Unequal Origins, Unequal Trajectories: Social Stratification over the Life Course

by

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Abstract

Social scientists and policy makers alike have long sought to understand the production, maintenance, and reproduction of inequality in society. While current scholarship on inequality tends to focus on the cross-sectional and inter-cohort variations in inequality, much less is known about how inequality is generated over the life course. My dissertation fills this intellectual gap by conducting an in-depth investigation of the patterns of inequality over the life course. It consists of three papers. The first paper establishes a life course trajectory framework for understanding the intracohort pattern of inequality, based on the random variability, trajectory heterogeneity, and cumulative advantage properties. This framework is formalized in mathematical and statistical forms, and then applied to analyze longitudinal survey data. The second paper examines the impact of marriage on people's long-term wage trajectories over the life course and shows how this long-term marriage effect, as well as its underlying mechanisms, is shaped simultaneously by gender and race. The third paper integrates the life course perspective with theoretical innovations in family research to examine the within-couple inter-temporal responsiveness in labor supply as a risk-sharing behavior that family members adopt to collectively reduce the instability of income flows to the family. The results lend strong support to the existence of risk-sharing behaviors in reality, and also point to the significant heterogeneity in responsiveness by gender and parenthood status. Taken together, these three papers show that social inequality does not occur instantaneously, but is generated gradually over the trajectories of the human life course. Further, they imply that the generation of inequality over the life course is situated in the context of a broad range of factors, including labor market regimes, racial disparities, family organization, demographic behaviors, and gender roles.

Chapter 1 Introduction

Social scientists and policy makers alike have long sought to understand the production, maintenance, and reproduction of inequality in society. While current scholarship on inequality tends to focus on the cross-sectional and inter-cohort variations in inequality, much less is known about how inequality is generated over the life course. My dissertation fills this gap by conducting an in-depth investigation of the patterns of inequality over the life course.

My dissertation consists of three papers. In the first paper, I argue that while much research has been devoted to cross-sectional and intercohort patterns of wage inequality, relatively little is known about the mechanisms for the *intracohort* pattern of wage inequality. This neglect is due to the absence of an integral framework that links the macrolevel inequality pattern to its microlevel basis in the life course wage trajectory. To fill this intellectual gap, this paper 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: (1) random variability, (2) trajectory heterogeneity, and (3) cumulative advantage. Then, the author establishes a mathematical formalization of the LCT framework based on these three essential properties. Both the theoretical conceptualization and the mathematical formalization consistently imply that intracohort wage inequality will increase over the life course due to random variability, trajectory heterogeneity, and cumulative advantage. Finally, the author applies the LCT framework to data from the NLSY79 using the multilevel growth curve model. The empirical analyses strongly support the significance of random variability, trajectory heterogeneity, and between-group cumulative advantage properties, yet do not support the within-group cumulative advantage property. Predictions based on empirical results show that the mechanisms of trajectory heterogeneity and cumulative advantage together explain 57.40%, and the accumulation of random variability explains 42.60%, of the increase in wage inequality over the 20 years analyzed.

The second paper of my dissertation addresses a long-standing sociological question: How does marriage affect wages? A growing literature on this question invokes the life course approach to examine the long-term wage effect of marriage. However, these works often focus on the population-average effect of marriage or limit themselves to the case of some particular gender or racial group. This paper, instead, conducts a comprehensive analysis on the intersection of gender and race in the total long-term effect of marriage as well as its underlying mechanisms. Applying fixed-effect models to the National Longitudinal Survey of Youth 1979 data, I found that the marriage wage premium grows steadily and at a similar pace among White and Black men. The marriage wage premium is small and declines towards the negative among White women, while on the contrary, the marriage premium grows steadily over years of marriage among Black women. Further, measured work experience explains a substantial amount of wage premium among Black men, yet it does little among White men, pointing to the importance of unobserved factors in determining White men's marriage premium. While the impact of childbearing and work experience on White women's accumulation of wage disadvantage after marriage is consistent with the specialization and human capital theory, the positive impact of work experience on married Black women's wage trajectories should be better understood in the context of their lower expectations for the husband's career success.

Taken together, the above two papers show that economic inequality does not occur instantaneously, but unfolds gradually over the life course. For the sake of analysis, the chapters isolate individuals' trajectories, examining each trajectory as if separate from that of other individuals. In my third dissertation paper, I shift to considering how individuals' life course trajectories may be interrelated, particularly when connected through social units such as the family. In recent years, the theoretical orientations in family research have undergone three major shifts: from the unitary to the individualistic perspective, from the static to the life-course perspective, and from the resource-sharing to the risk-sharing perspective. This paper aims to cross-fertilize these three theoretical shifts in family research through an in-depth examination of the case of within-couple inter-temporal responsiveness in labor supply among married individuals. I interpret the within-couple inter-temporal responsiveness in labor supply as an example of risk-sharing behaviors that family members adopt to collectively reduce the instability of income flows to the family.

Applying fixed effect models with lagged independent variables to the NLSY79 data, I found that, conditional on the couple's fixed characteristics and observed time-varying variables, married women's labor supply in a given year responds negative to their spouse's annual income, annual work hours, and hourly wage in the previous year. By contrast, no significant inter-temporal responsiveness is found among men, and this gender difference is statistically significant. Moreover, consistent with my expectation that the presence of a young child intensifies the need for financial stability, my results show that having a youngest child aged below 12 years old increases women's degree of responsiveness. My findings have important implications in the context of four lines of sociological inquiries: (1) the functions of family in the contemporary society; (2) the dimension of "risk" in social inequality; (3) the proper unit of analysis in stratification theories; (4) gender in the family.

Chapter 2 A Life Course Trajectory Framework for Understanding the Intracohort Pattern of Wage Inequality

INTRODUCTION

The impact of marriage on men and women's wages has long been conjectured, debated, and empirically tested. The dominant view so far is that marriage is associated with a significant wage premium for men, yet a much smaller wage premium, or even a wage penalty for women (Budig & England, 2001; Chun & Lee, 2001; Killewald & Gough, 2013). Some of these works attribute the gender differences in the wage effect of marriage to household specialization (Becker, 1991; Chun & Lee, 2001; Hersch & Stratton, 2000; Korenman & Neumark, 1991; Waite, 1995) and investment in human capita l(Becker, 1985; Kenny, 1983; Korenman & Neumark, 1991). Others emphasize the positive effect of marriage on men's motivation and responsibility at work and the opposite effect on women's work motivation (Ashwin & Isupova, 2014; Drobnič, Blossfeld, & Rohwer, 1999; Gorman, 2000; Korenman & Neumark, 1991; Mincer & Ofek, 1982; Pollmann-Schult, 2011; West & Zimmerman, 1987), or employers' discrimination favoring married men and disfavoring married women (Bartlett & Callahan, 1984; Correll, Benard, & Paik, 2007; May, 1982). To determine the wage effect of marriage, this line of works typically constructs a single measure based on comparison between the levels of wage earned by the married and the unmarried, termed the Marriage Wage Premium (MWP hereinafter), glossing over the temporal variation in the wage effect of marriage across years of marriage. For simplicity, I refer to this approach as the static approach.

One important limitation of the static approach is its ignorance of the simple but fundamental fact that the transition into marriage marks the beginning of a long-term life course experience (Elder, Johnson, & Crosnoe, 2003; Elder, 1985; Mayer, 2009). Marriage should be seen not as a one-time event, but as a major turning point that shapes the individual's life trajectory in all subsequent years. As a result, the wage effect of marriage may not occur instantaneously, but instead unfold gradually over the life course. To recognize the temporal variations in the MWP, research in this area needs to go beyond the static approach towards the life course approach.

Examining such temporal variations in the MWP is important, not just because such variations may exist, but also because describing these variations will deepen our understanding of existing theories on family and work. The theories mentioned at the beginning of this article all invoke mechanisms that are long-term and process-based in nature because they often hinge on the accumulation, socialization, ideology-formation, and behavior adjustments in everyday life after the marital transition. Hence, the prevailing static approach in the current literature does not adequately reflect such process-based consequences of marriage. The dynamic, long-term nature of such marriage-induced wage changes warrants the adoption of the life course approach.

Recently, a growing body of literature has started to recognize the possible temporal variations in the wage effect of marriage (Dougherty, 2006; Kenny, 1983; Korenman & Neumark, 1991; Loughran & Zissimopoulos, 2009). Dougherty (2006) studied the effect of marriage up to ten years after marriage and found that the marriage premium peaks about five years after marriage and then remains stable among males, yet among women, it peaks only two years after marriage and then starts to decline. Loughran and Zissimopoulos (2009), however, found that marriage lowers the rate of wage growth for both men and women. Rodgers & Stratton (2010) conducted separate analyses for both White and African American men, and found that a larger gross effect of marriage on wage exists among African American men, while there are no statistically distinguishable racial differences in the effect of marriage on wage growth. However, these works either treat race as an additive statistical control (Dougherty, 2006; Loughran & Zissimopoulos, 2009), or focus exclusively on the men's side of the story (Rodgers & Stratton 2010). But, if we look at the long-term wage effect of marriage through the gender lens, should we adopt different perspectives when we look at White and Black couples? If we are interested in how the marriage institution is divided along the racial line, should we assume this racial divide is similar or different for men and women? These questions have been left unresolved in the current literature. Analysis in this paper contributes to literature by reconsidering the wage effect of marriage over the life course with a particular emphasis on the intersection of gender and race. I hypothesize that because Blacks and Whites may differ significantly in regard to economic prospects in the labor market (McCall, 2001; Tomaskovic-Devey, Thomas, & Johnson, 2005; William Wilson, 1996), the division of gender roles in the household (John & Shelton, 1997; Kamo & Cohen, 1998), and attitudes and anticipations regarding their spouses (Daniel, 1995; Waite, 1995), the long-term pattern of the wage effect of marriage may vary across gender-race subgroups.

In addition, previous research often tests whether the empirical results are more consistent with some theories than with others, assuming or hypothesizing that there is a universal theory that fits all social subgroups. This paper challenges the view of a universal theory that explains the situation for everyone, arguing instead that the mechanisms underlying the total effect of marriage may vary substantially by gender-race subgroups. Drawing on the rich measures of individuals' time-varying family- and work-domain experiences provided by individual-level longitudinal data, I will investigate, separately for each gender-race subgroup, the contributions of two potential mechanisms underlying the total effect: childbearing and work experience. My results suggest that these two mechanisms affect different gender-race subgroups in different directions and to varying degrees, rejecting a universal theory in explaining the wage effect of marriage.

To sum up, this study conducts a comprehensive investigation on how gender and race simultaneously shape the long-term wage effect of marriage over the life course. The investigation is guided by three research questions. First, does the wage effect of marriage take place instantaneously or cumulatively? Second, does the life course pattern of the wage effect of marriage vary by race? Third, do the mechanisms underlying the total effect of marriage vary across gender-race subgroups? By answering these three questions, this study will depict a comprehensive picture about not just the process through which wage advantage and disadvantage accumulate over the life course, but also how the underlying mechanisms are shaped simultaneously by gender and race.

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 (Alwin and Krosnick 1991; Lynch 2003; Ryder 1965). 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 wage at different ages, and summarize an *age profile* of wage inequality (Crystal and Shea 1990; Crystal and Waehrer 1996; Danziger and Gottschalk 1993; Lam and Levison 1992; Lemieux 2006; O'Rand 1996). 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 inter-correlated life stages (Gottschalk et al. 2011; Mayer 2004; Mayer 2009; 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 inter-connecting 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 individuals rationally adjust their levels of consumption across the life course based on changes in personal income/wealth (Sorenson 2000). 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 where unpredictable variability in life course wage attainment is the norm (DiPrete and McManus 1996; Gottschalk and Danziger 2005; Kalleberg 2009; Mouw and Kalleberg 2010b; 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; Elder, Johnson, and Crosnoe 2003; Mayer 2009; Shanahan 2000; Wu 2003a). This perspective recognizes the influence of interrelated life conditions such as health status (Ross and Wu 1996; Wilson 2012), psychological traits (Sampson and Laub 1990; Shanahan 2000; Wheaton 1990) 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 (MacLean and Elder Jr 2007; Sampson and Laub 1996), job mobility (Rosenfeld 1992; Wegener 1991), 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 wellbeing. 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, pp. 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, they have, 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 (Bielby and Bielby 1996; Fernandez-Mateo 2009; Tomaskovic-Devey, Thomas, and Johnson 2005; Western 2002; Willson, Shuey, and Elder 2007). 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 percent. 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 2009; Nagin 1999; 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 a life course trajectory framework upon 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 (Althauser 1989; Briscoe and Kellogg 2011; Rosenbaum 1979; DiPrete 1981; Gangl 2006; Heckman and Borjas 1980; Mouw and Kalleberg 2010b). 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 had the highest “transitory variance in wage,” comprising 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 has increased significantly in the United States. Thus I propose that:

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 et al. 2011). Based on 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 due to 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 to 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 (Becker 1994; Ben-Porath 1967; Heckman, Lochner and Todd 2006; Mincer 1974; Schultz 1961). 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 heterogeniety (Heckman, Lochner and Todd 2006; Mincer 1996).

Heterogeneity in wage trajectories is also embedded in family, work, and organizational contexts. Individual experiences in non-market domains of life, such as marital transitions, childbearing, and co-residing with other family members, may spill over to the work domain, effecting 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 (Carbonaro 2007; Grodsky and Pager 2001; Weeden and Grusky 2012). Based on these ideas, I propose that

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. [1] Panel A of Figure 1 illustrates this phenomenon.[2] 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 due to the heterogeneity in the life course wage trajectories.*

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[1] The link between trajectory heterogeneity and inequality has also been noticed by earlier studies: for example, by devising a formal model of the trajectory of scientific productivity, Allison et al. (1982, pp. 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."

[2] Here, Figure 4 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.

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, pp. 62) put it: "[T]he rich get richer at a rate that makes the poor become relatively poorer."[3] 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. Adler 2001; Allison, Long and Krauze 1982; Cole 1979; Crystal and Shea 1990; Dannefer 1987; Dannefer 2003; DiPrete 1981; DiPrete and Eirich 2006; Elman and O'Rand 2004; Frank and Cook 1995; O'Rand 1996; Rao 1980; Rosen 1981; Ross and Wu 1996; Wilson 2012). 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, Shuey, and Elder 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

[3]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.

diverge at both the group and the individual level of observation" (DiPrete and Eirich 2006, pp. 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.[4] Prior works have documented evidence of between-group cumulative advantage, with group defined by gender (Fernandez-Mateo 2009; Noonan, Corcoran, and Courant 2005; Reskin 1978; Tomaskovic-Devey 1993), race (Kim and Miech 2009; Shuey and Willson 2008; Walsemann, Geronimus, and Gee 2008; Tomaskovic-Devey et al. 2005), and level of educational attainment (DiPrete and Eirich 2006; Elman and O'Rand 2004; Ross and Wu 1996).[5] 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 (Allison 1980; Cole and Cole 1973; Merton 1968; Xie 2014). This implies that even among individuals who are similar with regard to group membership, those who receive a higher wage

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

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

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 groups diminish, rather than magnify, over age (Elo and Preston 1996; Krieger and Fee 1994). 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, it is necessary that:

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.[6] Based on this idea, I propose the following hypothesis:

Hypothesis 3: *Intracohort inequality will increase over the life course due to the mechanism of cumulative advantage.*

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[6] For the sake of demonstration, the schematic illustration described here does not differentiate between “between-group cumulative advantage” and “within-group 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 mechansims. Here I formalize the LCT framework into a mathematical model, showing how the model can satisfy the three essential properties of 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 1.A summarizes four key assumptions of the framework and discusses alternative specifications.

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 2002b; 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 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.[7] $\mathrm{Y_{it}}$ denotes the wage for person i at t years in the labor market; $\mathrm{Y_{i0}}$ denotes beginning/baseline wage; and γ_i denotes the person-specific, time-invariant growth rate from $\mathrm{t}-1$ to t. I assume that $\mathrm{Y_{it}}$ is generated by the following process:

$$\begin{aligned}\mathrm{Y_{it}} &= (1+\gamma_\mathrm{i}) \cdot \mathrm{Y_{i,t-1}} \\ &= (1+\gamma_\mathrm{i})^2 \cdot \mathrm{Y_{i,t-2}} \\ &= (1+\gamma_\mathrm{i})^\mathrm{t} \cdot \mathrm{Y_{i0}}\ . \end{aligned} \tag{1.1}$$

Simply speaking, $\mathrm{Y_{it}}$ grows exponentially over t, as a function of the person's wage at the previous period $\mathrm{Y_{i,t-1}}$ 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" model, which is analogous to the process of "wealth accumulation through the mechanism of compound interest" (DiPrete and Eirich 2006, pp. 272).[8] This model represents the simplest form of cumulative advantage. The emphasis of this paper, however, are between-

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[7] 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 drop out of the labor force or works a minimal amount of time for some years, and later come 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 do not count in 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*.

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

and within-group cumulative advantage, which I will define and discuss in details 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 Eq. (1.1), which yields:

$$\ln Y_{it} = t \cdot \ln(1 + \gamma_i) + \ln Y_{i0}. \quad (1.2a)$$

The log transformation from Eq. (1.1) to Eq. (1.2a) 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 Eq. (1.2a) 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 Eq. (1.2a) into the non-deterministic form:

$$\ln Y_{it} = t \cdot \ln(1 + \gamma_i) + \ln Y_{i0} + e_{it}. \quad (1.2b)$$

Also, for the random variability property to exist, the random component e should take up a non-zero variance, as I formally state in the following Condition 1:

$$\mathrm{Var}(e) > 0 \text{ (Condition 1).}$$

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

For the sake of parsimony, I re-write the logarithm of wage in Eq. (1.2b) 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:

$$\ln Y_{it} = \theta_i \cdot t + \lambda_i + e_{it}\ , \quad \text{where } \theta_i = \ln(1 + \gamma_i) \text{ and } \lambda_i = \ln Y_{i0}. \quad (1.3)$$

The three components in Eq. (3) have intuitive interpretations: the slope on t, θ_i, is a function of γ_i, thus, it captures the person-specific wage growth rate. The person-specific intercept, λ_i, is the logarithm of baseline wage Y_{i0}, thus, it captures the person-specific baseline wage. Lastly, e_{it} captures the random variability in wage.[9]

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 Eq. (1.1), 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. $\frac{dY_{it}}{dt} = \gamma_i Y_{it}$). Similarly, from Eq. (1.1), 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, Eq. (1.1) 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 future interment 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

[9] While modeling the specific forms of the random component e_{it} is beyond the scope of this paper, the economic literature on *income process* offered some statistical strategies for modeling random variability (e.g. Gottschalk et al. 2011).Auxiliary analyses to be presented later will further explain the variations in the random component.

random component is essential to characterizing a social process.[10]

Third, my model can be viewed as an extended application of Mincer (1974)'s 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: $E(\ln Y|\, s_i, x_i) = \alpha_i + \rho_{si}s_i + \beta_{0i}x_i + \beta_{1i}x_i^2$, 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 (Heckman, Lochner and Todd 2006; Mincer 1996). As such, the β_{0i} in this human capital equation has similar interpretation as 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 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 simplification so as to keep this paper's main focus to 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 step-wise spline function, which captures the differences in wage growth rate across different stages of life. For example, suppose wage growth rate is 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

[10] Allison et al. (1982, pp. 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."

express θ_{it} as: $\theta_{it} = \theta_{i1}$ if $t_1 \leq t \leq t_2$, and $\theta_{it} = \theta_{i2}$ if $t_2 \leq t \leq t_3$. In this parameterization, θ_{i1} and θ_{i2} capture the individual's wage growth rate at the two different time period. 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 wage growth rate, and $\alpha_{1i}, \alpha_{2i}, \ldots \alpha_{pi}$ capture the dependence of 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 Eq. (1.3) to derive the macrolevel intracohort pattern of wage inequality. I choose the variance of log wage at t, denoted by $\mathrm{Var}(\ln Y_t)$, 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 increase by the same factor, the variance of log wage will not change.[11] Hence, the observed and predicted changes in this measure of inequality is free from any alternation in the scale of the metric measuring wage (Allison, Long and Krauze 1982; Faia 1975).[12] Second, given the generally accepted notion of diminishing marginal utility from monetary income – that is, the notion that

[11] In laying out the axiom of scale invariance as a key principle for measuring inequality, Schwartz and Winship (1980, pp.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."

