ (j = 1, 2, and 3, representing the coefficient for each of the three periods) is specified as

$$\beta^j_{1\text{i}} = \gamma^j_{10} + \gamma^j_{11} S_{1i} + \gamma^j_{12} S_{2i} + \gamma^j_{13} S_{3i} + u^j_{1i}, \tag{13}$$

for j = 1, 2, and 3. That is, the piecewise linear function estimates the effects of group attributes on the wage growth rate distinctively for each life stage. I estimate this model using the same data as used in the main analyses, and the selected coefficients on the S's and variance components are reported in panel A of appendix table D1.[36] Overall, the wage growth rate tends to be steepest during the individual's early career, and the growth rate shrinks at later life stages. The effects of gender, race, and educational attainment on the baseline wage are similar to those in the main analyses, yet their effects on the wage growth rate vary by life stages: The negative effect of being female on the wage growth rate is greater in the earlier stages of experience than in the later stage. The negative effect of being black on the wage growth rate is greatest and significant during seven to 13 years of labor market experience. The directions of the effects of gender and race on the wage growth rate during the three periods are all consistent with those in the main analyses. The case of education, however, is more complicated. The table shows that individuals with higher educational attainment experience faster wage growth in the zero to six years of labor market experience, and their advantage in the wage growth rate becomes small and insignificant during seven to 13 years. During the last period (14–20 years), however, the effect of higher educational attainment on the wage growth rate turns out to be negative and is significant between those with a high school diploma or less and those who have at least a college education. This suggests that the earnings advantage of more highly educated individuals tends to shrink slightly after 13 years of labor market experience. One possible explanation of this shrinkage is the "ceiling effect"; that is, wage increases are more difficult to achieve once the highly educated workers have already achieved a high level of absolute earnings. Another possibility is that highly educated individuals who earn extremely high wages are more likely to drop out of the sample at older ages, resulting in a moderate shrinkage in the wage gap between higher- and lower-educated individuals in the observed sample.

[36] While the partition of potential experience into three parts in the piecewise linear components is largely up to the discretion of the author, the findings do not alter substantially if I separate the 20 years of experience into four equal parts instead of three parts.

Panel B of appendix table D1, which gives the variance components of the model, suggests that the wage growth rate varies substantially throughout the three life stages.[37] Similar to the earlier figure 2, appendix figure D1 compares the predicted average log hourly wage by years of experience for different gender, race, and educational groups. The figure shows that although the speed at which the gaps between groups widen over the life course varies by life stage, the wage gaps between different dimensions of social groups are all wider at the end than at the beginning of this 20-year period. In short, the auxiliary analyses suggest that my main conclusions are not altered by allowing the wage growth rate to vary over the life course.

Introducing Time-Varying Controls for Work and Family Domain Experiences

My main analyses focus on the total effects of premarket time-invariant group attributes (gender, race, and educational attainment) on the wage growth rate. Those models do not control for work and family domain experiences that occurred during the individuals' labor market experience. Since these experiences mediate the effect of premarket characteristics on the wage growth rate, it is reasonable to expect that the effects of these group attributes on wage attainment will shrink after work and family domain experiences have been controlled for. In addition, since the occurrences and wage impacts of some experiences cannot be fully anticipated, one could expect the inclusion of these experiences to explain away part of the residual variance. In the following, I will add time-varying indicators of individuals' work and family domain experiences to the original multilevel growth curve model. Using X_{it} to denote these time-varying controls, I respecify equation (7) as

$$W_{it} = \beta_{0i} + \beta_{1i} \cdot t + \beta_2 \cdot t^2 + \sum_{k=1}^{k} \beta_k \cdot X_{itk} + e_{it}, \tag{14}$$

where $\sum_{k=1}^{k} \beta_k \cdot X_{itk}$ is the time-varying controls.

In equation (14), the variables in X contain work and family domain experiences. The work domain experiences include the individual's tenure

[37] The model reported in the table imposes the assumption that the covariances between u_0, $u_{1,1}$, $u_{1,2}$, and $u_{1,3}$ are zero, because otherwise the large number of unknown covariances will make their estimation computationally expensive and unstable. However, in a separate model not reported here, I replace this zero-covariance assumption with the assumption that the covariances between these terms are equal. That model yields a negative covariance between these terms, which is consistent with my main findings of the negative association between the baseline wage and the wage growth rate within social groups.

(measured in weeks) with his or her current employer, the total number of hours worked in the previous year, the number of weeks spent unemployed and out of the labor force in the previous year, and the interactions between these work experience variables and the individual's years of potential experience. The model also includes the individual's time-varying occupational categories coded on a 41-category scheme. The controls for family domain experiences include the individual's time-varying marital status and the number of children in the household, as well as the interactions between these variables with gender to capture the heterogeneity in the wage effects of these experiences.

The results are reported in appendix table D2. Model D1 does not include the effect of group attributes on the wage growth rate and model D2 includes them. As expected, controlling for time-varying work and family domain experiences leads to the shrinkage of the effect size of gender, race, and educational attainment on the baseline wage as well as the wage growth rate. For example, in predicting the baseline wage, the coefficient on being female shrinks in absolute size from −0.205 in the main analyses to −0.138 in the model with controls for work and family domain experiences. And in predicting wage growth rate, the coefficient on being female shrinks slightly in magnitude from −0.010 to −0.0082. Compared to those who did not receive a college education, the college-educated experience a significantly faster wage growth rate by 0.006 per year in the main analyses; yet the coefficient becomes much smaller (0.0027) and insignificant in the model with controls for work and family experiences. Thus, the auxiliary analyses suggest that part of the total effects of group attributes on the baseline wage and wage growth is mediated by work and family domain experiences that unfold gradually over the individual's life course.

The effect of including these controls on reducing the size of variance components, however, is minimal. The variance of u_1 in models D1 and D2 is 0.016 and is larger than that in model 1 and model 2 (which is 0.014).[38] As for the residual variance $\mathrm{Var}(e)$, there is only a very moderate decrease in the residual variance from the model without controls (0.165) to the model with controls (0.152). The next question is, does controlling for these experiences help explain some of the growth in residual variance over the life course? Appendix figure D2 plots the residual variance by years of potential experience under the model with and without time-varying controls. The figure shows that the inclusion of the work and family domain ex-

[38] Whether the difference between the two is significant is uncertain, but this at least implies that the between-person variation in the wage growth rate is no less in the model with controls for these observed work and family domain experiences than in the model without these controls.

periences reduces the amount or growth of residual variance by a very minimal amount.

The lack of explanatory power of these work and family experiences in accounting for the growth of residual variance over time may arise because more subtle mechanisms affecting life course wage trajectories lie within the organizational environment and network structure of the workplace, which are not directly measured by the NLSY79 data. For example, Tomaskovic-Devey et al. (2005) pointed out that workplace networks, organizational arrangement, and employer-employee relations are crucial to sociological understandings of career trajectories and wage inequality. With either quantitative or qualitative data that provide finer-grained measures of the organizational settings and workplace dynamics over time, this will be a promising area for future work to explore the underlying organizational dynamics that produce the intracohort pattern of wage inequality over individuals' lives.

DISCUSSION OF LIMITATIONS

Like all empirical investigations, the analyses in this study should be interpreted with careful consideration for several important limitations. The first limitation is the missing wage information. In the NLSY79 data, wage information is missing when the individual is not working at the time of the interview or when the individual simply did not answer the survey. This paragraph will focus on the first type of missing wage information and the next two paragraphs will discuss the second. Earlier, I noted that the multilevel growth curve model, in itself, is flexible with regard to missing observations and unbalanced data across individuals. Yet, if those who are not working are systematically different from those who are working, potential biases of model estimation may occur. It is possible that, if they had worked, those who chose not to work would have received lower wages than the population average, which would cause the estimated wages for those currently working to be upwardly biased with regard to the population. In addition, there may exist significant group differences in the likelihood of missing wage information: women are likely to spend more time not working than men and, thus, to have a higher likelihood of not reporting wage information. Therefore, the estimated coefficients may be more representative of the wages for men than for women. Even without such nonrandomness in missing wage information, the analyses could still benefit from an enlarged sample and thus a higher power of statistical estimation if some basic imputation for missing data is performed. To explore this briefly, I imputed an individual's missing hourly wage for a certain year using his or her own wage in the closest wage record prior to that year, provided that the closest wage record is within the previous three years. The results are reported in appendix table E1.[39] The results in model A3 and model A4 are consistent with those in model 1 and model 2 from table 3 of the main analyses.

The second limitation relates to survey nonresponse.[40] While the missing wage information discussed above generates missing data on the key dependent variable, a survey nonresponse generates missing data of an entire person-year observation. With regard to the overall amount, the problem of nonresponses is mild for the NLSY79 data, as the total nonresponse rate is reported to be very low.[41] Still, the systematic dependence of the likelihood of nonresponse on individual characteristics could potentially affect the estimation of the variance in wages (Lynch 2003). Hence, it is necessary to examine the temporal pattern of nonresponse. Appendix table F1 gives the means and standard deviations of the respondents' average wage in the previous three years by response status in the current year at 3, 5, 10, 15, and 18 years of potential experience, respectively. These numbers suggest that the nonresponse sample tends to have lower average wages but higher wage variations than the response sample, and thus the estimated wage inequality may understate the true level of inequality in the population. More important, the gap in wage variation between those who responded and those who did not grows from earlier to later life stages. This implies that it is possible that my estimation of life course growth of wage inequality based on the NLSY79 response sample understates the true increase of wage inequality in this cohort.[42]

Another pertinent pattern of survey nonresponses is the association between nonresponses and individuals' group characteristics. Appendix figure F1 plots the share of survey nonresponses as a proportion of the total sample in the first wave by years of potential experience for different social groups. Overall, the share of nonresponses increases over time and flattens out after about 10 years of experience. There exist some group differences in the pattern of nonresponses: males have a larger nonresponse

[39] After imputation, the number of person-year observations increased from 133,121 to 186,269.

[40] Here, I use the term "survey nonresponse" instead of "attribution" because, while some individuals drop out of the sample permanently after one wave of nonresponse (i.e., attrition), other individuals did not participate in certain waves of the survey (nonresponse) yet came back for later waves. Hence, the category of "survey nonresponse" covers a wider range of missing data problems.

[41] As the latest NLS handbook (U.S. Bureau of Labor Statistics 2005) indicates, the retention rate—i.e., the number of respondents interviewed divided by the number of respondents remaining eligible for interview at each wave—remained above 90% in the beginning years and was around 85% in most subsequent years. The handbook also indicates that in year 2002, over 75% of the respondents remained in the sample.