[12] 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 paper 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.

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, Eq. (1.3) 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:

$$\mathrm{Var}_t = \mathrm{Var}(\ln Y_t) = \underbrace{\mathrm{Var}(\lambda)}_{V1} + \underbrace{t^2 \cdot \mathrm{Var}(\theta)}_{V2} + \underbrace{2t \cdot \mathrm{Cov}(\lambda, \theta)}_{V3} + \underbrace{\mathrm{Var}(e_t)}_{V4} \qquad (1.4)$$

According to Eq. (1.4), the total wage inequality at time t can be written as the summation of four variance components: V1, V2, V3, and V4.[13] The first component V1 captures the variance in baseline wage, and because baseline wage do not change over time, this variance component does not contribute to the change of wage inequality over t. The last component V4 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, Hypotheses 1 is supported.

It takes some further calculations to show that the two variance components in the middle, V2 and V3, correspond to the trajectory heterogeneity property and cumulative advantage property 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

[13]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.

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, therefore:

$$\mathrm{Var}(\theta) > 0 \text{ (Condition 2).}$$

Condition 2 ensures that the model satisfies the requirement of the trajectory heterogeneity property (i.e. Property 2). Further, when $\mathrm{Var}(\theta) > 0$, $\mathrm{V2}(= t^2 \cdot \mathrm{Var}(\theta))$ 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, $\mathrm{V3}$, 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[14], 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):

$$\mathrm{Cov}(\lambda, \theta) = \underbrace{\mathrm{Cov}\big(\mathrm{E}(\lambda|\mathrm{S}), \mathrm{E}(\theta|\mathrm{S})\big)}_{\substack{\text{Between−group} \\ \text{component}}} + \underbrace{\mathrm{E}\big(\mathrm{Cov}(\lambda, \theta|\mathrm{S})\big)}_{\substack{\text{Within−group} \\ \text{component}}}. \qquad (1.5)$$

In the first component of Eq. (1.5), $\mathrm{E}(\lambda|\mathrm{S})$ represents the expectation of baseline wage conditional on the individual's social groups, and $\mathrm{E}(\theta|\mathrm{S})$ represents the expectation of wage growth rate conditional on the individual's social groups. Therefore, the covariance between

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[14] The *Law of Total Covariance* is a mathematical theorem which states that for three random variables, X, Y, and Z on the same probability space with the covariance of X and Y being finite, then we have: $\mathrm{Cov}(\mathrm{X}, \mathrm{Y}) = \mathrm{E}\big(\mathrm{Cov}(\mathrm{X}, \mathrm{Y}|\mathrm{Z})\big) + \mathrm{Cov}\big(\mathrm{E}(\mathrm{X}|\mathrm{Z}), \mathrm{E}(\mathrm{Y}|\mathrm{Z})\big)$.

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

$$\mathrm{Cov}\big(\mathrm{E}(\lambda|\mathrm{S}), \mathrm{E}(\theta|\mathrm{S})\big) > 0 \quad \text{(Condition 3a).}$$

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

$$\mathrm{E}(\mathrm{Cov}(\lambda, \theta|S) > 0 \quad \text{(Condition 3b).}$$

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

Given the expression in Eq. (5), we can re-write $\mathrm{V3}$ in Eq. (4) as a linear combination of two components ($\mathrm{V3a}$ and $\mathrm{V3b}$):

$$\mathrm{V3} = 2\mathrm{t} \cdot \mathrm{Cov}(\lambda, \theta) = \underbrace{2\mathrm{t} \cdot \mathrm{Cov}\big(\mathrm{E}(\lambda|\mathrm{S}), \mathrm{E}(\theta|\mathrm{S})\big)}_{\substack{\mathrm{V3a} \\ \text{(between-group component)}}} + \underbrace{2\mathrm{t} \cdot \mathrm{E}\big(\mathrm{Cov}(\lambda, \theta|\mathrm{S})\big)}_{\substack{\mathrm{V3b} \\ \text{(within-group component)}}} . \qquad (1.6)$$

Eq. (6) shows that under Condition 3a and Condition 3b, the slopes on t in $\mathrm{V3a}$ and $\mathrm{V3b}$ 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 Eq. (1.4) 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 wage growth rate on baseline wage. Hence, even if there is no association between baseline wage and wage growth rate – that is, the case in which $V3$ equals zero – the heterogeneity in 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, Eq. (1.4) suggests that mathematically, trajectory heterogeneity causes total wage inequality to increase by the 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 Condition 1, 2, 3a, and 3b, 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 Hypothesis 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 paper, 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 dataset 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 special and historical, 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 control for a set of time-varying indicators of work experience, occupation, and family-domain life transitions. Lastly, I discuss the limitations of my analyses and suggests potential directions for future extensions.

Data and Sample Restriction

To empirically examine the underlying mechanisms in individuals' life course trajectories, a longitudinal dataset 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 data (NLSY79 hereinafter) suits well with this purpose, in that it follows a nationally representative sample of

12,686 young people in the United States who were 14 to 22 years old when they were first surveyed in 1979. That it, this dataset 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 the year-to-year wage trajectories for these individuals from the beginning of their career to their mid- and late-career.[15]

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.[16]

Due 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 end of years of experience may over-represent those with longer records in the available and under-represent those with shorter records. Thus, to the extent that these

[15] My study favors the NLSY79 data over other datasets for several reasons. First, while other nationally-representative longitudinal datasets, 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 resent 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 is also preferred over such recent datasets.

[16] Recall that as explained earlier, my choice of labor market experience rather than biological age as the key dimension of 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 life course process. The results were consistent with those from using potential experience and are thus omitted from the paper.

individuals perform systematically in wage attainment, this over- and under- representativeness 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) to their mid-career (i.e. twenty years of potential experience). This restriction will reduce the above problem, because even for those in the youngest NLSY79 respondents (born in the year of 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.[17] All data analyses are weighted.

I use the logarithm of hourly wage of the individual's current or most recent job, which is adjusted to 1999 dollars by 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.[18] 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 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

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

[18] 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.

observations (Curran, Obeidat, and Losardo 2010).[19] Meanwhile, it is possible that individuals choose to work at multiple jobs. However, as several earlier works suggested, the decision to work multiple jobs is affected depends on the business cycle or macroeconomic conditions, therefore, the reported wage from the primary job the reporting may be more reliable than that from secondary jobs (Amuedo-Dorantes and Kimmel 2009; Nee 1989; Partridge 2002). Hence, in cases where an individual is concurrently working at more than one jobs, only hourly wage from the individual's primary job will be used.[20]

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 which 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 (DiPrete and Eirich 2006; Reskin 1978; Tomaskovic-Devey and Skaggs 2002). Despite the recent social movements towards promoting gender wage equality in America, males still earn significantly 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

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

[20] Given the relatively minimal proportion of individuals working at multiple jobs compared to those who are working at only one job, this simplification would only have 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 year 2000, about 50% of males were working, yet only 7% of men are working at multiple jobs.

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; Correll, Benard, and Paik 2007; Noonan et al. 2005). 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 attribute along which cumulative advantage may occur (Kim and Miech 2009; Shuey and Willson 2008; Walsemann, Geronimus, and Gee 2008; Tomaskovic-Devey et al. 2005). 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: Burt 1997; Royster 2003; Tilly 1998; Tomaskovic-Devey 1993). My analyses examine the difference in baseline wage as well as wage growth rate between whites, blacks and Hispanics.[21]

Thirdly, cumulative advantage in wage could occur between groups of different levels of educational attainment (DiPrete and Eirich 2006; Elman and O'Rand 2004; Ross and Wu 1996). Because people with higher educational attainment are usually believed to have greater stock of

[21] In NLSY79 data, the non-black and non-Hispanics are coded as white.

human capital, they likely receive higher wage 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 (Podolny and Stuart 1995), 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; Shrum and Wuthnow 1988), 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 leads to a faster rate of wage growth, resulting in the life course magnification of wage advantage of more highly-educated individuals. 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.[22]

Certainly, while the three dimensions of social group 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 the initial attempt in this paper 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,

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[22] 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.

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 wage 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 the Hispanics, and blacks earn the lowest. Average wage also increase 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 wage 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 0-5 years of potential experience to 0.74 ($= 0.86^2$) for the group with 16-20 years of potential experience.

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.[23] The multilevel

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

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.[24] 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.[25]

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:

$$W_{it} = \beta_{0i} + \beta_{1i} \cdot t + \beta_2 \cdot t^2 + e_{it}. \qquad (1.7)$$

In Eq. (1.7), 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,

[24] 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 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 violation.

[25] 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. Tomaskovic-Devey et al. 2005; Western 2002). This paper 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.

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 this coefficient is the same for everyone.[26] Yet, in preliminary analyses omitted from the paper, I assessed the possible variation of β_2 by social groups, and the results are consistent with those assuming a fixed β_2.[27] Lastly, 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:

$$\beta_{0i} = \gamma_{00} + \gamma_{01}S_{1i} + \gamma_{02}S_{2i} + \gamma_{03}S_{3i} + u_{0i}\,, \qquad (1.8)$$

$$\beta_{1i} = \gamma_{10} + \gamma_{11}S_{1i} + \gamma_{12}S_{2i} + \gamma_{13}S_{3i} + u_{1i}\,. \qquad (1.9)$$

Eq. (1.8) specifies person-specific baseline wage. 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 baseline wage respectively. The residual in baseline wage, u_{0i}, is the person-specific random component in baseline wage capturing the unobserved individual heterogeneity that is not explained by the indicators of the person's observed social groups. Eq. (1.9) specifies the person-specific wage growth rate. γ_{10} represents the constant part of the growth rate of log hourly wage over t, and γ_{11}, γ_{12} and γ_{13}

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

[27] 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.

represent effects of gender, race, and educational attainment on wage growth rate. The residual, u_{1i}, captures the random component in 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 non-zero.

Note that my main analyses here assume 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 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 baseline wage and wage growth rate, or they may have contributed to some of the residual variations in wage. Later auxiliary analyses will examine whether controlling for these time-varying variables explains away some of the variations left unexplained by the main analyses.

Specified by Eq. (1.7) – (1.9), the key elements in this multilevel growth curve model correpond directly to the essential properties in the LCT framework introduced earlier:

In Eq. (1.7), the residual e represents the random component in wage. If $\mathrm{Var}(e) > 0$, the random variability property will be supported.

In Eq. (1.9), 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.

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., $\gamma_{01}$and γ_{11}, $\gamma_{02}$and γ_{12}, $\gamma_{03}$and γ_{13}) are all significantly different from zero and have the same signs within each pair, this meansthat groups with higher baseline wage experience faster wage growth rate, and thus the between-group component of the cumulative advantage property will be supported.

For within-group cumulative advantage to exist in reality, the residual components in β_{0i} and β_{1i} should associate negatively. Thus, if $\mathrm{Cov}\,(u_0, u_1) > 0$, this means that within these groups, those with higher baseline wage tend to have 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 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 higher baseline wage than females; whites earn the highest among the three racial groups, followed by Hispanics, and then blacks; 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 degree 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 wage growth rate. That is, Model (1) allows wage growth rate to vary by person, yet does not allow it to depend systematically on indicators of their measured characteristics.[28] 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 significantly larger than zero. Recall that earlier I have 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 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 wage tend to experience higher wage growth rate – that is, by checking whether the three pairs of coefficients, γ_{01} and γ_{11}, γ_{02} and γ_{12}, 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 lower baseline wage as well as slower wage growth rate. This finding contrasts the conclusion in some earlier works that the disadvantage in wage for females remains unchanged or even diminishes over their life courses (e.g., Bielby and Bielby 1996). 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

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

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 wage and experience significantly slower wage growth rate. Third, individuals with higher educational attainment, especially those with an educational attainment beyond high school, not only receive a higher wage at the beginning of their career process, but also experience faster wage growth rate 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 wage as well as wage growth rate: 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 wage 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 baseline wage associates negatively with the residual in wage growth rate. This means that among individuals who share the same group-level attributes on the three measured dimensions, those with higher wage at the beginning tend to have 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 (Borjas and Rosen 2012; Johnson 1978). As such, the 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.[29] Fourth, one defining feature of the recent rise in economic inequality in the United Statesis the divergence of the income of the super-rich (e.g., the top 1%) from the income of the majority of wage earners (McCall and Percheski 2010; Piketty 2014; Volscho and Kelly 2012), which is likely driven by the top income earners’ cumulative advantage in obtaining higher earnings. The super-rich take 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

[29] 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.

sample of top income earners, however, it is possible that within-group cumulative advantage will be observed for this specific share of 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 ¼ 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 by a tick) or not (marked by a cross) by data. Both the random variability property and the trajectory heterogeneity property are supported by 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, trajectory heterogeneity property, and 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.[30]

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:

[30] 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.

$\widehat{W_{it}} = \widehat{\beta_{0i}} + \widehat{\beta_{1i}} \cdot t + \widehat{\beta_2} \cdot t^2$, where $\widehat{\beta_{0i}}$, $\widehat{\beta_{1i}}$ and $\widehat{\beta_2}$ are calculated by Eq. (8) and Eq. (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. Similar 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. Similar to Step 2, I calculate wage inequality using the log hourly wage at each year of potential experience predicted from Step 3, which form the trajectory of $\mathrm{Var}\left(\widehat{W_t^*}\right)$. Because $\mathrm{Var}\left(\widehat{W_t^*}\right)$ 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.[31] These two sequences of predictions then help me to discern the

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

contributions of trajectory heterogeneity and between-group cumulative advantage to the total intracohort pattern of wage inequality: if TH increases with t, this means 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 (Autor, Katz, and Kearney 2008; Lemieux 2006; 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 economy-wide increase in wage inequality, rather than 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 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 based on the year at which wage information was recorded. Lastly, 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.[32] 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 observed wage inequality – measured by the variance of log hourly wage – among NLSY79 respondents from zero to twenty 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 dash-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

[32] 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.

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 due to 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 twenty years of life course, the magnitude of random variability has grown gradually. Hence, this finding supports Hypothesis 1. Relating this result 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 Eq. (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 $\mathrm{Var_t}$ over the life course, denoted by $\Delta\mathrm{Var_t}$, can be decomposed as below:

$$\Delta\mathrm{Var_t} = \Delta\mathrm{V1} + \Delta\mathrm{V2} + \Delta\mathrm{V3} + \Delta\mathrm{V4}\ . \qquad (1.10)$$

Eq. (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 $\mathrm{V4}$, $\mathrm{V2}$ and $\mathrm{V3}$ 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 second and third columns give the level of wage inequality measured at the entrance and twentieth year of labor market experience respectively. The fourth 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 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 about two thirds (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.[33]

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 which is left unexplained by the observed variables incorporated in this model. The findings suggest that at least for the first twenty 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-1980 era is

[33] Yet, the relatively small size of the quantitative contribution of between-group cumulative advantage should not be taken as an indication of the non-significance of this mechanism. In fact, the significant effects of individuals' group attributes on both baseline wage and 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.

marked by substantial earnings volatility and economic insecurity (Gottschalk et al. 2011; 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 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 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 wage growth rate to the multilevel growth curve model by replacing the linear function of potential experience with a piece-wise linear function (i.e., a spline function). The spline function contains two knots, one at six years of potential experience and the other at fourteen years of potential experience, to separate the time period between zero to twenty years of potential experience into three parts. I define t_1, t_2 and t_3 as below:

$$t_1 = \begin{cases} t, & \text{if } t \in [0,6] \\ 6, & \text{if } t \in [7,20] \end{cases}; \quad t_2 = \begin{cases} 0, & \text{if } t \in [0,6] \\ t-6, & \text{if } t \in [7,13] \\ 7, & \text{if } t \in [14,20] \end{cases}; \quad t_3 = \begin{cases} 0, & \text{if } t \in [0,13] \\ t-13, & \text{if } t \in [14,20] \end{cases}. \tag{1.11}$$

With t_1, t_2 and t_3 defined as above, I re-write Eq. (1.7) into the piece-wise linear form:

$$W_{it} = \beta_{0i} + \beta_{1i}^{1} \cdot t_1 + \beta_{1i}^{2} \cdot t_2 + \beta_{1i}^{3} \cdot t_3 + e_{it} \ , \qquad (1.12)$$

where β_{0i} is specified in the same way as in Eq. (1.8), and each β_{1i}^{j} (j=1, 2, and 3, representing the coefficient for each of the three periods) is specified as:

$$\beta_{1i}^{j} = \gamma_{10}^{j} + \gamma_{11}^{j} S_{1i} + \gamma_{12}^{j} S_{2i} + \gamma_{13}^{j} S_{3i} + u_{1i}^{j}, \quad \text{for } j = 1,2, \text{and } 3. \qquad (1.13)$$

That is, the piece-wise linear function estimates the effects of group attributes on 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 1.D1.[34] Overall, wage growth rate tend 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 baseline wage are similar to those in the main analyses, yet their effects on wage growth rate vary by life stages: The negative effect of being female on wage growth rate is greater in the earlier stages of experience than in the later stage. The negative effect of being black on wage growth rate is greatest and significant during 7–13 years of labor market experience. The directions of the effects of gender and race on 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 0–6 years of labor market experience, and their advantage in wage growth rate become small and insignificant during 7–13 years. During the last

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

period (14–20 years), however, the effect of higher educational attainment on wage growth rate turns out to be negative and is significant between those with high school degree 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 14 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 wage gap between highly- and lowly-educated individuals in the observed sample. Panel B of Appendix Table 1.D1, which gives the variance components of the model, suggests wage growth rate varies substantially throughout the three life stages.[35] Similar to the earlier Figure 2, Appendix Figure 1.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 spped at which the gaps between groups widen over the life course vary by life stage, the wage gaps between different dimensions of social groups are all wider at the end than at the beginning of this twenty-year period. In short, the auxiliary analyses suggest that my main conclusions are not altered by allowing 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 pre-market time-invariant group attributes (gender, race, and educational attainment) on wage growth rate. Those models do not control for work

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[35] The model reported in the table imposes the assumption that the covariances between u_0, $u_{1,1}$. u_{12}, 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 baseline wage and wage growth rate within social groups.

and family domain experiences that occurred during the individuals' labor market experience. Since these experiences mediate the effect of pre-market characteristics on 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 re-specify Eq. 1. (7) as:

$$W_{it} = \beta_{0i} + \beta_{1i} \cdot t + \beta_2 \cdot t^2 + \underbrace{\sum_{k=1}^{K} \beta_k \cdot X_{it}}_{\substack{\text{Time-varying} \\ \text{controls}}} + e_{it}. \qquad (1.14)$$

In Eq. (1.14), the variables in X contains work and family domain experiences. The work domain experiences include the individual's tenure (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 1.D2. Model D1 does not include the effect of group attributes on 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 baseline wage as well as wage growth rate. For example, in predicting 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 -0.0092. Compared to those who did not receive 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 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 Model A1 and A2 is 0.016 and is larger than that in Model (1) and Model (2) (which is 0.014).[36] 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 1.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 experiences 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 be due to the fact that more subtle mechanisms affecting life course wage trajectories lie within the organizational environment and network

[36] Whether the difference between the two is significant is uncertain, but this at least implies that the between-person variation in 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.

structure of the workplace, which are not directly measured by the NLSY79 data. For example, Tomaskovic-Devey and colleagues (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 works 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 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 wage 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 non-randomness 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 1.E.[37] 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.[38] 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.[39] Still, the systematic dependence of the likelihood of nonresponse upon 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 1.F 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

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

[38] 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.