[42] Some other studies have also found similar patterns of wage distribution in survey nonresponse in the NLSY data (e.g., MaCurdy, Mroz, and Gritz 1998).

share than females, and whites have a larger nonresponse share than racial minorities. Thus, the sample may underrepresent men and whites in later years. Individuals' different levels of educational attainment alter the timing of nonresponse: the nonresponse share of those with some college but less than four years starts to rise the earliest, while that of those with high school education or less remains low in the beginning years and starts to catch up at around 10 years of experience. Hence, individuals with lower educational attainment may be overrepresented during early life stages. With the presence of such group differences in the pattern of survey nonresponses, the representativeness of variance estimations may be affected accordingly. However, such group differences are unlikely to cause much bias to the model coefficients, as these observed characteristics are already included as covariates in the multilevel growth curve models. Yet the presence of selective nonresponses based on unobserved characteristics could still cause more complex biases in the estimated coefficients (Solon, Haider, and Wooldridge 2013).

Third, because of data limitations, my analytic sample is restricted to the span of life up to the respondent's twentieth year of potential experience. Whether the results could be extrapolated to later stages of life depends critically on whether mechanisms affecting individuals' wage trajectories in early and midcareer will continue to affect these wage trajectories in the same manner during late career. Meanwhile, some unique features of later life inequality are worth noting when making such extrapolations: mortality rate will be higher at later stages, and the dependence of mortality rate on gender, race, education, and earnings is likely to affect economic inequality at later life stages. In addition, with the growing hazards of physical and mental problems in later life, disparities in these outcomes, rather than economic standings alone, are worth considering for an older population. I await future waves of NLSY79 to allow for investigation of the inequality-generating process at later life stages.

Fourth, while hourly wage is a good indicator of an individual's earning ability in the labor market—a site where economic inequality is initially generated—this measure may not capture the total material resources available in the family, another focal site of economic stratification. A number of family-level indicators, such as the family's total disposable income and total assets, may provide better measures of the consumption capability and living conditions for the individual. In addition, recent works have emphasized that the effects of economic fluctuations, especially those due to adverse events, are mitigated by risk pooling within the family as well as policy aids for low-income families (Western, Bloome, and Percheski 2008; Western et al. 2012). In future works, family-level indicators of economic resources may be further explored to form a more comprehensive picture of the changes in inequality over the life course.

Last but not least, the NLSY79 cohort was exposed to the labor market at a specific historical period (1979–2010) in the United States. Earlier, in an attempt to correct for the drastic growth of macrolevel wage inequality during this period in the United States, my analyses borrowed external information from the Current Population Survey to adjust accordingly. However, this adjustment is certainly not sufficient to account for all contextual features as many other profound processes specific to this social and historical context may have shaped wage trajectories. These processes include structural trends such as rising returns to skills, technological advances, deindustrialization, financialization, de-unionization, and globalization; demographic trends such as the decline in marriage and fertility rates and the increase in nonmarital childbearing; as well as business fluctuations such as the economic recession in the early 1980s and the recent recession from 2007 to 2009. To the extent that microlevel mechanisms have interacted with these contextual processes in producing the intracohort pattern of wage inequality, the mechanisms revealed by my empirical analyses may not operate in the exact same way for another cohort within a different social and historical context. I believe that applications of this framework to other social and historical contexts will greatly enrich the sociological knowledge of the interaction between social context and the individual life course and should thus be a promising field of future investigations. And furthermore, with longitudinal data that follow a wider range of cohorts of population over time, such as the Panel Study of Income Dynamics, it would be possible to extend the LCT framework to separate the effect of age from the effect of period trends on wage inequality.

CONCLUSION

Over the past decades, sociologists have engaged in a collective endeavor to understand patterns of wage inequality in society. Following this line of inquiry, a large body of research has been devoted to examining the cross-sectional and intercohort patterns of wage inequality. Yet, these two areas of inequality research generally treat each individual as a single point of observation, overlooking the process through which wage inequality develops over individuals' life courses. As a result, relatively little is known about the intracohort pattern of wage inequality. Much of this neglect is due to the lack of an integral framework to study this macrolevel pattern of inequality from its microlevel basis in the life course wage trajectories. To fill this gap, this article established a life course trajectory (LCT) framework for understanding the intracohort pattern of wage inequality.

The LCT framework brings the life course perspective into inequality research. Specifically, it identifies the life course wage trajectory as the basis for the intracohort pattern of wage inequality. The framework is based on the central thesis that an appropriate framework for understanding the intracohort pattern of wage inequality should satisfy three essential properties: (1) random variability, (2) trajectory heterogeneity, and (3) cumulative advantage. After theoretically conceptualizing these three properties, I proposed a mathematical formalization of the LCT framework that integrates them under a common model. Both the theoretical argument and the mathematical formalization implied that intracohort wage inequality will increase over the life course as a result of the accumulation of random variability, the heterogeneity in wage trajectories, and the mechanism of cumulative advantage. Finally, I combined the LCT framework with the multilevel growth curve model and applied it to a nationally representative longitudinal data set. Empirical analyses not only enabled testing for the existence of the proposed essential properties in reality but also revealed the contributions of the three mechanisms to the total increase in wage inequality over the life course.

The LCT framework contributes to the sociological literature on three levels: theoretical, empirical, and methodological. In recent decades, the sociological community has become increasingly interested in understanding the microlevel foundations of macrolevel social phenomena. As such, a growing demand has emerged for theoretical frameworks that help conceptualize the macro-micro linkage in the stratification system. By examining the case of life course inequality, this study provides future researchers with a theoretical framework that explicates the process through which the life course wage dynamics on the individual level give rise to the pattern of intracohort wage inequality on the aggregate level. It shows that the aggregate pattern of inequality should, and could, be understood from its basis in the life course trajectory.