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

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 importantly, 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.[40]

Another pertinent pattern of survey nonresponses is the association between nonresponses and individuals' group characteristics. Appendix Figure 1.F 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 ten years of experience. There exist some group differences in the pattern of nonresponses: males have a larger nonresponse share than females; whites have a larger nonresponse share than racial minorities. Thus, the sample may under-represent men and whites at 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 ten years of experience. Hence, individuals with lower educational attainment may be over-represented 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

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

nonresponses based on unobserved characteristics could still cause more complex biases in the estimated coefficients (Solon, Haider, and Wooldridge 2013).

Third, due to 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 mid-career 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 et al. 2012; Western, Bloome, and Percheski 2008). 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 U.S., my analyses borrowed external information from the Current Population Survey to adjust accordingly. However, this adjustment is certainly not sufficient to account 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 non-marital 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 paper 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 due to 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 dataset. 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., Willson et al. 2007; Tomaskovic-Devey et al. 2002), 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 multi-generational 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 (Chan and Boliver 2013; Mare 2011). When applied in this way, the framework could be utilized to answer 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).

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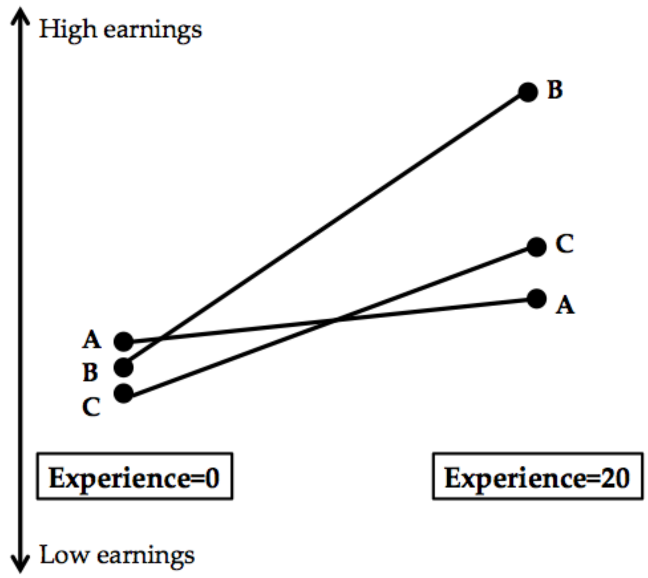
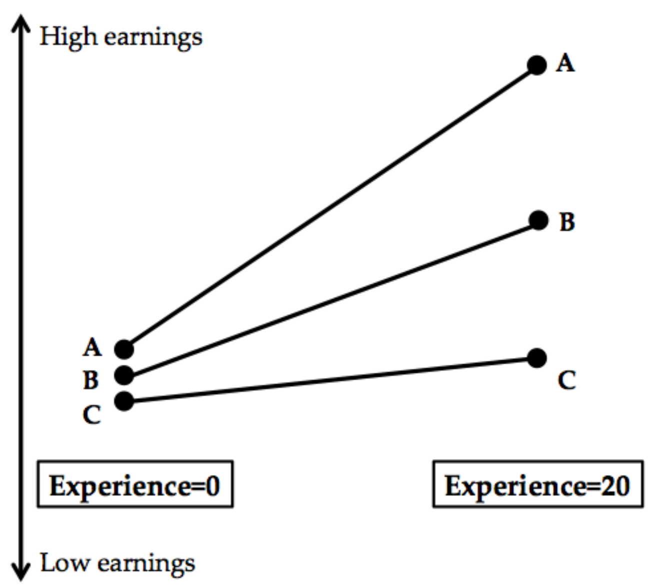
Figure 1 Schematic demonstration of the contributions of trajectory heterogeneity and cumulative advantage to the intracohort pattern of wage inequality.

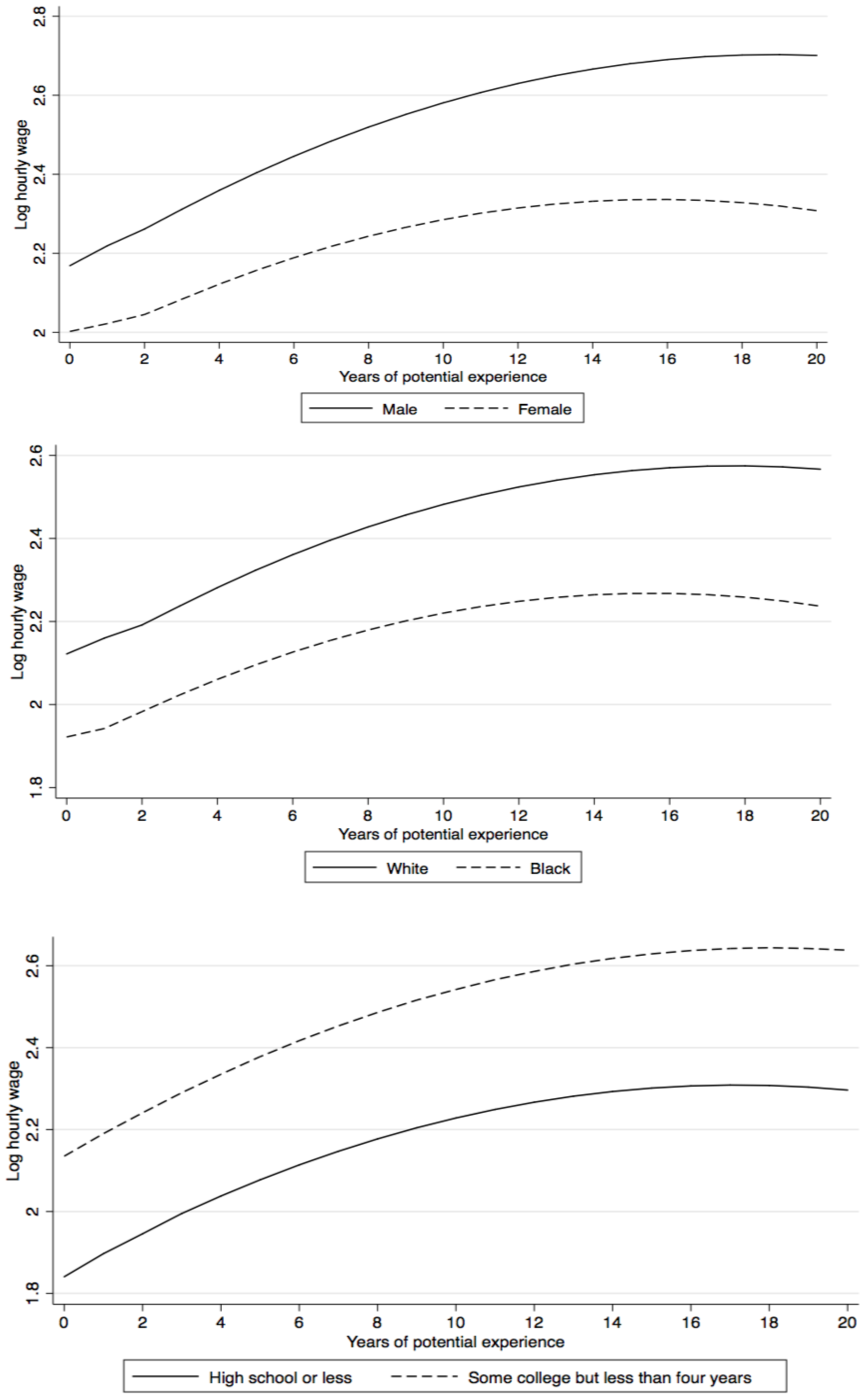


Panel A Illustration of trajectory heterogeneity



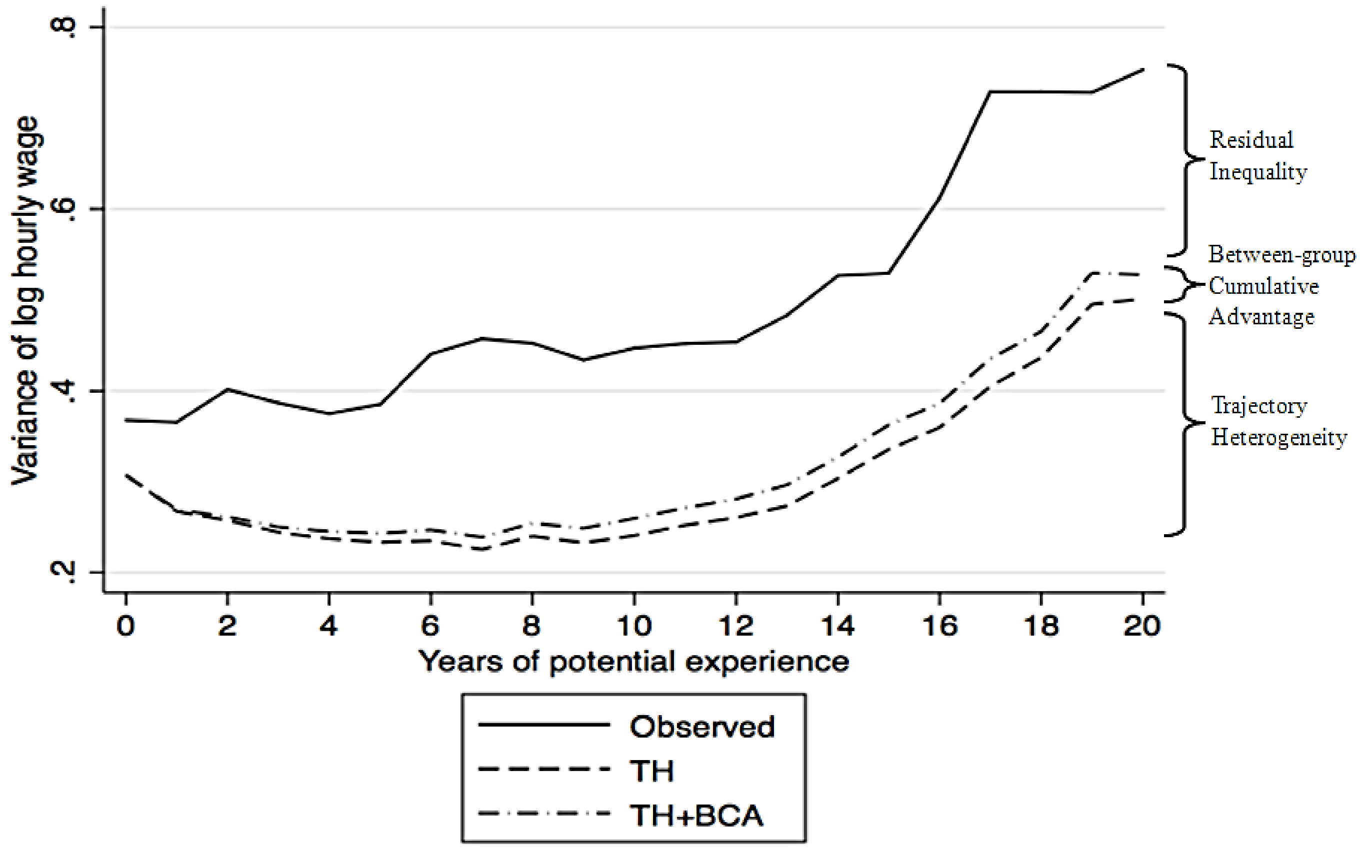
Panel B Illustration of cumulative advantage

Figure 2 Predicted average log hourly wage by years of potential experience, by gender, race and educational groups



SOURCE. - National Longitudinal Survey of Youth 1979-2010, Bureau of Labor Statistics.

Figure 3 Observed and predicted variance of log hourly wage by years of potential experience



SOURCE. - National Longitudinal Survey of Youth 1979-2010, Bureau of Labor Statistics.
NOTE. - 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.

Table 1 Summary of the essential properties, corresponding hypotheses, conditions in the mathematicla 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 due to the accumulation of random variability.	$\mathrm{Var(e)} > 0$		$\mathrm{Var(e)} > 0$	✔
Trajectory heterogeneity property	Intracohort inequality will *increases* over the life course due to trajectory heterogeneity.	$\mathrm{Var}(\theta) > 0$		$\mathrm{Var}(\beta_1) > 0$	✔
Cumulative advantage property	Intracohort inequality will *increases* over the life course due to cumulative advantage.	Between-group	$Cov\big(E(\lambda\|S), E(\theta\|S)\big)$>0	The pairs of γ_{01} and γ_{11}, γ_{02} and γ_{12}, γ_{03} and γ_{13} are significant and have the same signs within each pair.	✔
		Within-group	$E(Cov(\lambda, \theta\|S) > 0$	$Cov(u_1, u_0) > 0$	✗

Table 2 Descriptive statistics of the NLSY79 sample used in the empirical analysis

Panel A: Time-invariant variables		Percentage
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 lease four years of college	19.91

Panel B: Log hourly wage by demographic characteristics		Mean log hourly wage	S.D. of log hourly wage
By gender	Male	2.48	0.68
	Female	2.22	0.70
By race	White	2.38	0.71
	Hispanic	2.30	0.68
	Black	2.20	0.64
By educational attainment	High school or less	2.24	0.61
	Some college but less than four years	2.40	0.69
	At least four years of college	2.59	0.85

Panel C: Log hourly wage by potential experience	Mean log hourly wage	S.D. of log hourly wage
0-5 years of potential experience	2.26	0.57
6-10 years of potential experience	2.39	0.64
11-15 years of potential experience	2.45	0.69
16-20 years of potential experience	2.52	0.86

SOURCE.- National Longitudinal Survey of Youth 1979-2010, Bureau of Labor Statistics.
NOTE.- All sample statistics are weighted.

Table 3 Estimated coefficients from multilevel growth curve models predicting log hourly wage

	Model (1)			Model (2)		
	Coeff.	**S.E.**	**Sig.**	**Coeff.**	**S.E.**	**Sig.**
Coefficients predicting baseline wage β_0						
Constant intercept (γ_{00})	1.952	(0.011)	***	1.926	(0.013)	***
Gender (γ_{01}) [*Reference: male*]						
Female	-0.252	(0.011)	***	-0.205	(0.015)	***
Race(γ_{02}) [*Reference: white*]						
Hispanic	-0.011	(0.013)		0.007	(0.017)	
Black	-0.118	(0.013)	***	-0.083	(0.019)	***
Educational attainment(γ_{03}) [*Reference: high school or less*]						
Some college but less than four years	0.331	(0.012)	***	0.302	(0.016)	***
At least four years of college	0.734	(0.017)	***	0.723	(0.018)	***
Coefficients predicting wage growth rate β_1						
Constant slope (γ_{10})	0.052	(0.002)	***	0.058	(0.002)	***
Gender (γ_{11}) [*Reference: male*]						
Female				-0.010	(0.002)	***
Race (γ_{12}) [*Reference: white*]						
Hispanic				-0.004	(0.002)	
Black				-0.008	(0.002)	**
Educational attainment (γ_{13}) [*Reference: high school or less*]						
Some college but less than four years				0.006	(0.003)	*
At least four years of college				0.002	(0.004)	
Other coefficient						
Squared experience (β_2)	-0.002	(0.000)	***	-0.002	(0.000)	***
Variance components						
$Var(u_0)$	0.637	(0.082)	***	0.636	(0.081)	***
$Var(u_1)$	0.014	(0.001)	***	0.014	(0.001)	***
$Cov(u_0, u_1)$	-0.065	(0.007)	***	-0.065	(0.007)	***
$Var(e)$	0.165	(0.004)	***	0.165	(0.004)	***
Number of individuals	12099				12099	
Number of person-year observations	133121				133121	

SOURCE.- National Longitudinal Survey of Youth 1979-2010, Bureau of Labor Statistics.
NOTE.- *** p<0.001; ** p<0.01; * p<0.05. Robust standard errors are in parentheses. All analyses are weighted.

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	0.368	0.753	0.385	100.00%
TH	0.307	0.501	0.194	50.39%
TH + BCA	0.307	0.528	0.221	57.40%
Residual inequality	0.061	0.225	0.164	42.60%

SOURCE.- National Longitudinal Survey of Youth 1979-2010, Bureau of Labor Statistics.
NOTE.- The columns of "t=0" and "t=20" indicate variance of log hourly wage among this cohort at zero and twenty years of labor market experience respectively, Δ_{var} is the change in variance of log hourly wage between zero and twenty 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%.

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 1.A below, 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 Table 1.A can be kept as a reference when applying the LCT framework to address different research questions. I recommend future works to use this table as the basis for potential extensions of the LCT framework.

Table 1.A 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, 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 rate at different life stages. (2) Use polynomial function to approximate the temporal variation of wage growth rate.	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 by 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 explain 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	Inclusion of other dimensions of group attributes may increase the share of wage variance between groups and decrease its

		introduced as important dimensions of social groups that affect wage and wage growth.	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 tend 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:

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

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

I predict β_1^* by the following equation: $\widehat{\beta_{1i}^*} = \widehat{\gamma_{10}} + \phi_i + \widehat{u_{1i}}$. It follows that $Var(\widehat{\beta_{1i}^*}) = Var(\phi) + Var(\widehat{u_{1i}})$. Recall that according to the original setting (i.e. Eq. (7)), I have generated $\widehat{\beta_{1i}}$ by the following: $\widehat{\beta_{1i}} = \widehat{\gamma_{10}} + \widehat{\gamma_{11}} S_{1i} + \widehat{\gamma_{12}} S_{2i} + \widehat{\gamma_{13}} S_{3i} + \widehat{u_{1i}}$. It is implied that $Var(\widehat{\beta_1}) = Var(\psi) + Var(\widehat{u_1})$ (assuming no association between S's and u_1). Also recall that in (2), I showed that $Var(\phi) = Var(\psi)$. Therefore, $Var(\widehat{\beta_1^*}) = Var(\widehat{\beta_1})$, 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.

Lastly, 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 rule out the possibility that the increase in wage inequality for a cohort of population as they grow old is actually the result of the economy-wide 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 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: $F_m = \frac{\mathrm{I}_{2000}}{I_m}$, and the adjusted wage inequality in year *m* is: $\mathrm{V}_{\mathrm{m,adjusted}} = V_m \cdot F_m$. For example, I_{1996} is 0.365 and I_{2000} is 0.37 in year 2000, therefore, $F_{1996} = \frac{0.37}{0.365} = 1.014$. So the adjusted wage inequality in year 1996 is: $\mathrm{V}_{1996,\mathrm{adjusted}} = V_{1996} \cdot 1.014$. 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 1.C. 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 1.C 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	0.287	1.289
1981	0.289	1.280
1982	0.308	1.201
1983	0.316	1.171
1984	0.321	1.153
1985	0.326	1.135
1986	0.329	1.125
1987	0.332	1.114
1988	0.328	1.128
1989	0.339	1.091
1990	0.339	1.091
1991	0.333	1.111
1992	0.333	1.111
1993	0.336	1.101
1994	0.382	0.969
1995	0.366	1.011
1996	0.365	1.014
1997	0.362	1.022
1998	0.357	1.036
1999	0.357	1.036
2000	0.370	1.000
2001	0.375	0.987
2002	0.383	0.966
2003	0.404	0.916
2004	0.389	0.951
2005	0.400	0.925
2006	0.400	0.925
2007	0.419	0.883
2008	0.419	0.883
2009	0.425	0.871
2010	0.429	0.862

SOURCE.- Merged Outgoing Rotation Groups of Current Population Survey 1980-2010.
NOTE.- Wage inequality is calculated as the variance of log hourly wage for the working population between age 20 to age 60. Data are available at the NBER website: http://www.nber.org/data/morg.html.