Second, the LCT framework does not limit itself to pedagogical illustrations. In fact, this framework can be combined with the statistical strategy of the multilevel growth curve model and tested with real data. Empirical evidence confirms the significance of the random variability, trajectory heterogeneity, and between-group cumulative advantage properties in reality. In addition, my empirical analysis is the first to reveal the contributions of different mechanisms to the intracohort growth in wage inequality for this cohort in the United States: the results suggest that the mechanisms of trajectory heterogeneity and between-group cumulative advantage together explain over half (57.40%) of the increase in wage inequality across the 20-year life span, and the rest of the inequality growth is due to the accumulation of random variability.

The third contribution of the LCT framework is methodological. On the one hand, although earlier studies have invoked the multilevel growth curve model in analyzing inequality across the life course (e.g., Tomaskovic-Devey et al. 2002; Willson et al. 2007), they have not situated this statistical method within an integral framework. My LCT framework complements these earlier applications by allowing researchers to interpret the statistical parameters within the context of a sociologically meaningful framework (refer to table 1 for a brief review). On the other hand, while previous works typically use the multilevel growth curve models to test for the significance of one or more long-term mechanisms, few have adopted this strategy to quantitatively assess the contributions of various distinct microlevel mechanisms to total wage inequality. My empirical application, instead, illustrated a method for decomposing the change in total wage inequality into separable components that are due to different mechanisms.

The LCT framework is part of an ongoing sociological effort to understand the production and reproduction of social inequality. In particular, I offer two recommendations for future research to utilize and extend the LCT framework. First, as I discussed earlier, human lives proceed through the interaction of multiple domains of life course outcomes. While my LCT framework was originally designed to study wage inequality, it has the potential to extend to other domains of individual outcomes, such as cognitive development, physical and mental well-being, political opinions, and family living conditions. Second, in essence, the LCT framework focuses specifically on the life course mobility process from year to year for the same individual. Yet, more broadly, the trajectory of inequality could occur among social units that are larger than the individual. For example, family has long been considered as the key structural unit in the stratification system. If we change the unit of analysis from the individual to the family and replace the individual's life course trajectory with the multigenerational family lineage, this framework could be used to study intergenerational mobility within the same family—a process crucial to patterns of intergenerational and historical inequality (Mare 2011; Chan and Boliver 2013). When applied in this way, the framework could be utilized to answer several questions such as Does the heterogeneity in the trajectories of family lineages contribute to the growth of inequality among different families over generations (i.e., a question corresponding to trajectory heterogeneity)? Or does the advantage of high-status families persist, magnify, or diminish over multiple generations (i.e., a question corresponding to cumulative advantage)?

APPENDIX A

Summary of Assumptions and Alternative Specifications in the Mathematical and Statistical Model of the LCT Framework

The mathematical formalization for the LCT framework is designed for the general case and thus inevitably relies on some simplifying assumptions. In table A1, I summarize some key assumptions, propose some alternative specifications to extend the model, and list the implications of relaxing these assumptions. Although this summary may not exhaust all possible extensions of the framework, I do believe that the table can be kept as a reference when applying the LCT framework to address different research questions. I recommend that future works use this table as the basis for potential extensions of the LCT framework.

TABLE A1

Summary of Key Assumptions, Alternative Specifications, and Implications of Relaxing These Assumptions of the LCT Framework

Simplifying Assumption	In Mathematical Language	Example of Alternative Specifications	Implications of Relaxing the Assumption
1. For each individual, the wage growth rate is linear and remains unchanged over the life course	γ_i in eq. (1) (or θ_i in eq. [3]) does not change over t	(1) Specify a linear spline function with different growth rates at different life stages; (2) use polynomial function to approximate the temporal variation of wage growth rates.	The implications are examined empirically in preliminary analyses and in the auxiliary analysis; this assumption is not consequential for the main results
2. An individual's years of labor market experience accumulate at the same rate regardless of how many hours/weeks he or she has worked in the year	γ_i in eq. (1) (or θ_i in eq. [3]) does not depend on the hours/weeks worked in year $t-1$	(1) Specify eq. (1) as $Y_{it} = (1 + \gamma_i') \cdot Y_{i,t-1}$ if the person stays a significant amount of time out of the labor market in year $t-1$, where $\gamma_i' \neq \gamma_i$; (2) include controls for employment experience	The implications are examined empirically in the auxiliary analysis; including work experience and family domain events explains some, but a limited amount, of the total wage variation
3. Social groups are represented by three key indicators: gender, race, and educational attainment	The vector of group indicators, S, contains three dimensions (gender, race, and educational attainment)	Other person-specific group indicators, such as parental social class, religion, region of residence, could also be introduced as important dimensions of social groups that affect wage and wage growth	Inclusion of other dimensions of group attributes may increase the share of wage variance between groups and decrease its share within groups
4. There is no (or only minimal) selective attrition or selective mortality in the data	The likelihood of nonresponse at year t does not depend on S or W_{t-1}	As is true for the NLSY79 data, the likelihood of attrition/mortality may depend on the individual's fixed characteristics, as well as on the individual's wage attainment in previous periods	Auxiliary analysis reveals that the nonresponse sample tends to have lower average wage but higher wage variations, causing the estimated wage inequality based on the observed sample to be likely downwardly biased

APPENDIX B

Technical Details for Constructing the "Counterfactual" of Log Hourly Wage

In empirical analyses, I introduced a four-step procedure for assessing the contributions of trajectory heterogeneity and between-group cumulative advantage to the increase in total wage inequality. In step 3 of this procedure, I predicted the "counterfactual" of log hourly wage W^*_{it} under the assumption that only trajectory heterogeneity is at work but between-group cumulative advantage is not. This prediction is implemented by taking the following technical steps:

1. On the basis of the estimated coefficients from model 2, I generate an intermediate variable ψ to capture the part of the wage growth rate β_1 that is determined by S_1, S_2, and S_3, that is, $\psi_i = \widehat{\gamma_{11}}S_{1i} + \widehat{\gamma_{12}}S_{2i} + \widehat{\gamma_{13}}S_{3i}$.