Appendix D

Tables and Figures for Auxiliary Analyses

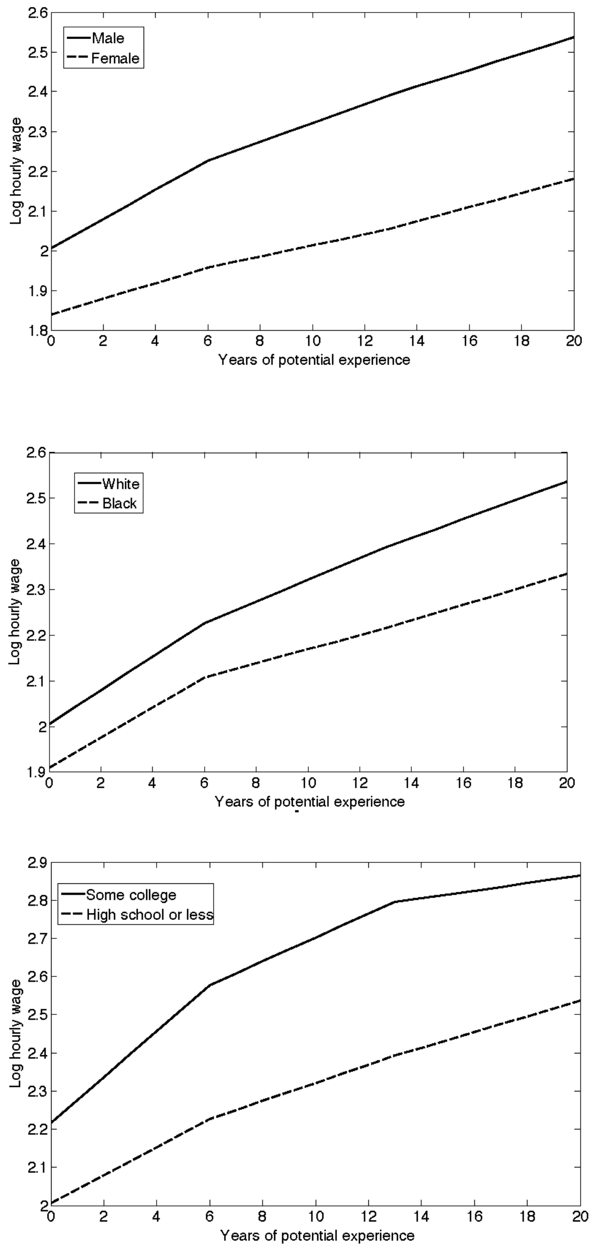
Table 1.D1 Selected coefficients from multilevel growth curve model predicting log hourly wage, using the piece-wise linear model

Panel 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		0.0367***	0.0237***	0.0206***
Gender (reference: male)				
Female	-0.1665***	-0.0171***	-0.0098**	-0.0025
Race (reference: white)				
Hispanic	0.0288	-0.0049	-0.0051	-0.0069
Black	-0.0967***	-0.0036	-0.0084*	-0.0036
Education (reference: high school or less)				
Some college	0.2103***	0.0235***	0.0074	-0.0108
College and above	0.5991***	0.0253***	0.0048	-0.0548***

Panel B: Variance components	
$Var(u_0)$	0.8694
$Var(u_{1,1})$	0.0412
$Var(u_{1,2})$	0.0368
$Var(u_{1,3})$	0.0444
$Var(e)$	0.1168

SOURCE.- National Longitudinal Survey of Youth 1979-2010, Bureau of Labor Statistics.
NOTE.- *** p<0.001; ** p<0.01; * p<0.05; Robust standard errors are in parentheses. All analyses are weighted.

Figure 1.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



NOTE: Data source: National Longitudinal Survey of Youth 1979-2010, Bureau of Labor Statistics.

Table 1.D2 Estimated coefficients from multilevel growth curve models predicting log hourly wage, with controls for work and family domain experiences

	Model D1			Model D2		
	Coeff.	S.E.	Sig.	Coeff.	S.E.	Sig.
Coefficients predicting baseline wage β_0						
Constant intercept (γ_{00})	1.9090	0.0514	***	1.8892	0.0522	***
Gender (γ_{01}) [*Reference: male*]						
Female	-0.1777	0.0179	***	-0.1378	0.0193	***
Race(γ_{02}) [*Reference: white*]						
Hispanic	0.0119	0.0165		0.0177	0.0223	
Black	-0.1003	0.0148	***	-0.0734	0.0219	**
Educational attainment(γ_{03}) [*Reference: high school or less*]						
Some college but less than four years	0.2675	0.0165	***	0.2543	0.0187	***
At least four years of college	0.6493	0.0183	***	0.6196	0.0230	***
Coefficients predicting wage growth rate β_1						
Constant slope (γ_{10})	0.0557	0.0028	***	0.0597	0.0036	***
Gender (γ_{11}) [*Reference: male*]						
Female				-0.0082	0.0026	**
Race (γ_{12}) [*Reference: white*]						
Hispanic				-0.0012	0.0026	
Black				-0.0055	0.0028	*
Educational attainment (γ_{13}) [*Reference: high school or less*]						
Some college but less than four years				0.0027	0.0034	
At least four years of college				0.0061	0.0033	†
Controls for work experience						
Job tenure	0.0007	0.0000	***	0.0007	0.0000	***
Job tenure $\times$ t	-0.00004	0.00000	***	-0.00004	0.00000	***
hours worked	0.00002	0.00001	**	0.00002	0.00001	**
hours worked $\times$ t	0.00000	0.00000	***	0.00000	0.00000	***
Weeks unemployed	0.0008	0.0006		0.00083	0.00061	
Weeks unemployed $\times$ t	-0.0004	0.0001	***	-0.0004	0.0001	***
Weeks out of labor force	-0.0004	0.0005		-0.0004	0.0005	
Weeks out of labor force $\times$ t	-0.0003	0.0001	***	-0.0003	0.0001	***
Controls for occupation	Yes			Yes		
Controls for family-related life events						
Cohabiting	0.0244	0.0167		0.0244	0.0167	
Cohabiting $\times$ female	-0.0063	0.0225		-0.0063	0.0225	
Married	0.0426	0.0128	**	0.0426	0.0128	**
Married $\times$ female	-0.0584	0.0181	**	-0.0584	0.0181	**
Widowed or divorced	-0.0118	0.0190		-0.0118	0.0190	
Widowed or divorced $\times$ female	0.0330	0.0261		0.0330	0.0261	
# of children in the household	-0.0076	0.0057		-0.0076	0.0057	

# of children in the household × female	-0.0201	0.0096	*	-0.0201	0.0096	*
Other coefficient						
Squared experience (β_2)	-0.0010	0.0001		-0.0010	0.0001	***
Variance components						
$Var(u_0)$	0.7948	0.1091	***	0.7942	0.1089	***
$Var(u_1)$	0.0162	0.0018	***	0.0161	0.0018	***
$Cov(u_0, u_1)$	-0.0788	0.0112	***	-0.0787	0.0112	***
$Var(e)$	0.1520	0.0044	***	0.1520	0.0044	***
Number of individuals	11543			11543		
Number of person-year observations	110114			110114		

SOURCE.- National Longitudinal Survey of Youth 1979-2010, Bureau of Labor Statistics.
NOTE.- *** p<0.001; ** p<0.01; * p<0.05; † p<0.1 Robust standard errors are in parentheses. All analyses are weighted.

Figure 1.D2 Residual variance in log hourly wage by years of potential experience, with and without controls for work and family domain experiences

SOURCE. - National Longitudinal Survey of Youth 1979-2010, Bureau of Labor Statistics.

Appendix E

Results with Imputed Values for Missing Hourly Wage

Table 1.E Estimated coefficients from multilevel growth curve models predicting log hourly wage, with imputed values for missing hourly wage

	Model A3			Model A4		
	Coeff.	**S.E.**	**Sig.**	**Coeff.**	**S.E.**	**Sig.**
Coefficients predicting baseline earnings β_0						
Constant intercept (γ_{00})	1.9627	0.0100	***	1.9422	0.0100	***
Gender (γ_{01}) [*Reference: male*]						
Female	-0.2619	0.0094	***	-0.2126	0.0124	***
Race(γ_{02}) [*Reference: white*]						
Hispanic	-0.0112	0.0122		-0.0040	0.0159	
Black	-0.1309	0.0114	***	-0.1120	0.0161	***
Educational attainment(γ_{03}) [*Reference: high school or less*]						
Some college but less than four years	0.3220	0.0106	***	0.3001	0.0134	***
At least four years of college	0.7173	0.0147	***	0.7308	0.0166	***
Coefficients predicting earnings growth rate β_1						
Constant slope (γ_{10})	0.0494	0.0016	***	0.0534	0.0018	***
Gender (γ_{11}) [*Reference: male*]						
Female				-0.0073	0.0012	***
Race (γ_{12}) [*Reference: white*]						
Hispanic				-0.0011	0.0015	
Black				-0.0028	0.0014	*
Educational attainment (γ_{13}) [*Reference: high school or less*]						
Some college but less than four years				0.0032	0.0013	*
At least four years of college				-0.0020	0.0021	
Other coefficient						
Squared experience (β_2)	-0.0016	0.0001	***	-0.0016	0.0001	***
Variance components						
$Var(u_0)$	0.4583	0.0874	***	0.4576	0.0873	***
$Var(u_1)$	0.0042	0.0004	***	0.0042	0.0004	***
$Cov(u_0, u_1)$	-0.0286	0.0057	***	-0.0285	0.0057	***
$Var(e)$	0.1682	0.0047	***	0.1682	0.0047	***
Number of individuals	12192				12192	
Number of person-year observations	186269				186269	

SOURCE.- National Longitudinal Survey of Youth 1979-2010, Bureau of Labor Statistics.
NOTE.- *** p<0.001; ** p<0.01; * p<0.05; † p<0.1 Robust standard errors are in parentheses. All analyses are weighted.

Appendix F

Demonstration of Nonresponse Pattern

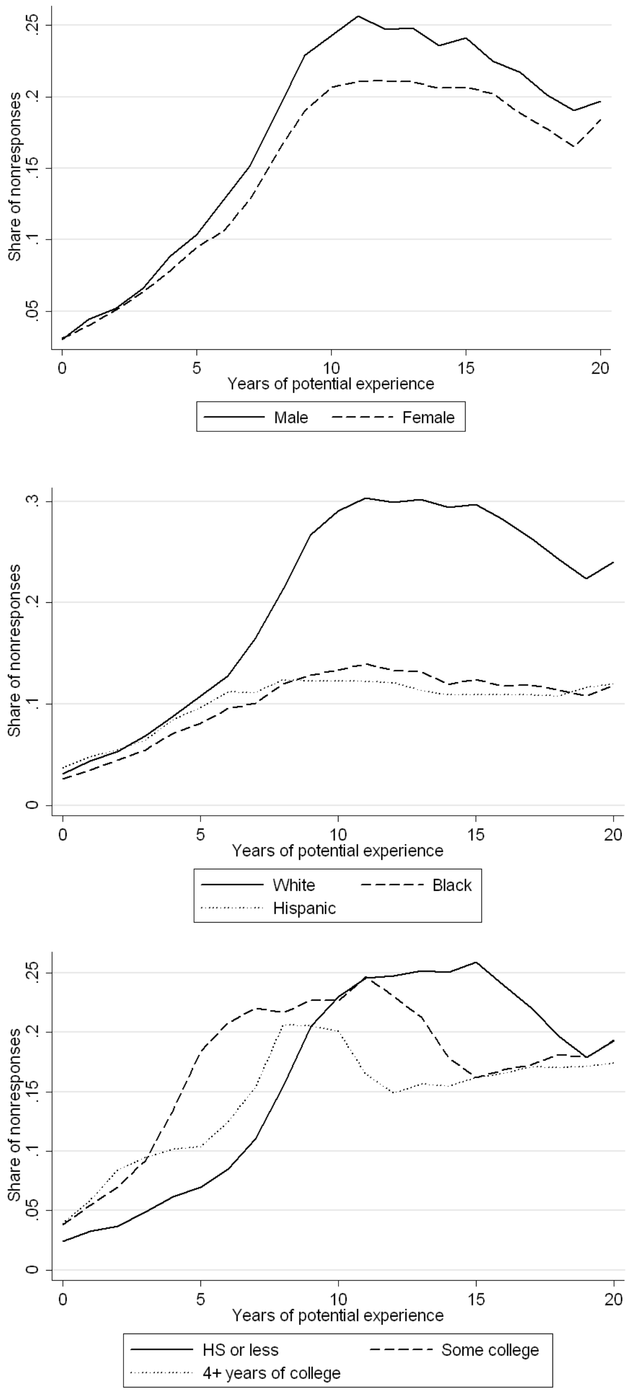
Table 1.F Mean and standard deviation of average log hourly wage in previous three years by response status in the current period, at different years of potential experience

	Responded at *t*			Nonresponse at *t*		
Years of potential experience	Mean log hourly wage in previous 3 years	S.D. of log hourly wage in previous 3 years	# of respondents	Mean log hourly wage in previous 3 years	S.D. of log hourly wage in previous 3 years	# of non-respondents
t=2	2.10	0.50	8758	2.23	0.52	480
t=5	2.17	0.52	9596	2.24	0.52	705
t=10	2.32	0.59	8585	2.26	0.61	1269
t=15	2.42	0.66	7649	2.22	0.67	585
t=18	2.43	0.75	7375	2.38	0.81	269

SOURCE.- National Longitudinal Survey of Youth 1979-2010, Bureau of Labor Statistics.

NOTE.- 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 non-missing and missing sample at different years of potential experience.

Figure 1.F Share of nonresponses by years of potential experience, by gender, race, and educational attainment



SOURCE. - National Longitudinal Survey of Youth 1979-2010, Bureau of Labor Statistics.

Chapter 3 The Accumulation of (Dis)advantage: The Intersection of Gender and Race in the Long-Term Wage Effect of Marriage

INTRODUCTION

The impact of marriage on men and women's wages has long been conjectured, debated, and empirically tested. The dominant view so far is that marriage is associated with a significant wage premium for men, yet a much smaller wage premium, or even a wage penalty for women (Budig & England, 2001; Chun & Lee, 2001; Killewald & Gough, 2013). Some of these works attribute the gender differences in the wage effect of marriage to household specialization (Becker, 1991; Chun & Lee, 2001; Hersch & Stratton, 2000; Korenman & Neumark, 1991; Waite, 1995) and investment in human capital(Becker, 1985; Kenny, 1983; Korenman & Neumark, 1991). Others emphasize the positive effect of marriage on men's motivation and responsibility at work and the opposite effect on women's work motivation (Ashwin & Isupova, 2014; Drobnič, Blossfeld, & Rohwer, 1999; Gorman, 2000; Korenman & Neumark, 1991; Mincer & Ofek, 1982; Pollmann-Schult, 2011; West & Zimmerman, 1987), or employers' discrimination favoring married men and disfavoring married women (Bartlett & Callahan, 1984; Correll, Benard, & Paik, 2007; May, 1982). To determine the wage effect of marriage, this line of work typically constructs a single measure based on a comparison between the levels of wage earned by the married and the unmarried, termed the *Marriage Wage Premium* (MWP hereinafter), glossing over the temporal variation in the wage effect of marriage across years of marriage. For simplicity, I refer to this approach as the *static approach*.

One important limitation of the static approach is its ignorance of the simple but fundamental fact that the transition into marriage marks the beginning of a long-term life course experience (Elder, Johnson, & Crosnoe, 2003; Elder, 1985; Mayer, 2009). Marriage should be seen, not as a one-time event, but as a major turning point that shapes the individual's life trajectory in all subsequent years. As a result, the wage effect of marriage may not occur instantaneously, but instead unfold gradually over the life course. To recognize the temporal variations in the MWP, research in this area needs to go beyond the static approach towards the life course approach.

Examining such temporal variations in the MWP is important, not just because such variations may exist, but also because describing these variations will deepen our understandings about existing theories on family and work. The theories mentioned at the beginning of this article all invoke mechanisms that are long-term, process-based in nature, because they hinge on the accumulation, socialization, ideology-formation, and behavior adjustments in everyday life after the marital transition. Hence, the prevailing static approach in current literature does not well reflect such process-based consequences of marriage. The dynamic, long-term nature of marriage-induced wage changes warrants the adoption of the life course approach.

Recently, a growing body of literature has started to recognize the possible temporal variations in the wage effect of marriage (Dougherty, 2006; Kenny, 1983; Korenman & Neumark, 1991; Loughran & Zissimopoulos, 2009). Dougherty (2006) studied the effect of marriage up to ten years after marriage and found that the MWP peaks about five years after marriage and then remained stable among males, yet among women, it peaks only two years after marriage and then starts to decline. Loughran and Zissimopoulos (2009), however, found that marriage lowers the rate of wage growth for both men and women. Rodgers & Stratton (2010) conducted separate analyses for both White and African American men, and found that a larger gross effect of marriage on wage exists among African American men, while there is no statistically distinguishable racial differences in the effect of marriage on wage growth.

However, these works either treat race as an additive statistical control (Dougherty, 2006; Loughran & Zissimopoulos, 2009), or focus exclusively on the men's side of the story (Rodgers & Stratton 2010). But, if we look at the long-term wage effect of marriage through a gender lens, should we adopt different perspectives when we look at White and Black couples? If we are interested in how the marriage institution is divided along the racial line, should we assume this racial divide is similar or different for men and women? These questions have been left unresolved in current literature. Analysis in this paper contributes to literature by reconsidering the wage effect of marriage over the life course with a particular emphasis on the *intersection* of gender and race. I hypothesize that, because Blacks and Whites may differ significantly in regard to the economic prospects in the labor market (McCall, 2001; Tomaskovic-Devey, Thomas, & Johnson, 2005; William Wilson, 1996), the division of gender roles in the household (John & Shelton, 1997; Kamo & Cohen, 1998) and attitudes and anticipations for their spouses (Daniel, 1995; Waite, 1995), the long-term pattern of the wage effect of marriage may vary across gender-race subgroups.

In addition, previous research often tests whether the empirical results are more consistent with some theories than with others, assuming or hypothesizing that there is a universal theory that fits all social subgroups. This paper challenges the view of a universal theory that explains the situation for everyone, arguing instead that, the mechanisms underlying the total effect of marriage may vary substantially by gender-race subgroups. Drawing on the rich measures of individuals' time-varying family- and work-domain experiences provided by individual-level longitudinal data, I will investigate, separately for each gender-race subgroup, the contributions of two potential mechanisms underlying the total effect: childbearing and work experience. My results suggest that these two mechanisms affect different gender-race subgroups in different directions and to varying degrees, rejecting a universal theory in explaining the wage effect of marriage.

To sum up, this study conducts a comprehensive investigation on how gender and racial simultaneously shape the long-term wage effect of marriage over the life course. The investigation is guided by three research questions. First, does the wage effect of marriage take place instantaneously or cumulatively? Second, does the life course pattern of the wage effect of marriage vary by race? Third, do the mechanisms underlying the total effect of marriage vary across gender-race subgroups? By answering these three questions, this study will depict a comprehensive picture about not just the process through which wage advantage and disadvantage accumulate over the life course, but also how the underlying mechanisms are shaped simultaneously by gender and race.

SHIFTING FROM STATIC TO LIFE COURSE APPROACH

Existing literature often captures the wage effect of marriage by the term marriage wage premium (MWP). A positive MWP indicates a positive wage effect of marriage, while a negative MWP, sometimes also called the "marriage penalty", indicates a negative wage effect of marriage. Prior research typically determines the MWP by comparing the wage earned by those who are married and unmarried of similar demographic and educational background (e.g. OLS regression estimator), or by comparing the wages of the same person when the person is married and when the person is single (e.g. the fixed-effect estimator). For simplicity, I call this perspective the "static approach," because it assumes that the wage effect of marriage is uniformly distributed over a person's years of marriage, or marginalizes the temporal variation in this wage effect into an average measure. Figure 4 illustrates the static approach with the case for men. The horizontal axis is years of marriage, and the vertical axis is wage. The vertical straight line indicates the point at which the person gets married. The solid line plots the wage trajectory if the person had remained single, and the dashed line plots the wage trajectory after the person got married under the static approach. As the figure shows, being married moves the person's wage trajectory upward. The MWP can be measured as the vertical difference between the solid and the dashed line. In the static approach, the wage trajectories of being married and being single are *parallel* to each other, resulting in a *constant* wage advantage of being married over being single.

The static approach ignores the *temporal* variations of the MWP. The life course approach, however, emphasizes that marriage should be seen as a life-turning event that initiate a period of long-term, dynamic interactions between marriage, fertility experiences, work history, and labor market institutions (Elder, Johnson, and Crosnoe 2003; Shanahan 2008; Warren, Sheridan, and Hauser 2002). The dotted line in Figure 4 demonstrates the wage trajectory for being married under the life course approach. The line moves upwards upon getting married, and the wage trajectory grows with a steeper slope for being married than being single. As a result, the figure illustrates an example in which married men's wage advantage accumulates gradually over years of marriage. As such, the life course approach helps the researcher visualize the process through which the MWP unfolds over time.

THEORETICAL FRAMEWORK

Describing the temporal variations in the MWP is sociologically significant, not just because such variations may exist, but because this engages existing theories. Below, I review existing theories about the wage effect of marriage, placing emphasis on what they imply about the temporal variations in the MWP.

Specialization theory argues that marriage leads men to specialize in more productivity-enhancing activities while women to specialize in domestic responsibilities (Becker, 1991). As a result, marriage is associated with a large and significant MWP for men, yet a much smaller, and even negative MWP for women (Budig & England, 2001; Chun & Lee, 2001; Glauber, 2007; Gupta, 1999; Jacobsen & Rayack, 1996; Killewald & Gough, 2013; Korenman & Neumark, 1991). It thus follows that the impact of marriage will intensify over years of marriage, because the demand and complexity of household labor generally increase over time, particularly with the arrival of children in the household. That is, the MWP for men will grow over years of marriage, while the MWP for women will decline over years of marriage.

Human capital theory attributes the wage differences between the married and the unmarried to productivity differences due to the additional investment in human capital among married men and the reduced human capital investment among married women (Akerlof, 1998; Becker, 1985; Daniel, 1995; Greenhalgh, 1980; Kenny, 1983; Korenman & Neumark, 1991). This theory has similar implications about the temporal variations in the MWP: The additional investment in human capital among married men from year to year likely leads to the increase in the MWP over years of marriage, while the reduction in women's human capital investment due to repeated work experience disruptions will slow down women's wage growth, resulting in the decline in the MWP for women. If the human capital theory holds, in reality, we also expect to see a significant reduction in the MWP after work experience variables are controlled for.

Motivation theory describes the couple's life course trajectory after getting married as a socialization process that produces and reproduces gender roles at home and in the workplace (Ashwin & Isupova, 2014; Rodgers & Stratton, 2010; Thébaud, 2010; West & Zimmerman, 1987). For example, Ashwin & Isupova (2014) drew on qualitative data to show that not only do married men "do gender" by performing their breadwinner roles as hard-working earners in the workplace, but also married women actively hold their husband accountable to provide income and resolve financial difficulties. As such, marriage motivates men to earn higher wages while discourages women from being career-oriented, and part of such motivational effect may operate through childbearing (Townsend, 2002). To the extent that such gender-biased within-couple socialization process continue to affect the husband's and wife's career motivation differently over time, the wage advantage for married men and the wage disadvantage for married women are likely to accumulate gradually over years of marriage.

Unlike the above theories that focus primarily on the *supply side* of labor in explaining the MWP, the employer discrimination theory provides a perspective on the *demand side*. This line of works suggest that employers may rely on the ideology that married men become the family's bread-earner and married women the secondary wage earners, which lead them to favor married men over unmarried men, and unmarried women over married women in employment decisions and wage allocation (Bartlett & Callahan, 1984; Hersch & Stratton, 2000; Hill, 1979; Kilbourne, England, & Beron, 1994; Malkiel & Malkiel, 1973; May, 1982). Following this logic, the MWP will be constant if employers do not distinguish between individuals who are married for different lengths of time. Yet the MWP could vary over time if the employer's perception depends on years of marriage. For example, if employers consider men who have stayed longer in marriage as more reliable, men's marriage premium will increase over time. In addition, such gender-based discrimination may intensify with the birth of children, as employers may form gender-biased ideologies about working mothers and fathers, resulting in a further increase of MWP for men and decrease of MWP for women (Benard & Correll, 2010; Correll et al., 2007; Glauber & Gozjolko, 2011; Kmec, 2011; Ridgeway & Correll, 2004).

INTERSECTION OF GENDER AND RACE

A growing literature shows that the intersection of gender and race on earnings is a central feature of the stratification system in the United States (Browne & Misra, 2003; Glauber, 2008; Greenman & Xie, 2008; Kilbourne et al., 1994; McCall, 2005). Unfortunately, literature on the wage effect of marriage has yet to combine the life course approach with the intersectional perspective. Previous works on the racial differences in the MWP for men and women often center around one gender and yield mixed evidence. Some research shows that men's MWP is greater for Whites than for Blacks (Blackburn & Korenman, 1994; Daniel, 1995; Korenman & Neumark, 1991; Waite, 1995), some suggested similar MWP for White and Black men (Kilbourne et al., 1994), while others found a larger male marriage premium for Blacks (Loh, 1996; Rodgers & Stratton, 2010). As for women, marriage has been found to be associated with a wage penalty for White women, yet a marriage premium, though small in size, for Black women (Kilbourne et al., 1994; Waite, 1995). In addition, the motherhood penalty literature showed that Black women receive a smaller wage penalty for having a child than White women do (Hill, 1979; Lehrer, 1992; Waldfogel, 1997).[41] To the extent that there are some shared mechanisms

[41] Budig & England (2001), however, showed that Black women receive smaller motherhood penalties than their White counterparts only for the third and subsequent births.

underlying the impact of marriage and childbearing on wages, one could expect the racial differences in the motherhood penalty to exhibit similar patterns in the wage effect of marriage.

Why would Whites and Blacks differ in the wage effect of marriage? One plausible explanation lies in the work domain. For example, Rodgers & Stratton (2010) showed that the *gross* effect of marriage – the effect without controls for human capital and work-related variables - is almost 50% as large for Black men than for their White counterparts at the time of marriage, yet, much of this racial difference is explained by differences in observed variables such as actual experience and job tenure. Other possible explanations may come from the family domain. A number of qualitative works suggest that that when Black men get married, marriage and family responsibilities carry the meaning of lifelong commitment and promote psychological stableness, which help them sustain a stable long-term relationship with their partner (Hurt, 2013; Marks et al., 2008). Others found that marriage provides Black men social and financial resources that are critical to their career successes (Waite & Gallagher, 2002). Alternatively, one's change in wages from before to after marriage could also depend on the person's mode of interaction with his or her spouse, as well as the attitudes and expectations of the spouse. It was suggested that the intensity of intrahousehold specialization may be lower among Black couples than among White couples (Rodgers & Stratton, 2010). Several studies, for instance, showed that married Black men do a larger share of housework than married White men (John & Shelton, 1997; Kamo & Cohen, 1998). Finally, the work and family domains may be intertwined: partly due to Black men's disadvantage in the labor market in general, wives in Black families tend to have lower expectations for their Black husband's career success (Daniel, 1995; Waite, 1995), which is likely to reduce Black men's gains from marriage and mitigate Black women's wage loss due to marriage.

However, current literature on the intersection of gender and race in the wage effect of marriage has left two issues unresolved. First, previous works adopting the intersectional perspective are static, focusing mainly on the gender and racial differences in the average wage effect of marriage but not its temporal variations. My analysis extends to the life course approach, recognizing that Blacks and Whites may differ, not only in terms of the immediate effect of marriage, but also in the pattern by which the impact of marriage endures, magnifies, or diminishes over years of marriage. Second, when examining the racial differences, previous works often focus on one gender, rendering it impossible to compare the underlying mechanisms by race and gender. My analysis covers a full range of gender-race subgroups, which enables us to compare their differences not just in the total impact of marriage, but also in the mechanisms leading to this total effect.

TESTABLE HYPOTHESES

Drawing on the preceding arguments, I will test four sets of hypotheses relating to three research questions. First, does the wage effect of marriage take place instantaneously or cumulatively? Hypotheses 1A and 1B concern the total effect of marriage in the sample where Whites and Blacks are pooled together (i.e. the "pooled sample"):

Hypothesis 1A: In the pooled sample, marriage is associated with an increasing wage premium for men.

Hypothesis 1B: In the pooled sample, marriage is associated with a decreasing (and even negative) wage premium for women.

Second, does the life course pattern of the wage effect of marriage vary by race? Hypotheses 2A and 2B present two competing hypotheses about the racial differences in the total effect of marriage among men, to be testing in the separated samples:

Hypothesis 2A:Black men's marriage wage premium increases at a greater rate over years of marriage than White men's marriage wage premium.

Hypothesis 2B: Black men's marriage wage premium increases at a slower rate over years of marriage than White men's marriage wage premium.

Hypotheses 3A and 3B present two competing hypotheses about the racial differences in the total effect of marriage among women:

Hypothesis 3A: Black women's marriage wage premium decreases at a greater rate (or increases at a slower rate) over years of marriage than White women's marriage wage premium.

Hypothesis 3B: Black women's marriage wage premium decreases at a slower rate (or increases at a greater rate) over years of marriage than White women's marriage wage premium.

Third, do the mechanisms underlying the total effect of marriage vary across gender-race subgroups? Following the discussion in the Theoretical Framework Section, I test two additional hypotheses about mechanisms:

Hypothesis 4 (childbearing): Marriage can affect wages through affecting childbearing. Thus, controlling for childbearing will reduce the magnitude of the total wage effect of marriage over the life course.

Hypothesis 5 (work experience): Marriage can affect wages through affecting work experience. Thus, controlling for measured work experience will reduce the magnitude of the total wage effect of marriage over the life course.

DATA, SAMPLE, AND MEASURES

Data

To analyze changes in wage trajectories before and after marriage, a longitudinal dataset that contains within-individual repeated measures on work history and family transitions is needed. The National Longitudinal Survey of Youth 1979 data (NLSY79 hereinafter) fits well with the purpose of this study, as it follows a nationally representative sample of 12,686 young people aged 14 to 22 when they were first surveyed in 1979. These individuals were interviewed annually through 1994 and on a biennial basis thereafter. The NLSY79 dataset provides rich information about the year-to-year variations of individual family transitions, work experiences, and wage trajectories, and has thus been chosen by numerous studies to examine the association between family transitions and labor market outcomes (Budig & England, 2001; Fuller, 2008; Hodges & Budig, 2010; Killewald & Gough, 2013; Killewald, 2013; Loughran & Zissimopoulos, 2009). My analysis draws on 1979-2010 waves of the NLSY79 data. The sample is weighted in all analyses below.

Sample Restrictions

I restrict the sample in several ways. Because those who become parents before any work experience may experience different impact of marriage and childbearing from those who become parents after the individual has entered the labor market, I follow Killewald & Gough (2013) to exclude the respondents who have at least one child in the household before age 18. Because the identification in fixed-effect models relies on *within-person changes* (Killewald & Gough, 2013; Rodgers & Stratton, 2010), I restrict my sample to individuals who have at least two non-missing wage observations. These two restrictions lead to the dropping of about 30% of the White person-years, and about 40% of the Black person-years. I will focus on the part of the sample that has at least one year of potential experience (dropping an additional 8%-14% of total person-years) and has non-missing wage information in the current period (dropping an additional 6%-11% of total person-years). Finally, to minimize the influence of selectivity in the timing of entry and exit from marriage, I restrict the sample to be more homogeneous in terms of duration of marriage. I exclude those individuals who remain never-married until age 45, and focus my analysis on those who got married between age 18 and 30. I also restrict my sample to the person-year observations in which the individual has spent less than 10 years divorced. These further restrictions drop an additional 11%-14% of the total person-year observations. Appendix Table 2.B gives the detailed statistics for my sample restrictions procedure by gender and race. After sample restrictions, my analytic sample comes to total numbers of person-year observations of 24,623 for While men, 20,381 for While women, 8,104 for Black men and 6,245 for Black women respectively.

Measures

Wage. The key dependent variable is the logarithm of hourly wage of the individual's current/most recent job, which is adjusted to 1999 dollars according to the national-level Consumer Price Index. Log hourly wage is preferred to annual earnings, because unlike annual earnings, hourly wage is not affected by the total hours worked by the individual and thus is a better measure of the economic return that the individual receives for one hour of labor that he or she provides (Killewald & Gough, 2013). The major advantage of taking the log transformation of wage is that the change in log hourly wage from year *t-1* to year *t* directly reflects the *percentage change* in earnings over one year. I code the individual's wage as missing if he or she is not working at the time. The fixed-effect models to be used in this study are flexible with these missing values and unbalanced data between different individuals.[42]

Marital status. I categorize marital status by three mutually exclusive groups: (1) never-married; (2) married and spouse present in the household, (3) other (including divorced, widowed or separated, referred to as "divorced" hereinafter). For missing observations on marital status, I impute the individual's marital status at the current period using the record of marital status in the previous record.

Years of marriage. To capture the long-run effect of marriage on wage trajectories, I construct a key indicator termed "years of marriage." This variable is calculated as current age minus the person's age at first marriage, and minus the years of gaps between marriages if the person has experienced multiple marriages.[43] For example, consider a person who first got married at age 25, then got divorced at age 30. Suppose that five years after this divorce, the person re-married at age 35 and remained in this marriage thereafter. Then this person's "years of marriage" at age 40 is calculated as:

40 (current age) – 25 (age at first marriage) – 5 (between-marriage gap) = 10 years.[44]

In addition, my measure of "years of marriage" also includes up to five years (denoted by -5, -4, -3, -2, and -1) prior to the transition into first marriage. This is for two reasons. First, it is possible that the wage effect of marriage will start prior to the point of marital transition, thus extending the time window to pre-marriage years will provide some evidence on the timing of the wage effect of marriage (Dougherty, 2006). Second, accounting for the years leading up to

[42] In preliminary analysis not reported, I conducted my analysis with imputed missing wages using the person's wage record in the past three years, and the results are not changed.

[43] In preliminary analysis not reported, I conducted my analysis with imputed missing wages using the person's wage record in the past three years, and the results are not changed.

[44] The main results are not altered if we censor the sample at the end of their first marriage (results available from the author upon request). Because restricting to first marriages will reduce the number of person-year observations with longer years of marriage, the main analysis will keep those with more than one marriages in the sample.

marriage may shed light on the possible impact of cohabitation, an important alternative option of union formation (Cohen, 2002; Kiernan, 2001; Seltzer, 2000; Thornton, Axinn, & Xie, 2008). Because the starting and ending dates of cohabitation is subject to relatively more reporting errors than the reporting for marriage history due to conceptual ambiguities (Manning & Smock, 2005; Seltzer, 2000), analyzing the wage effect of cohabitation may require a different set of specification and tests and is thus left out of the main analysis. Sensitivity analysis to be presented later will show results on the wage impact of years of cohabitation experience.

Parenthood status. I measure the demand for child care by two indicators. The first is the number of children in the household. Excluding children residing elsewhere means that my analysis focuses on the actual demand for childcare in the immediate household. The second is set of dummy variables indicating whether there is a children 0-6 years old, 7-12 years old, or 12-18 years old.

Work experience. Time-varying work experience is measured by a set of job-related variables, including the individual's tenure (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 cumulative number of weeks spent unemployed and out of the labor force in the past. Work experiences also include time-varying dummies for individual's occupation classified using a 41-category coding scheme to capture the within-person between-occupation job mobility on wages and wage growth.[45]

Other control variables. My models also control for potential experience and its square term. Potential experience differs from actual experience, which is captured in the "work experience" controls, in that it measures the length of time in the life cycle elapsed since entering the labor

[45] The coding scheme of 41 collapsed occupational categories is available from the author upon request.

market, unaffected by the actual amount of experience gained through working. Potential experience is calculated as age minus 18 for those with high school education or less, age minus 22 for those with some college education, and age minus 25 for those with college education and above.[46] Other controlling variables include race and educational attainment (coded as high school and below, some college education, and college an above). These variables are controlled not only additively, but also in interaction with potential experience to capture the heterogeneity in wage growth. The individual's timing of entrance into marriage is measured by the variables age at first marriage (AFM), and the individual's history of divorce is captured by the variable total years of divorce (TYD), measured by the total number of years that the individual has ever spent divorced in the sample.[47]

ANALYTIC STRATEGY

Selection Concerns

One key challenge to empirical studies on the wage effect of marriage is how to distinguish the causal effect of marriage from selectivity associated with marital transitions. Ideally, if individuals who are unmarried, recently married, and married for a long time are similar in terms of observed and unobserved characteristics associated with wage level and wage growth rate, the wage premium associated with *t* years of marriage can be simply calculated as taking the difference in wage between those who are married for *t* years and those who are single. Yet, since those who get married and those who stay longer in marriage may be selective on these

[46] Potential experience indicates the number of years that a person could potentially accumulate his or her experience after leaving school, but not how individuals actually behave on the labor market over these years, which is likely to differ by social groups such as gender and race.

[47] If the individual has no divorce record, years of divorce will equal zero.

wage-associated characteristics, the estimated wage difference among individuals with different marital status may be due to selection rather than the causal effect of marriage (Cohen, 2002; Ginther & Zavodny, 2001; Gray, 1997; Pollmann-Schult, 2010; Rodgers & Stratton, 2010). For example, sizable research has shown that earnings potential is a strong and positive predictor of the likelihood of marriage for men (Goldscheider & Waite, 1986; Mare & Winship, 1991; Oppenheimer, Kalmijn, & Lim, 1997; Oppenheimer, 2003; Sweeney, 2002; Xie, Raymo, Goyette, & Thornton, 2003). Other works suggest that women's economic standing has become an increasingly strong determinant of marriage (Oppenheimer, 1988; Sweeney, 2002).

In addition, selection could occur when individuals with different years of marriage differ systematically in regard to the rate of *wage growth*, a concern raised by Loughran and Zissimopoulos 2009. For example, past works suggest that men's timing of marriage depends on their economic prospects, which may be reflected in either overall wage level or wage growth (Krashinsky, 2004; Oppenheimer, 1988; Xie et al., 2003). Others suggest that that women with higher wage growth potential choose to delay marriage to avoid some of the negative impact of marriage on their career development (Goldin & Katz, 2000; Loughran & Zissimopoulos, 2009). In addition, the likelihood and timing of divorce may also depend on characteristics that are associated with the person's earnings prospects, particularly among women (Kalmijn & Poortman, 2006; Moore & Waite, 1981; Rogers, 2004; South & Spitze, 1994; White, 1990). Such selectivity in regard to wage growth lead to *sample composition bias* in the estimating the association between MWP and years of marriage (Vaupel & Yashin, 1985; Xie, 2013). Appendix G provides a detailed discussion on the taxonomy of different selection problems.

Model Specification

To address the selection based on overall wage level, my analysis will follow prior works to apply fixed-effect models to longitudinal data in order to identify the effect of marriage by comparing wages of the *same* individual when he or she is in different marital statuses (Dougherty, 2006; Gray, 1997; Hausman & Taylor, 1981; Kilbourne et al., 1994; Killewald & Gough, 2013; Korenman & Neumark, 1991; Pollmann-Schult, 2011). Yet, my model differs from those in the previous static approaches by including dummies for years of marriage as independent variables, similar to Dougherty (2006):

$lnW_{it} = \alpha_0 + \alpha_1 Exp_{it} + \alpha_2 Exp_{it}^2$ (wage and wage growth)

$+ \sum_{j=2}^{J} \beta_j X_{jt}$ (time-varying control variables)

$+ \sum_{k=-4}^{K} \gamma_k \cdot D_k^{Years\ of\ Marriage}$ (dummies for years of marriage)

$+\eta_i$ (individual fixed effects)

$+ AFM \cdot Exp_{it}$ (selection into marriage based on wage growth)

$+TYD \cdot Exp_{it}$ (selection out of marriage based on wage growth)

$+\epsilon_{it}$. (residual)

In the above, the dependent variable, lnW_{it}, is log hourly wage, Exp_{it} and Exp_{it}^2 represent the linear and square term of potential experience respectively. $X_{jt}{}'s$ are person-specific and time-varying variables pertaining to childbearing and work experience. $X_{jt}{}'s$ also include a dummy indicator for divorced person years. $D^{Years\ of\ Marriage}$ contains a set of dummies indicating years of marriage, with five year or more prior to first marriage (i.e. years of marriage $= -5$) held as the reference category. This dummy variable specification is favorable because of its flexibility of the shape of the wage trajectory. The key coefficients of interest are the $\gamma' s$, which represents the difference in wage at each year of marriage compared to the reference wage earned at five years or more prior to marriage. By looking at the changes in γ over years of marriage, we will know *how much steeper* a married person's wage trajectory will be relative to the wage trajectory if the person had remained single. The person-specific fixed effect, η_i, captures the time-invariant unobserved characteristics that simultaneously affect marriage and wage level throughout the person's life.