2. I generate another variable, ϕ, by drawing from a normal distribution that has the same mean and variance of ψ. That is, $\text{Var}(\phi) = \text{Var}(\psi)$. Yet, ϕ does not depend on S_1, S_2, or S_3.

3. I predict β^*_1 by the following equation: $\widehat{\beta^*_{1i}} = \widehat{\gamma_{10}} + \phi_i + \widehat{u_{1i}}$. It follows that $\text{Var}(\widehat{\beta^*_{1i}}) = \text{Var}(\phi) + \text{Var}(\widehat{u_{1i}})$. Recall that according to the original setting (i.e., eq. [7]), I have generated $\widehat{\beta_{1i}}$ by

$$\widehat{\beta_{1i}} = \widehat{\gamma_{10}} + \widehat{\gamma_{11}}S_{1i} + \widehat{\gamma_{12}}S_{2i} + \widehat{\gamma_{13}}S_{3i} + \widehat{u_{1i}}.$$

It is implied that $\text{Var}(\widehat{\beta_1}) = \text{Var}(\psi) + \text{Var}(\widehat{u_1})$ (assuming no association between the S's and u_1). Also recall that in (2), I showed that $\text{Var}(\phi) = \text{Var}(\psi)$. Therefore, $\text{Var}(\widehat{\beta^*_1}) = \text{Var}(\widehat{\beta_1})$, and $\widehat{\beta^*_1}$ does not depend on S_1, S_2, or S_3. That is to say, in this step, I have generated $\widehat{\beta^*_1}$ in a way that keeps the heterogeneity of wage trajectories while "shutting down" the group-based cumulative advantage in wage attainment.

4. Finally, I predict the counterfactual wage for person i at time t: $\widehat{W^*_{it}} = \widehat{\beta_{0i}} + \widehat{\beta^*_{1i}} \cdot t + \widehat{\beta_2} \cdot t^2$. This is the "counterfactual" log hourly wage under the assumption that only the mechanism of trajectory heterogeneity is at work while between-group cumulative advantage is not.

APPENDIX C

Adjustment Method for the Historical Trend of Wage Inequality

Because wage inequality in America has increased drastically from 1979 to 2010, a period in which wage data were collected from the NLSY79 sample, it is important that my analysis rules out the possibility that the increase in wage inequality for a cohort of the population as they grow old is actually the result of the economywide increase in wage inequality. I adjust for wage inequality in the macreconomy by conducting a standardization of wage inequality by transforming the wage inequality in each year of observation to the comparable level of wage inequality in year 2000. This standardization process is analogous to the better-known adjustment for inflation and is implemented as follows: let V_m denote the variance of log hourly wage measured in year m, and let I_m and I_{2000} denote the wage inequality in the macroeconomy in year m and year 2000, respectively. The wage inequality in the macroeconomy is calculated by the variance of log hourly wage among the working labor force aged between 20 and 60 from the Current Population Survey for each year. Then, the "adjustment factor" for year m, F_m, is calculated by $F_m = I_{2000}/I_m$, and the adjusted wage inequality in year m is $V_{m,\text{adjusted}} = V_m \cdot F_m$. For example, I_{1996} is 0.365 and I_{2000} is 0.37 in year 2000; therefore, $F_{1996} = 0.37/0.365 = 1.014$. So the adjusted wage inequality in year 1996 is $V_{1996,\text{adjusted}} = V_{1996} \cdot 1.014$. The complete information of the wage inequality and the adjustment factor based on the Current Population Survey data by calendar year is presented in table C1. I also note that because wage inequality is calculated by individuals' years of potential experience, it is likely that individual observations for each year of potential experience are recorded at different calendar years. In this case, I will average the adjustment factor across the individual observations recorded at different calendar years and construct the average adjustment factor in my calculation of adjusted wage inequality.

TABLE C1
Calculated Wage Inequality in the Macroeconomy and Adjustment Factor for the Cross-Year Standardization of Wage Inequality

Year	Wage Inequality (I_m)	Adjustment Factor (F_m)
1980	.287	1.289
1981	.289	1.280
1982	.308	1.201
1983	.316	1.171
1984	.321	1.153
1985	.326	1.135
1986	.329	1.125
1987	.332	1.114
1988	.328	1.128
1989	.339	1.091
1990	.339	1.091
1991	.333	1.111
1992	.333	1.111
1993	.336	1.101
1994	.382	.969
1995	.366	1.011
1996	.365	1.014

TABLE C1 (*Continued*)

Year	Wage Inequality (I_m)	Adjustment Factor (F_m)
1997	.362	1.022
1998	.357	1.036
1999	.357	1.036
2000	.370	1.000
2001	.375	.987
2002	.383	.966
2003	.404	.916
2004	.389	.951
2005	.400	.925
2006	.400	.925
2007	.419	.883
2008	.419	.883
2009	.425	.871
2010	.429	.862

NOTE.—Data are from the Merged Outgoing Rotation Groups of the Current Population Survey, 1980–2010 (http://www.nber.org/data/morg.html). Wage inequality is calculated as the variance of log hourly wage for the working population between ages 20 and 60.