I address the selection into and out of marriage based on the rate of wage growth in two ways. To account for the selectivity in the timing of transition into marriage, I control for the interaction between AFM (age at first marriage) and potential experience.[48] To account for the selection out of marriage, I control for the interaction between TYD (total years of divorce) and potential experience.[49] In addition, to minimize the influence of selectivity in terms of age of marriage and propensity to divorce, my empirical analysis will focus on a relatively homogeneous sample of individuals who entered first marriage between age 18 and 30 and who have not stayed for more than 10 years out of marriage.[50]

[48] Similar specification has been adopted by a recent work by Killewald & Gough (2013).

[49] Loughran & Zissimopoulos (2009) accounted for this selection problem by applying first-differencing at the first stage and then the individual-demeaning specification at the second stage. Yet, the two states together create measurement errors that are usually larger and more complicated than the cross-sectional and conventional fixed-effect estimates. Instead, here, I choose to address wage growth associated selection by explicitly controlling for individual-level wage growth differences.

[50] Beyond the selectivity problems as described above, three addition problems may complicate the interpretation of the estimated MWP. The first concerns the *timing* of marriage's treatment effect: because individuals may anticipate their upcoming marriage and adjust their behaviors in advance, it is possible that the wage effect of marriage occurs before the actual marital transition (Antonovics & Town, 2004; Cohen, 2002). This is likely to lead to the underestimation of the "gross effect" of marriage. The second problem concerns the *reverse causality*: individuals may postpone marriage until they know that they have passed a certain threshold in economic standing or having a positive expectation of their career growth (Antonovics & Town, 2004; Edin & Kefalas, 2011; Smock, Manning, & Porter, 2005; Xie et al., 2003). The third problem arises from the *co-occurrence* of the marital transition and career advancement due to an underlying maturation process that differs among individuals (Killewald & Lundberg, 2014; Winship, 1986). The second and third problems could lead to the overstatement of the actual causal effect of marriage.

EMPIRICAL RESULTS

Descriptive Statistics

Weighted descriptive statistics of the NLSY79 data are given in Table 5. Among my analytic sample, which excludes those who are never-married until age 45, average educational attainment is higher for Whites than for Blacks, particular in terms of the attainment of the college degree.[51] For both Whites and Blacks, throughout the life course, a smaller share of men are married than of women. There are significant racial differences in the pattern of marriage for both sexes. A greater proportion of Whites marry: At age 25, 35, and 45, the proportion of never-married is greater for Black men (with 35.96% unmarried at age 45) than for White men (with 21.82% unmarried at age 45), and greater for Black women (with 29.85% unmarried at age 45) than for White women (with 12.53% unmarried at age 45). Similar pattern of gender and racial differences is reflected in terms of age at first marriage: Women get married at an earlier age than men do, and this gender gap in age at first marriage is greater among Blacks (2.08 years) than among Whites (1.83 years). Among those who were married before age 45, the average age at first marriage is later for Black men (26.61) than for White men (24.05), and later for Black women (24.53) than for White women (22.22).[52] With regard to divorce history, the percentage of ever divorced is greater for women than for men, and greater for Blacks than for Whites. However, among those who ever got divorced, there Whites are divorced at an earlier wage than Blacks. The racial differences in the pattern of entry into and exit from marriage give rise to the racial differences in the length of marriage: In my analytic sample, among the married person-years, the length of marriage is greater for White men (12.47 years) than for Black men (10.41 years), and

[51] Since my sample exclude those who are never-married until age 45, the gap in educational attainment between White and Black is smaller compared to the racial gap in educational attainment in the general population.

[52] If we include the never-married individuals in the sample, the median age at first marriage is 23 and 25 for White and Black males respectively, and 21 and 23 for White and Black females respectively.

greater for White women (13.13 years) than for Black women (11.18 years).[53]

Analysis on Pooled Sample

First, I apply the model as specified in Equation 1 to examine the long-term wage effect of marriage based on the pooled sample with White and Black individuals lumped together. The key coefficients of interests in this set of analysis are the coefficients on the dummies for years of marriage. To present these coefficients, I first align these coefficients on the axis of years of marriage, ranging from five years or more prior to marriage (years of marriage$= -5$) to twenty years after marriage (years of marriage$= 20$), and then plot the Lowess-smoothed line of wage trajectory by years of marriage, with the wage earned at five years prior to marriage held as the reference level. For simplicity, I refer to the wage relative to wage at five years or more prior to marriage as the MWP (Marriage Wage Premium) in my context. Figure 5 demonstrates the Lowess-smoothed trajectories of MWP in the pooled sample. The red horizontal line is the reference line indicating zero marriage wage premium. Among men, the wage effect of marriage started as early as five years prior to marriage. This pre-marriage wage trend is consistent with results from previous studies (Dougherty, 2006; Krashinsky, 2004) and may be due to several reasons. It may be that the anticipation of marriage makes soon-to-be-married men better workers, or that men tend to get married after they have demonstrated some earnings potential by having substantial wage growth. It is also possible that marriage and career advancement are outcomes of latent maturation process. The growth of MWP for men continues until about five years after marriage, slows down from 5 to 15 years of marriage, and speeds up again after 15 years of marriage.[54] After twenty years of marriage, men accumulate over 20% of wage

[53] Distributions of Black and White's years of marriage and years of divorce are presented in Appendix J.

[54] As later sensitivity analysis will show, similar pattern holds under alternative specifications of potential experience.

premium relative to five years or more prior to marriage.[55]

The pattern for women differs substantially from that for men. Among women, there is a small but positive wage premium prior to marriage, but this wage premium starts to decline gradually after getting married. About five years after marriage, women's wage premium becomes negative and continues to decline. After twenty years of marriage, controlling for experience, married women earn about 10% lower than what they earned five years or more prior to marriage. That is, married women experience an accumulation of wage disadvantage over years of marriage. Statistical tests indicate that both the increase in the MWP for men and the decrease in the MWP for women are significant. Hence, in the pooled sample, Hypothesis 1A and 1B are both supported.

Analysis on Separated Samples

The analysis in the pooled sample is informative about the population-average wage effect of marriage for men and women. Yet, does this population-average estimate conceal important between-race heterogeneity? Next, I replicate the above analysis on the Black and White sample separately. Figure 6 demonstrates the Lowess-smoothed trajectories of selection-adjusted MWP by race and gender over years of marriage.[56] Throughout the married years, Black men receive a higher MWP than White men, and the level of wage premium between the two races is significantly different, but there is no statistically distinguishable racial difference in the rate of growth of the wage premium of marriage, a finding that corroborates that from Rodgers &

[55] As a note on the causal interpretation, this suggests that the reverse causality is unlikely to explain all of the wage effect of marriage, because if wage growth is for the mere purpose of satisfying a pre-marital threshold, we should not expect wage to rise after marriage. In addition, the latent maturation process is also unlikely to explain the whole story, because otherwise we would not expect to observe the maintenance and increase of the MWP many years after marriage. Hence, the results suggest that there is a positive and increasing treatment effect of marriage on men's wages.

[56] The estimated results for the separated sample with different set of controls are presented in Appendix D.

Stratton (2010). Hence, both Hypothesis 2A and 2B are rejected.[57]

Significant racial differences exist for women. Black and White women started off with similar levels of wage premium prior to marriage. Yet, after getting married, White women experience a decline in the MWP over years of marriage, while Black women experience an increase in the MWP over years of marriage. The decline in the MWP for White women and the increase in the MWP for Black are both statistically significant. This implies marriage limits White women's wage growth yet promotes Black women's career prospect. After twenty years of marriage, White women have incurred about 15% wage penalty compared to their own wage at five years or more prior to marriage, while Black women have gained about 15% wage premium compared to their own wage at five years or more prior to marriage. Hence, my findings support Hypothesis 3B and reject Hypothesis 3A.

Comparing the results from separate samples with those from the pooled sample, we see that the pooled sample masks important racial differences in how marriage affects life course wage trajectories. Such racial difference is more important for women than for men. Since White women take up a majority of the female sample, the estimated wage effect of marriage in the pooled sample is driven almost entirely by the pattern for White women, concealing the story for Black women in the pooled sample.

Childbearing as a Mediating Mechanism

Next, I turn to the mediating effects of two specific mechanisms in producing the total effect of marriage. I start with the mechanism of childbearing. Appendix Table 2.E1 plots the trajectory of

[57] To test for the significance of between-group differences, I regress the MWP on years of marriage for each gender-race subgroup separately and then compare the point estimates and standard deviations of the estimated coefficient on years of marriage. Full results of the tests are available from the author.

number of children in the household by years of marriage by race and gender.[58] Does the size of the total effect of marriage on wage growth shrink after childbearing is controlled for in the model? To test this, I add controls for the number of children in the household and age groups of youngest child to the total effect model. Since specialization theory suggests that the wage effect of childbearing may depend on the person's marital status (Budig and England 2001; Killewald and Gough 2013), I also include the interaction between the number of children in the household with dummies of marital status to capture the heterogeneous effect of childbearing by marital status. I further control for dummy indicators of the age range of youngest child (0-6 years, 7-12 years, and 12-18 years). The full model is presented in Appendix Table 2.F1. The number of children in the household has a significantly negative impact for married White female and married Black female (resulting in a 4.3% penalty for White women and a 4.4% penalty for Black women), yet it does not have significant impact on unmarried women. This is consistent with the specialization theory that specialization intensifies when the demand of domestic labor increases with childbearing, leading to a reduction in women's wages. For White women, an additional 10.7% penalty is associated with having a youngest child aged 7-12 years, and an additional 6.4% penalty is associated with having a youngest child aged 13-18 years. Number of children has no significant impact on men's wages, yet having a youngest child aged six years old or less is associated with a 4.3% fatherhood premium for Whites and a 3.7% fatherhood premium for Blacks. For Blacks, similar level (4.1%) of fatherhood premium holds when their youngest child reach 7-12 years of age, yet no significant premium is found for White men at this age range. This finding offers new evidence to the fatherhood premium literature (Glauber, 2008;

[58] The number of children increases over years of marriage and peaks at about fifteen years after marriage. Blacks, particular Black women, have greater number of children in the household than their White counterparts, especially during the five years prior to marriage and the first ten years of marriage. This racial gap closes up fifteen years after getting married for both sexes.

Hodges & Budig, 2010; Killewald, 2013), highlighting the importance of accounting for the age of child as well as the differences by race.

My main focus is whether including controls for childbearing explains the total effect of marriage on wage over years of marriage. The results are presented visually in the line for "Baseline+childbearing" in Figure 7 (male) and Figure 8 (female) respectively. Including childbearing controls shifts White and Black men's wage trajectory slightly downward. Controlling for childbearing makes White women's wage trajectories flatter, but only to a moderate degree. Childbearing controls move Black women's wage trajectories significantly upward, implying that childbearing has a negative impact on Black women's wage level and wage growth: Had the negative impact of childbearing on Black women's wages been eliminated, married Black women would have enjoyed greater growth of the MWP. The finding of a larger impact of childbearing on women's accumulation of wage disadvantage after marriage but not on men's accumulation of wage advantage is consistent with earlier works (Dougherty, 2006; Loughran & Zissimopoulos, 2009), yet it highlights the differences in the degree to which childbearing matters by different gender-race subgroups. Overall, this round of results lends weak support for Hypothesis 4 among White men, Black men, and White women, yet provides strong support for Hypothesis 4 among Black women.

Work Experience as a Mediating Mechanism

Next, I examine the extent to which changes in work experience in married years explain the changes in men and women's wage trajectories due to marriage. Work experience is measured by seven variables: job tenure, total hours worked in the year, annual number of weeks unemployed, annual number of weeks out of the labor force, cumulative number of weeks unemployed, cumulative number of weeks out of the labor force, occupation on a 41-category scheme. The descriptive trajectories of work experience variables over years of marriage are presented in Appendix Figure 2.E2 and 2.E3.[59]

I add controls for work experience in two ways: First, I add these controls to the previous "Baseline + childbearing" model, which yields the "Baseline+ childbearing + workexp" model. Here, the contribution of work experience is captured by the changes in the wage trajectory from the former to the latter model. Second, I add these controls to the total effect model, yielding the "Baseline + workexp" model. Here, the contribution of work experience is represented by the change from the "Baseline" model to the "Baseline + workexp" model.[60] The first case is the contribution of work experience with controls for childbearing, and the second without such controls. The key results are presented visually in Figure 7 (male) and Figure 8 (female).[61] For White men, including measured work experience variables in the model does not alter the trajectory of MWP. This may be due to two reasons. First, the increase in productivity due to marriage may come from motivational changes that are not measured by survey data. Second, it may be that White men receive marriage premium, not because they alter behaviors in these measured work experience, but because of unobserved employer preferences that favor the

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[59] The trajectories suggest that overall, White men work more hours and more weeks than Black men. The average White women, however, work less than Black women. While the annual number of weeks unemployed is greater for Black women is greater than that for White women, the gap closes quickly as they enter into marriage. Black women spent a greater number of weeks out of the labor force than White women prior to marriage, yet the pattern quickly reverses as they get married: over the married years, the average White women spent a greater amount of time out of the labor force than Black women. Although these trajectories are descriptive, they reveal patterns that are consistent with previous findings that intrahousehold specialization may be less intense among Black families than among White families (Daniel, 1995; Waite, 1995).

[60] The full coefficients of these models are presented in Appendix Table 2.F2. Longer job tenure and longer work hours are associated higher wage, yet their impact decreases over years of experience. The numbers of weeks unemployed and out of the labor force are negatively associated with wage, and the interaction terms indicate that this impact is greater at later stages of labor market experience.

[61] Controls for work experience include the seven time-varying indicators of work experience as described above, as well as the interactions between these variables (except for the cumulative measures and occupation) with potential experience to capture the heterogeneity in their effects at different career stages.

married over unmarried, or those who are married for a long time over those who are recently married. For Black men, controlling for work experience beyond childbearing shifts the MWP trajectory substantially downward. This suggests married Black men's increased participation in productivity-enhancing labor market activities operates as a key mechanism through which they accumulate their wage advantage over married years.

Substantial Black-White differences are also found for the case of women. Controlling for work experience shifts White women's trajectory of negative and declining MWP in the baseline model upward towards the red zero premium line, which implies that changes in work experience limit White women's wage growth over their lives. This finding is consistent with the specialization and human capital theory, as the decline of MWP over married women's life course could be a result of the increased intrahousehold specialization that deters women's accumulation of productivity-enhancing experiences. It also lends some support to the motivation and discrimination theory, as married women may become more family-oriented and retreat from the labor market or the employers would perceive so. On the contrary, controlling for measured work experience shifts Black women's trajectory of MWP downward. This means that, unlike what would be predicted by the specialization or human capital theory, changes in work experience actually help Black women counteract the negative wage impact of childbearing and maintain a good wage trajectory over years of marriage. This finding implies that intrahousehold specialization may not be an appropriate perspective for understanding the wage impact of marriage for Black women. Rather, my results is consistent with previous arguments that the labor market experience and outcomes among married Black women should be better understood in relation to Black men's disadvantage in the labor market and the wife's lower expectations for the husband's career success in Black families (Daniel, 1995; Waite, 1995).

Overall, among these gender-race subgroups, Hypothesis 5 is only supported for Black men and White women.

Quantitative Assessment of the Contributions of Mediating Mechanisms

I conclude my empirical analysis with a quantitative assessment of the relative contributions of childbearing and work experience to the accumulation of wage (dis)advantage by gender-race subgroups. In keeping with the life course approach, the focus of my results is the contributions of each mechanism to the *changes* in the MWP over time rather than the overall level of the MWP. First, for each group of race-gender combination, I calculate the predicted beginning and ending premium, expressed as percentages of hourly wage, according to the models as described in the previous sub-section.[62] Then, I calculate the *changes* in premium over this period. A positive change indicates a growth in the MWP, and a negative change indicates a drop in the MWP. The results are presented in Table 6 (for men) and Table 7 (for women). The wage advantage for White and Black men accumulates gradually as years of marriage grow: Among White men, the MWP grows from 0.4% to 21.37% after twenty years of married life. Among Black men, the MWP increases from 5.21% to 27.45% over this period. While the level of the MWP is greater for Black men than for White men, the amount of growth in MWP is similar for the two races. The MWP trajectories for White and Black women, however, are in sharp contrast: Although the two groups both start with similar MWP (1.85% for Whites and 1.46% for Blacks) at the beginning of this period, the MWP drops to negative (-13.49%) for White women while increases to 11.63% for Black women.

Finally, drawing on results from Table 6 and 2.3, I go on to calculate the contributions of the

[62] To smooth out transitory fluctuations, the beginning premium is calculated as the average of the first three years of the analytic time window (years of marriage = -4, -3, and -2); ending premium is calculated as the average marriage premium for the three ending years of the analytic time window (years of marriage = 18, 19, and 20).

two mechanisms according to how much of the growth in the MWP is changed by controlling for each of the two mechanisms, which provides a quantitative assessment of the patterns visualized in Figure 7 and 2.5. The contribution of each mechanism is calculated first with and then without the other mechanism controlled for (termed “controlled contribution” and “uncontrolled contribution” respectively). The results are presented in Table 8. A positive sign means that the mechanism has a positive impact on the growth of the MWP over years of marriage, and a negative sign means the opposite. The table suggests that the controlled and uncontrolled contributions are very similar for the two mechanisms. As is consistent with the finding from Figure 7, neither childbearing nor work experience explains much of White men’s accumulation of wage advantage. However, as much as half of Black men’s growth of MWP over this period is explained by their changes in work experience following marriage, yielding strong support for the human capital theory.

The findings also reveal important racial differences for women. Childbearing has a negative impact for the growth of MWP among White and Black women, yet its negative impact is larger for Black women (6%-7%) than for White women (3%-5%). Also, the contribution of childbearing holds regardless of whether work experience is controlled for, implying that the negative impact of childbearing on women’s wages does not necessarily operate though altering their measured work experience. Changes in work experience affect White and Black women’s wage trajectories to similar degrees, yet in opposite directions. For Black women, the accumulation of wage disadvantage due to childbearing is counteracted by their changes in measured work experience.

SENSITIVITY ANALYSIS

Linear spline specification and test for significance of MWP growth. This specification of dummy variables for years of marriage is more flexible with the shape of the wage trajectory, yet it comes at the cost of efficiency: The standard deviation around each coefficient on the dummy is relative large, making it difficult to test whether the *changes* in the MWP is statistically significant. In the sensitivity analysis, presented in Appendix G, I align these dummies of years of marriage in the order of time and then estimate the changes in the MWP by the linear spline function, with splines separated by 0, 7, and 14 years of marriage. The results suggest that while the speed of growth or decline in the MWP varies by stage of marriage, overall, the life course patterns of the MWP in the linear spline specification are consistent with those in the dummy variable specification.[63]

Alternative Control for Selection out of Marriage. Next, I test whether the main results are sensitive to how I control for selection. While it is a common practice in previous works to control for age at first marriage in accounting for the influence of selection into marriage, it is not clear in current literature how divorce should be controlled for. In this round of sensitivity analysis, I replace the total years of divorce in the main analysis with the proportion of divorced years among all observed years as adjustment for selection out of marriage. The results, presented in Appendix Figure 2.H, are not altered by this different specification.