APPENDIX D

Tables and Figures for Auxiliary Analyses

TABLE D1

SELECTED COEFFICIENTS FROM MULTILEVEL GROWTH CURVE MODEL PREDICTING LOG HOURLY WAGE, USING THE PIECEWISE LINEAR MODEL

	A. SELECTED COEFFICIENTS ON OBSERVED SOCIAL GROUPS			
		Coefficient on Wage Growth Rate		
	Coefficient on Baseline Wage	0–6 Years	7–13 Years	14–20 Years
Universal coefficient		.0367***	.0237***	.0206***
Gender (reference: male):				
Female	−.1665***	−.0171***	−.0098**	−.0025
Race (reference: white):				
Hispanic	.0288	−.0049	−.0051	−.0069
Black	−.0967***	−.0036	−.0084*	−.0036
Education (reference: high school or less):				
Some college	.2103***	.0235***	.0074	−.0108
College and above	.5991***	.0253***	.0048	−.0548***

TABLE D1 (*Continued*)

	B. Variance Components
Var(u_0)	.8694
Var($u_{1,1}$)	.0412
Var($u_{1,2}$)	.0368
Var($u_{1,3}$)	.0444
Var(e)	.1168

NOTE.—Data are from the National Longitudinal Survey of Youth 1979–2010, Bureau of Labor Statistics. All analyses are weighted.

* $P < .05$.

** $P < .01$.

*** $P < .001$.

TABLE D2

ESTIMATED COEFFICIENTS FROM MULTILEVEL GROWTH CURVE MODELS PREDICTING LOG HOURLY WAGE, WITH CONTROLS FOR WORK AND FAMILY DOMAIN EXPERIENCES

	Model D1	Model D2
Coefficients predicting baseline wage β_0:		
Constant intercept (γ_{00})	1.9090***	1.8892***
	(.0514)	(.0522)
Gender (γ_{01}) (reference: male):		
Female	−.1777***	−.1378***
	(.0179)	(.0193)
Race (γ_{02}) (reference: white):		
Hispanic	.0119	.0177
	(.0165)	(.0223)
Black	−.1003***	−.0734**
	(.0148)	(.0219)
Educational attainment (γ_{03}) (reference: high school or less):		
Some college but less than four years	.2675***	.2543***
	(.0165)	(.0187)
At least four years of college	.6493***	.6196***
	(.0183)	(.0230)
Coefficients predicting wage growth rate β_1:		
Constant slope (γ_{10})	.0557***	.0597***
	(.0028)	(.0036)
Gender (γ_{11}) (reference: male):		
Female		−.0082**
		(.0026)
Race (γ_{12}) (reference: white):		
Hispanic		−.0012
		(.0026)
Black		−.0055*
		(.0028)
Educational attainment (γ_{13}) (reference: high school or less):		
Some college but less than four years		.0027
		(.0034)
At least four years of college		.0061^{+}
		(.0033)

Table D2 (*Continued*)

	Model D1	Model D2
Controls for work experience:		
Job tenure	.0007***	.0007***
	(.0000)	(.0000)
Job tenure × t	−.00004***	−.00004***
	(.00000)	(.00000)
Hours worked	.00002**	.00002**
	(.00001)	(.00001)
Hours worked × t	.00000***	.00000***
	(.00000)	(.00000)
Weeks unemployed	.0008	.00083
	(.0006)	(.00061)
Weeks unemployed × t	−.0004***	−.0004***
	(.0001)	(.0001)
Weeks out of labor force	−.0004	−.0004
	(.0005)	(.0005)
Weeks out of labor force × t	−.0003***	−.0003***
	(.0001)	(.0001)
Controls for occupation	Yes	Yes
Controls for family-related life events:		
Cohabiting	.0244	.0244
	(.0167)	(.0167)
Cohabiting × female	−.0063	−.0063
	(.0225)	(.0225)
Married	.0426**	.0426**
	(.0128)	(.0128)
Married × female	−.0584**	−.0584**
	(.0181)	(.0181)
Widowed or divorced	−.0118	−.0118
	(.0190)	(.0190)
Widowed or divorced × female	.0330	.0330
	(.0261)	(.0261)
No. children in the household	−.0076	−.0076
	(.0057)	(.0057)
No. children in the household × female	−.0201*	−.0201*
	(.0096)	(.0096)
Other coefficient:		
Squared experience (β_2)	−.0010	−.0010***
	(.0001)	(.0001)
Variance components:		
var(u_0)	.7948***	.7942***
	(.1091)	(.1089)
var(u_1)	.0162***	.0161***
	(.0018)	(.0018)
cov(u_0, u_1)	−.0788***	−.0787***
	(.0112)	(.0112)
var(e)	.1520***	.1520***
	(.0044)	(.0044)

NOTE.—Data are from the National Longitudinal Survey of Youth 1979–2010, Bureau of Labor Statistics. Number of individuals is 11,543; number of person-year observations is 110,114. Robust SEs are in parentheses. All analyses are weighted.

$^{+}$ $P < .1$.

* $P < .05$.

** $P < .01$.

*** $P < .001$.

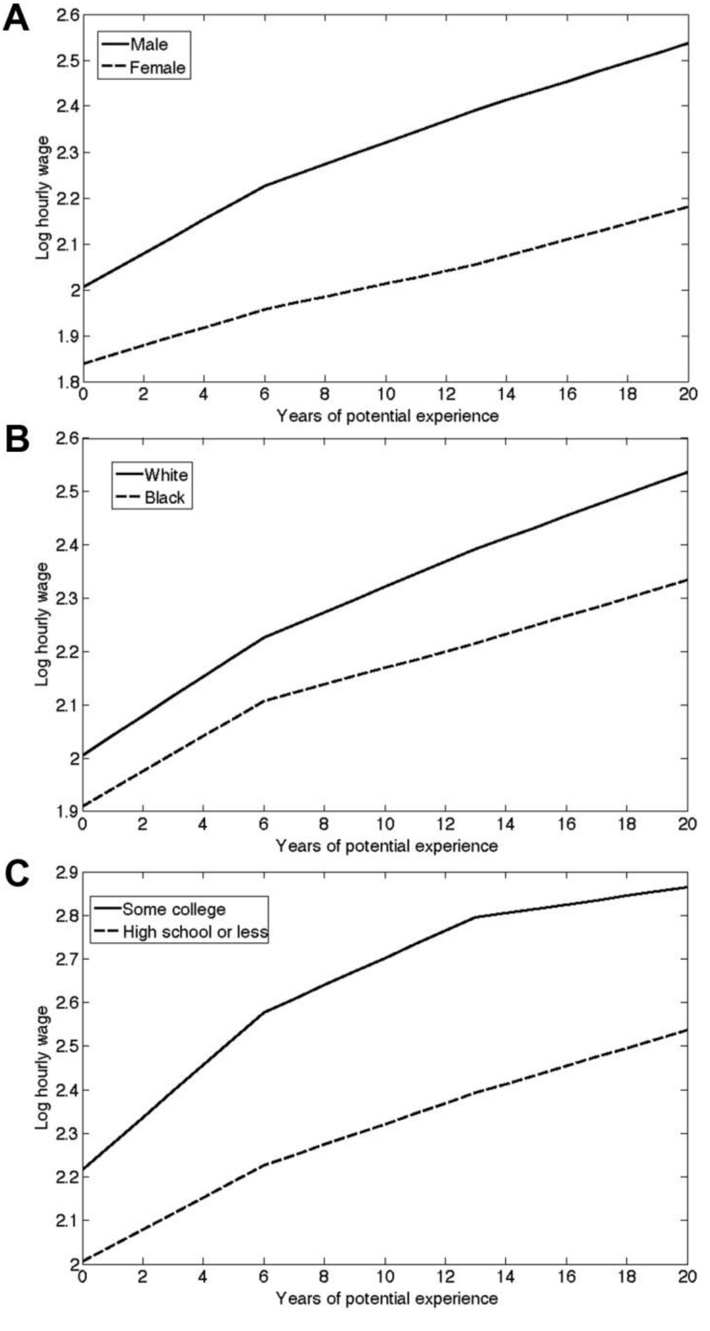

FIG. D1.—Predicted average log hourly wage by years of potential experience, by gender, race, and educational groups, as illustrations of the mechanism of cumulative advantage, the piecewise linear model. Data are from the National Longitudinal Survey of Youth 1979–2010, Bureau of Labor Statistics.

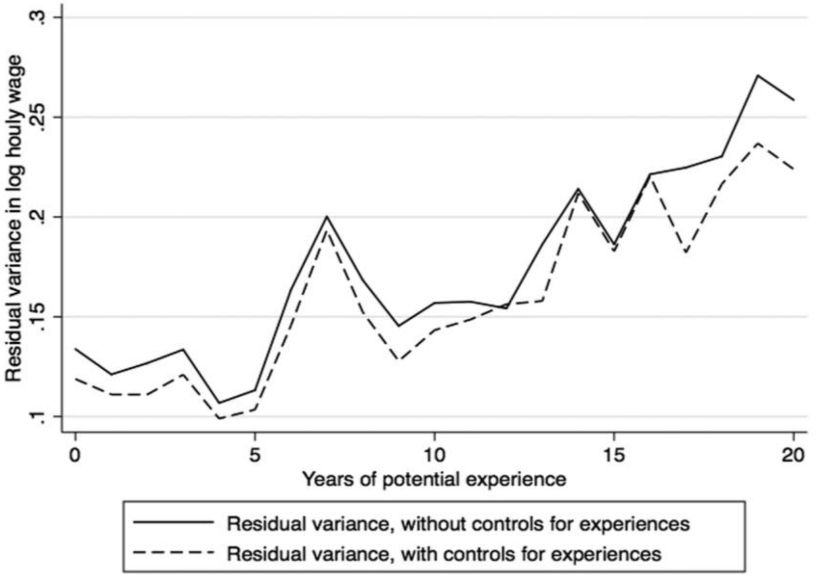

FIG. D2.—Residual variance in log hourly wage by years of potential experience, with and without controls for work and family domain experiences. Data are from the National Longitudinal Survey of Youth 1979–2010, Bureau of Labor Statistics.

APPENDIX E

Results with Imputed Values for Missing Hourly Wage

TABLE E1
ESTIMATED COEFFICIENTS FROM MULTILEVEL GROWTH CURVE MODELS PREDICTING LOG HOURLY WAGE, WITH IMPUTED VALUES FOR MISSING HOURLY WAGE

	Model A3	Model A4
Coefficients predicting baseline earnings β_0:		
Constant intercept (γ_{00})	1.9627***	1.9422***
	(.0100)	(.0100)
Gender (γ_{01}) (reference: male):		
Female	−.2619***	−.2126***
	(.0094)	(.0124)
Race (γ_{02}) (reference: white):		
Hispanic	−.0112	−.0040
	(.0122)	(.0159)
Black	−.1309***	−.1120***
	(.0114)	(.0161)
Educational attainment (γ_{03}) (reference: high school or less):		
Some college but less than four years	.3220***	.3001***
	(.0106)	(.0134)
At least four years of college	.7173***	.7308***
	(.0147)	(.0166)
Coefficients predicting earnings growth rate β_1:		
Constant slope (γ_{10})	.0494***	.0534***
	(.0016)	(.0018)
Gender (γ_{11}) (reference: male):		
Female		−.0073***
		(.0012)
Race (γ_{12}) (reference: white):		
Hispanic		−.0011
		(.0015)
Black		−.0028*
		(.0014)
Educational attainment (γ_{13}) (reference: high school or less):		
Some college but less than four years		.0032*
		(.0013)
At least four years of college		−.0020
		(.0021)
Other coefficient:		
Squared experience (β_2)	−.0016***	−.0016***
	(.0001)	(.0001)
Variance components:		
var(u_0)	.4583***	.4576***
	(.0874)	(.0873)