Alternative Specifications for Potential Experience. One may question whether the temporal patterns of the MWP depends on how potential experience is specified in the model (Killewald &

[63] The growth of the MWP is positive and significant for White and Black men, except for the period between 8 and 14 years of marriage. The results suggest that the growth of the MWP is positive and significant for White and Black men, except for the period between 8 and 14 years of marriage. Among White and Black men, the pace of growth in the MWP is most pronounced during the pre-marriage years and fifteen years after marriage. White women experience a statistically significant decline of the MWP during the latter two period of marriage, and the Black women experience a statistically significant growth of the MWP during the four years prior to marriage and fifteen years of marriage. The wage advantage of Black women did not start to increase until later stages of marriage, while for White women, the pace of decline in the MWP remains stable in married years.

Lundberg, 2014). The main analysis adopts the linear and quadratic specification, and as sensitivity analysis, I experimented with two alternative specifications for potential experience: the logarithm of experience (results shown in Figure 2.I1) and linear spline function (results shown in Figure 2.I2). The results hold in these two alternative specifications.

Restricting to First Marriage and Childless Years. The main analysis treats childbearing as a mediating variable between years of marriage and wage. But it remains unclear whether the changes in MWP over years of marriage depend on whether there is a child in the household. In this sensitivity analysis, I restrict my sample to those marriage and childless person-years. The results, as presented in Appendix Figure 2.J, show similar patterns of MWP trajectory over years of marriage.

Replicating the Analysis on Cohabitation History. With the emergence of cohabitation as an important alternative option of union formation (Cohen, 2002; Kiernan, 2001; Seltzer, 2000; Thornton et al., 2008), it is worthwhile, as a preliminary investigation, to replicate the analysis on cohabitation history. I ran fixed-effect models among those who are never-married, adding dummy indicators for those with different years of cohabitation history. The estimated "cohabitation premium" – the wage difference between the cohabiting unmarried individuals and the non-cohabiting unmarried individuals – up to five years of cohabitation by gender and race is presented in in Appendix Figure 2.K. White and Black men experience a small increase in the cohabitation premium, particularly for those with three or more years of cohabitation history. Similar as marriage premium, the cohabitation premium is greater for Black men than for White men. White women experience a small cohabitation penalty, and Black women's cohabitation premium demonstrates an interesting U-shape. The growing prevalence of cohabitation and the emerging diversity of family forms warrant future investigation to follow in this direction.

DISCUSSION OF LIMITATIONS

The first limitation comes from the possibility that individuals – especially women – may optimize their wage attainment by *self-selecting* into jobs that are associated with relatively higher wage gains or lower wage cost of marriage or childbearing (Becker 1985; England 2005; Polachek 1981). For example, some women may have already *mitigated* some of the wage cost to their via this self-selection process, which may lead to the under-estimation of the negative wage effect of marriage for them: if these women had not buffered against their anticipated risks of wage losses by purposefully selecting "more optimal" jobs, the negative effect of marriage would have been even larger.

The second limitation is the lack of measures about work experiences on the finer-grained organizational level in the data. Previous works suggest that more subtle mechanisms affecting individuals' life course wage trajectories, such as workplace networks, organizational arrangement, and employer-employee relations, are likely to lie within the organizational environment and the workplace network structure (Tomaskovic-Devey, Thomas, and Johnson 2005; Tomaskovic-Devey and Skaggs 2002). Due to data limitation, many of these factors are unfortunately not accounted for in my analysis. Thus, my results may not well-reflect the impact of these unobserved experiences on wage trajectories.

The third limitation is that my analysis does not test the possible differences in the temporal variations in the MWP by social class. Prior works have pointed to the possibility that the gender display, dependence, and division of labor within the family may depend critically on the husband and wife's earnings (Budig & Hodges, 2010; Gupta, 2006, 2007) and education (Bianchi, Milkie, Sayer, & Robinson, 2000; Davis & Greenstein, 2004; Gershuny & Sullivan, 2003). Future research is needed to explore the three-way intersection between gender, race, and social class in determining the long-term wage effect of marriage.

The fourth limitation consists in the inability of the currently available NLSY79 data to account for individuals at their older ages, as most of the respondents have not passed age 50 in the currently available waves. Thus, my results are most informative of the effect of marriage on wage growth during early- and mid-stages of their careers and marriages. Given my finding that the rate at which MWP changes over years of marriage depends on durations of marriage, it is reasonable to expect that marriage may affect wage growth differently at older ages. With the continuing collection of NLSY79 data, it would be possible in the future to extend my analyses to the effect of marriage on post-marital wage trajectories at older ages.

CONCLUSION AND DISCUSSION

How does marriage affect wages? Growing availability of longitudinal data and statistical methods has enabled recent literature to invoke the life course approach in understanding the long-term impact of marriage on labor market outcomes. However, current scholarship on this topic tends to focus on the population-average effect of marriage or limit themselves to the case of some particular gender or racial group. This paper, instead, conducts a comprehensive analysis on the *intersection* of gender and race in the total long-term effect of marriage as well as its underlying mechanisms.

Does the wage effect of marriage take place instantaneously or cumulatively? I showed that marriage accelerates wage growth for men yet limits wage growth for women, resulting in a cumulative effect of marriage. This finding can be seen as a long-term, life course extension of the well-documented consensus that marriage generally benefits men's earnings substantially, yet has little impact on, or even hurts women's earnings (Waite, 1995). Further, to put this finding in the context of the broad literature on life course gender inequality, the gender difference in the cumulative wage effect of marriage can be seen as an important micro-level pathway through which gender inequality is maintained and reproduced over the life course (Bielby & Bielby, 1992; Blau & Ferber, 1992; Budig, 2002; Fernandez-Mateo, 2009; Noonan, Corcoran, & Courant, 2005; Don Tomaskovic-Devey & Skaggs, 2002).

Does the life course pattern of the wage effect of marriage vary by race? My answer is gender-dependent: for men, no; and for women, yes. While Black men receive greater marriage premium than White men in the overall level of wage, the impact of marriage on the rate of wage growth is similar for both groups. For women, however, the wage effects of marriage are in sharp contrast for the two races: White women incur a growing wage penalty after marriage, while Black women experience a slowly but steadily growing wage premium after getting married. Hence, marriage holds back White women' careers, yet promotes Black women's wage growth. This finding suggests that previous analysis based on the pooled sample is representative of the pattern for White women, yet obscures the different story for Black women.

Do the mechanisms underlying the total effect of marriage vary across gender-race subgroups? My short answer is yes. The impact of marriage on White and Black men's earnings is driven by different factors: For Black men, work experience – measured by a set of variables including job tenure, employment hours, labor market attachment, and occupation – explains a substantial amount of the positive effect of marriage on their wage growth, a finding that accords with the specialization theory and human capital theory (Becker, 1985; Mincer & Ofek, 1982). However, for White men, neither childbearing nor work experience explains much of their growth of MWP over years of marriage. Hence, married White men's accumulation of wage advantage is more consistent with the motivation argument and the discrimination theory that emphasize the unobserved determinants of wages. In the case of women, consistent with the motherhood penalty literature (Budig and England 2001; Budig and Hodges 2010; Gough and Noonan 2013; Hochschild and Machung 1989), childbearing is found to be a career impediment for both White and Black women, regardless of whether work experience is controlled for. Work experience, however, imposes opposite impact for Black and White women: Black women gain, while White women lose, from changes in work experience induced by marriage. This implies that specialization theory may not be an appropriate perspective for understanding the wage impact of marriage for Black women. Rather, their wage trajectories should be better understood in the context of Black men's disadvantage in the labor market and the wife's lower expectations for the husband's career success. Failure to account for the intersection of gender and race in the mechanisms leading up to the wage effect of marriage will lead to over-simplification of the complex, heterogeneous nature of contemporary marriages.

My findings also stimulate two methodological implications. First, the revealed temporal variations in the wage effect of marriage imply that when comparing the estimated MWP among different studies, overlooking the temporal variations in the wage effect of marriage may lead to the misinterpretation of the systematic differences in sample composition as the actual differences in the wage effect of marriage. I recommend future researchers to explicitly model the temporal variation of the MWP in their models. Second, studies that aim to model the likelihood or timing of the entrance into marriage often takes interest in constructing a summary measure to represent an individual's expected amount of long-term economic potential in post-marital years (e.g. Xie et al. 2003). The construction of this measure relies on a basic knowledge about the *trajectories* of wages after marriage. The estimated trajectory of wages after marriage can be utilized by this line of works as the basis for constructing the indicator of this "economic potential" variable.

Findings from this paper point to new directions in research on work and family. In explaining the association between family transitions and economic wellbeing, previous research often asks whether the reality is more consistent with some theory than with others. However, my results show, with the case of marriage, that a universally-applicable theory in work and family may not always exist. Rather, some theories are more applicable to some gender-race subgroups than others. I call for future works in this area to combine intersectional perspective with the life course approach so as to fully comprehend the important heterogeneity in the long-term impact of family transitions.

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Figure 4 Graphic illustration of wage effect of marriage for men under the static and life course perspectives.

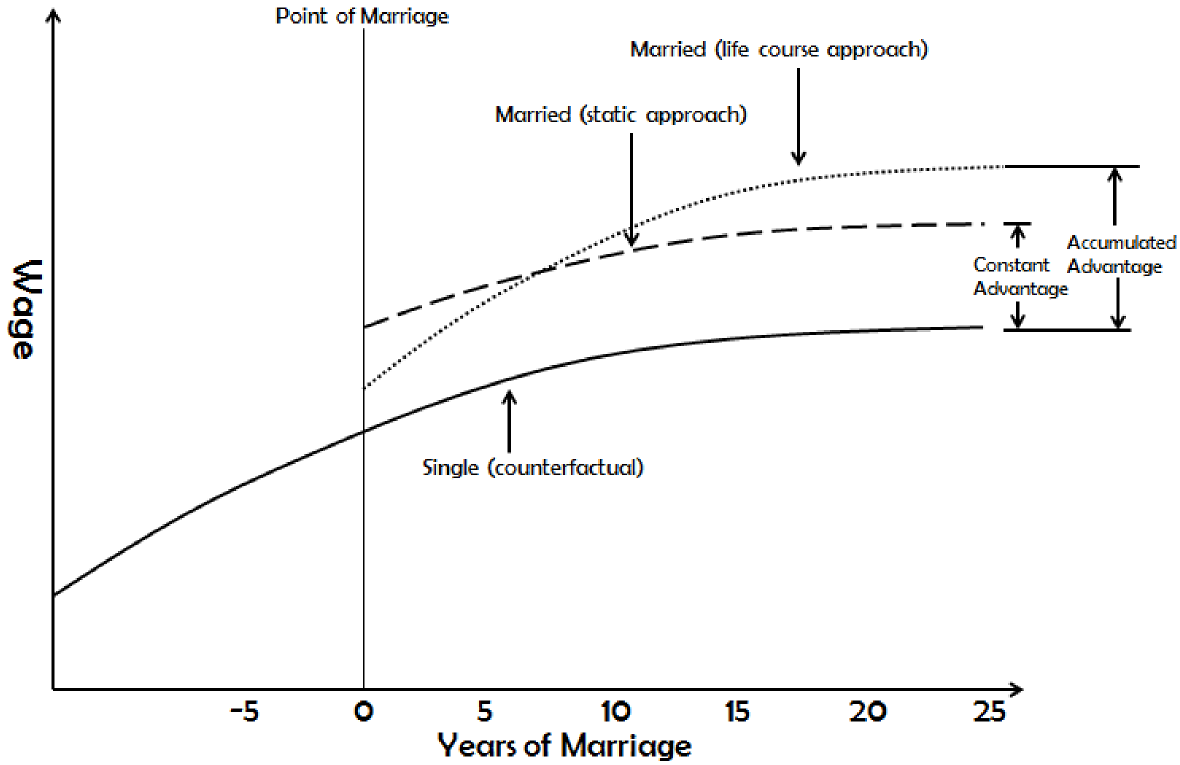
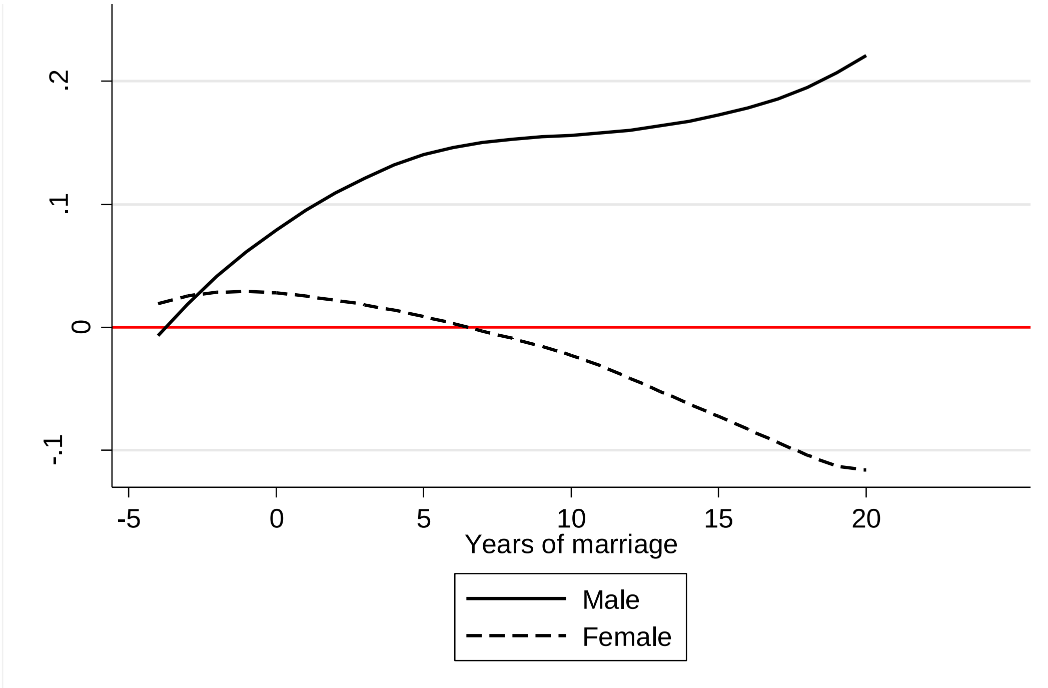
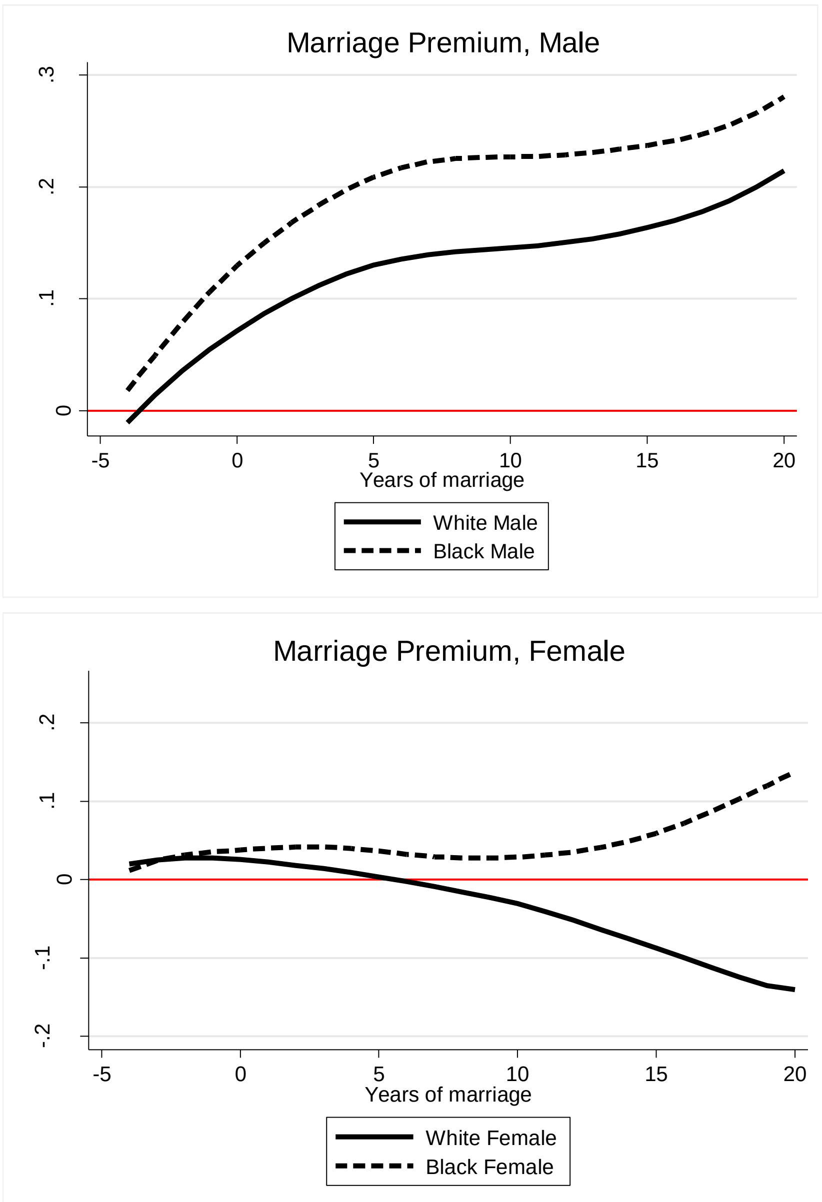


Figure 5 Marriage Wage Premium by Years of Marriage in Total Effect Model by Gender in Pooled Sample



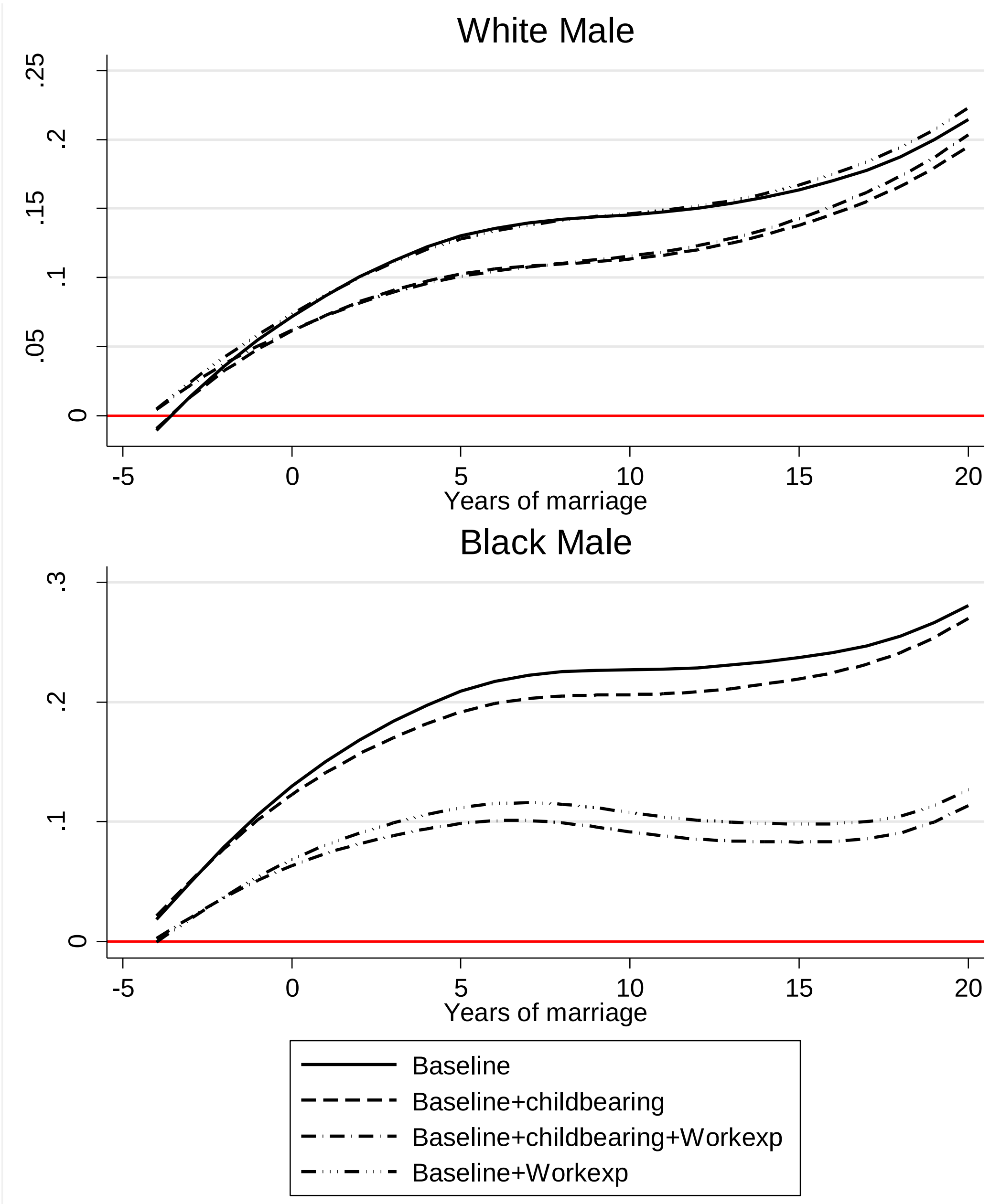
NOTE: Data Source: National Longitudinal Survey of Youth 1979-2010, Bureau of Labor Statistics. The models also include a dummy for a person being either divorced or married but separated from their spouse. The models control for selection into marriage by including the interaction between age at first marriage and potential experience, and control for selection out pf marriage by including the interaction between total years of divorce and potential experience. The models control for potential experience and its square term. Other baseline controlling variables include: the interactions between racial categories (coded as white, black and Hispanics) with potential experience, and the interactions between educational attainment (coded as high school and below, college educated, and beyond college education) with potential experience.