TABLE E1 (*Continued*)

	Model A3	Model A4
var(u_1)	.0042***	.0042***
	(.0004)	(.0004)
cov(u_0, u_1)	−.0286***	−.0285***
	(.0057)	(.0057)
var(e)	.1682***	.1682***
	(.0047)	(.0047)

Note.—Data are from the National Longitudinal Survey of Youth 1979–2010, Bureau of Labor Statistics. Number of individuals is 12,192; number of person-year observations is 186,269. Robust SEs are in parentheses. All analyses are weighted.

$^{+}P < .1$.

* $P < .05$.

** $P < .01$.

*** $P < .001$.

APPENDIX F

Demonstration of the Nonresponse Pattern

TABLE F1
MEAN AND STANDARD DEVIATION OF AVERAGE LOG HOURLY WAGE IN PREVIOUS THREE YEARS BY RESPONSE STATUS IN THE CURRENT PERIOD, AT DIFFERENT YEARS OF POTENTIAL EXPERIENCE

	Responded at t			Nonresponse at t		
Years of Potential Experience	Mean Log Hourly Wage in Previous 3 Years	SD Log Hourly Wage in Previous 3 Years	N Respondents	Mean Log Hourly Wage in Previous 3 Years	SD Log Hourly Wage in Previous 3 Years	N Nonrespondents
$t = 3$	2.10	.50	8,758	2.23	.52	480
$t = 5$	2.17	.52	9,596	2.24	.52	705
$t = 10$	2.32	.59	8,585	2.26	.61	1,269
$t = 15$	2.42	.66	7,649	2.22	.67	585
$t = 18$	2.43	.75	7,375	2.38	.81	269

NOTE.—Data are from the National Longitudinal Survey of Youth 1979–2010, Bureau of Labor Statistics. In the table, t refers to years of potential experience. The means and standard deviations of wages are calculated for the average of the respondent's log hourly wage during the previous three years. Thus, the comparison of previous wage by response status illustrates the difference in wage levels between the nonmissing and missing samples at different years of potential experience.

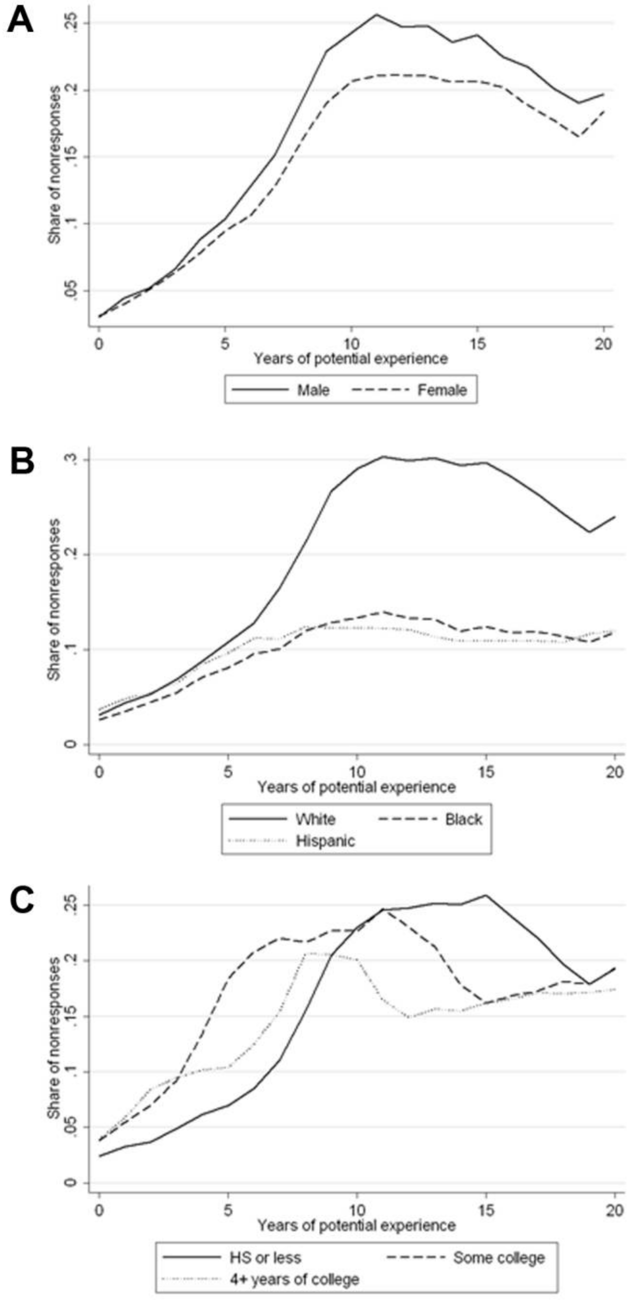

FIG. F1.—Share of nonresponses by years of potential experience, by gender, race, and educational attainment. Data are from the National Longitudinal Survey of Youth 1979–2010, Bureau of Labor Statistics.

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