Figure 6 Marriage Wage Premium by Years of Marriage in Total Effect Model by Gender and Race



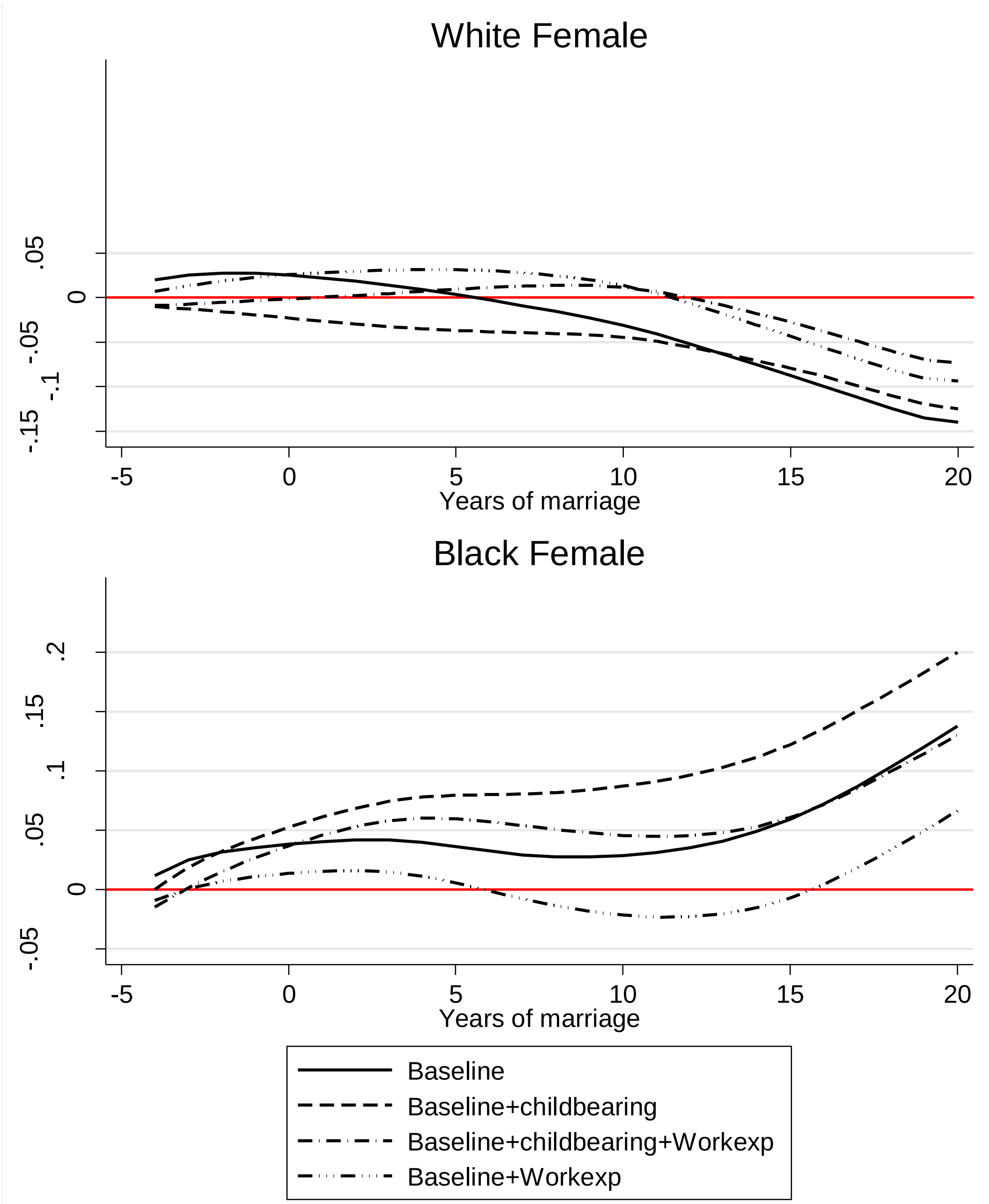
NOTE: Data Source: National Longitudinal Survey of Youth 1979-2010, Bureau of Labor Statistics. The models also include a dummy for a person being either divorced or married but separated from their spouse. The models control for selection into marriage by including the interaction between age at first marriage and potential experience, and control for selection out pf marriage by including the interaction between total years of divorce and potential experience. The models control for potential experience and its square term. Other baseline controlling variables include: the interactions between racial categories (coded as white, black and Hispanics) with potential experience, and the interactions between educational attainment (coded as high school and below, college educated, and beyond college education) with potential experience.

Figure 7 Selection-adjusted Marriage Wage Premium by Years of Marriage by Race in Models with Different Controls of Potential Mechanisms, Male



NOTE: Data Source: National Longitudinal Survey of Youth 1979-2010, Bureau of Labor Statistics. The models also include a dummy for a person being either divorced or married but separated from their spouse. The models control for potential experience and its square term. Other baseline controlling variables include: the interactions between racial categories (coded as white, black and Hispanics) with potential experience, and the interactions between educational attainment (coded as high school and below, college educated, and beyond college education) with potential experience. Controls for childbearing are implemented by including the number of biological/step/adopted children in the household, as well as the interaction between this variable with marital status. Controls for work experience include job tenure, total hour worked in the previous year, annual and cumulative weeks unemployed, annual and cumulative weeks out of the labor force, as well as the interactions between these variables and potential experience (except for cumulative measures). All models are weighted.

Figure 8 Selection-adjusted Marriage Wage Premium by Years of Marriage by Race in Models with Different Controls of Potential Mechanisms, Female



NOTE: Data Source: National Longitudinal Survey of Youth 1979-2010, Bureau of Labor Statistics. The models also include a dummy for a person being either divorced or married but separated from their spouse. The models control for potential experience and its square term. Other baseline controlling variables include: the interactions between racial categories (coded as white, black and Hispanics) with potential experience, and the interactions between educational attainment (coded as high school and below, college educated, and beyond college education) with potential experience. Controls for childbearing are implemented by including the number of biological/step/adopted children in the household, as well as the interaction between this variable with marital status. Controls for work experience include job tenure, total hour worked in the previous year, annual and cumulative weeks unemployed, annual and cumulative weeks out of the labor force, as well as the interactions between these variables and potential experience (except for cumulative measures). All models are weighted.

Table 5 Descriptive Statistics by Race and Gender

	White (N= 14,349)		Black (N=45,004)	
	Male (54.71%)	Female (45.29%)	Male (56.48%)	Female (43.52%)
Educational Attainment at Age 25 (Analytic Sample)				
High School or less	64.75%	55.09%	69.90%	53.53%
Some College	17.65%	23.56%	18.57%	32.71%
At Least 4 years of college	17.60%	21.35%	11.53%	13.76%
Marital History				
Never Married at Age 25	42.45 %	26.59 %	60.32 %	49.52 %
Never Married at Age 35	24.88 %	14.62 %	41.23 %	34.72 %
Never Married at Age 45	21.82 %	12.53 %	35.96 %	29.85 %
Age at First Marriage among Those Ever Married				
Mean	24.05	22.22	26.61	24.53
S.D.	(4.97)	(4.99)	(6.30)	(6.58)
Percentage Ever Divorced				
Percentage	33.85 %	43.9 %	43.15 %	49.52 %
Age of First Divorce Among Those Ever Divorced				
	29.54	28.08	31.95	29.83
	(7.59)	(7.88)	(7.87)	(7.96)
Years of Marriage among Married Person-years				
Mean	12.47	13.13	10.41	11.18
S.D.	(7.96)	(8.17)	(7.42)	(7.86)

NOTE: Data Source: National Longitudinal Survey of Youth 1979-2010, Bureau of Labor Statistics. Standard deviations are presented in parentheses. All sample statistics are weighted.

Table 6 Beginning, Ending, and Change in Marriage Wage Premium for White Male and Black Male

Model	Beginning Premium	Ending Premium	Change in Premium
White Male			
Baseline	0.40%	21.37%	20.97%
Baseline+Childbearing	0.21%	19.30%	19.09%
Baseline+Work Experience	1.66%	22.18%	20.52%
Baseline+Childbearing+Work Experience	1.32%	20.14%	18.82%
Black Male			
Baseline	5.21%	27.45%	22.24%
Baseline+Childbearing	5.24%	26.26%	21.02%
Baseline+Work Experience	2.19%	12.92%	10.73%
Baseline+Childbearing+Work Experience	2.27%	11.58%	9.31%

NOTE: Beginning premium is calculated as the average marriage premium for the three beginning years of the analytic time window (years of marriage = -4, -3, and -2); ending premium is calculated as the average marriage premium for the three ending years of the analytic time window (years of marriage = 18, 19, and 20). Estimation of beginning premium and ending premium is based on the models as presented in Appendix Table 2.F1 and 2.F2. Change in premium is calculated as the difference between ending premium and beginning premium.

Table 7 Beginning, Ending, and Change in Marriage Wage Premium for White Female and Black Female

Model	Beginning Premium	Ending Premium	Change in Premium
White Female			
Baseline	1.85%	-13.49%	-15.34%
Baseline+Childbearing	-1.61%	-12.13%	-10.52%
Baseline+Work Experience	0.69%	-8.75%	-9.44%
Baseline+Childbearing+Work Experience	-1.19%	-6.84%	-5.65%
Black Female			
Baseline	1.46%	11.63%	10.17%
Baseline+Childbearing	1.02%	17.78%	16.76%
Baseline+Work Experience	-0.35%	5.09%	5.45%
Baseline+Childbearing+Work Experience	-0.11%	11.53%	11.65%

NOTE: Beginning premium is calculated as the average marriage premium for the three beginning years of the analytic time window (years of marriage = -4, -3, and -2); ending premium is calculated as the average marriage premium for the three ending years of the analytic time window (years of marriage = 18, 19, and 20). Estimation of beginning premium and ending premium is based on the models as presented in Appendix Table 2.F1 and 2.F2. Change in premium is calculated as the difference between ending premium and beginning premium.

Table 8 Total Change in Marriage Wage Premium and Contributions of Childbearing and Work Experience, Expressed as Percentage of Wage

	Total Change in MWP	Childbearing		Work Experience	
		Uncontrolled Contribution	Controlled Contribution	Uncontrolled Contribution	Controlled Contribution
White Male	20.97%	1.88%	1.70%	0.45%	0.27%
Black Male	22.24%	1.22%	1.42%	11.51%	11.71%
White Female	-15.34%	-4.82%	-3.78%	-5.90%	-4.86%
Black Female	10.17%	-6.60%	-6.20%	4.72%	5.12%

NOTE: Estimation is based on the models as presented in Appendix Table 2.F1 and 2.F2 and the calculation in Table 3 and 4. The contribution of each mechanism is calculated both with and without the other mechanism controlled for (termed "controlled contribution" and "uncontrolled contribution" respectively). A positive sign means that the mechanism has a positive impact on the growth of the MWP over years of marriage, and a negative sign means that the mechanism has a positive impact on the growth of the MWP over years of marriage.

Appendix G

Detailed Discussion of Selection Problems

In the main text, I presented the potential selection problems involving marital sorting and my analytic strategies to address these problems. Here, I offer a more detailed discussion of these selection problems. In this discussion, I start with a simple taxonomy of selection problems. The taxonomy begins by identifying two general types of selection, namely the wage level based selection (termed "Type 1 Selection" in Table 2.A) and the wage growth based selection (termed "Type 2 Selection" in Table 2.A). In prior works that focus exclusively on the static comparison between the married and unmarried, the researcher's major concern is the selection into and out of marriage based on individual characteristics that simultaneously affect their wage level throughout their lives (i.e. Type 1 Selection). However, this paper concerns not just how marriage affects one's overall wage level, but also the pattern by which such wage impact of marriage changes over years of marriage. Hence, another type of selection may be involved: selection into and out of marriage based on characteristics that simultaneously affect the person's wage growth rate (i.e. Type 2 Selection).

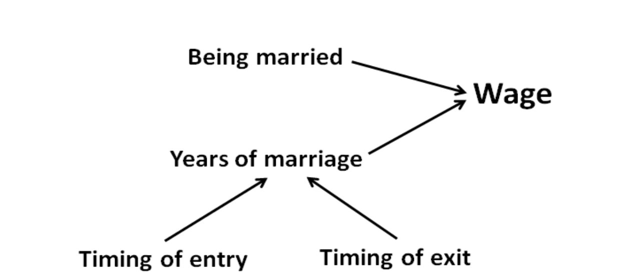
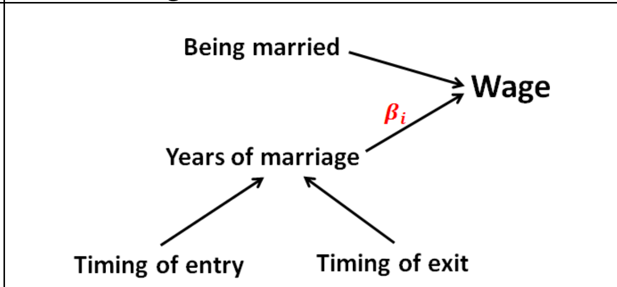
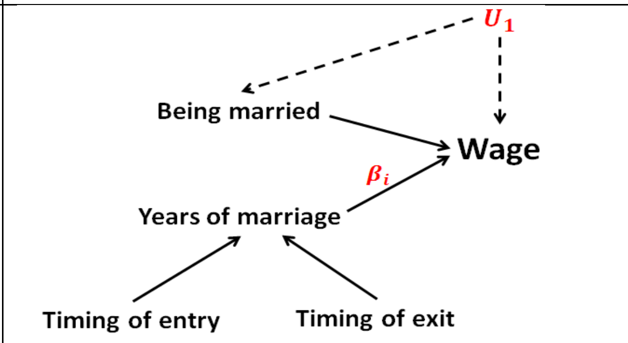
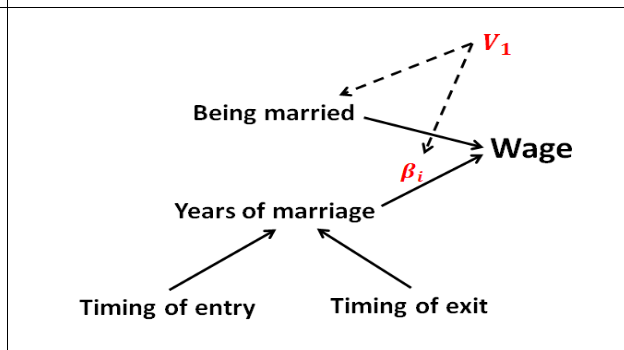
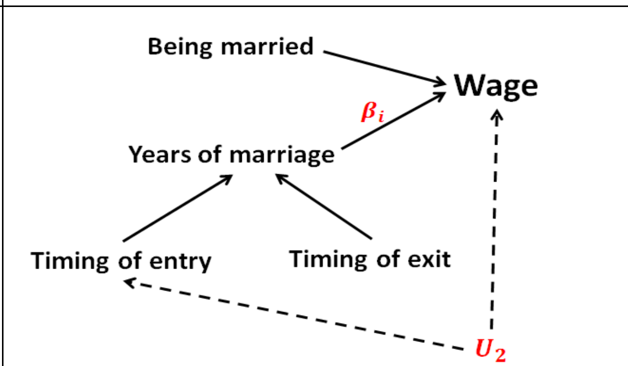
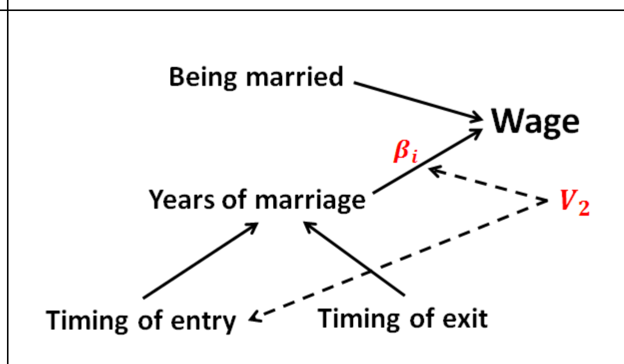
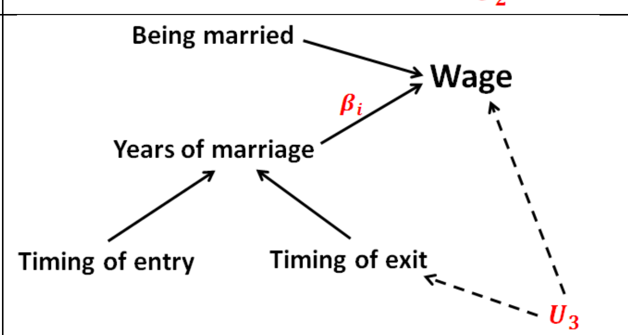
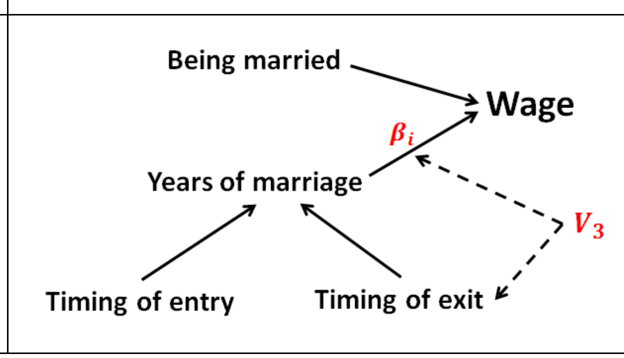
It is also possible to illustrate Type 1 and Type 2 selection using a basic wage determination equation. Consider, for example, the wage determination equation: $\mathrm{Wage}_{\mathrm{it}} = \beta_0 + \beta_1 \cdot \mathrm{t} + \beta_2 \cdot \mathrm{t}^2 + \sum_{\mathrm{k}=3}^{\mathrm{K}} \beta_{\mathrm{k}} \mathrm{X}_{\mathrm{itk}} + \lambda \cdot \mathrm{D}^{\mathrm{Married}} + \gamma \cdot \mathrm{T}^{\mathrm{Years\ of\ marriage}} + \epsilon_{\mathrm{it}}$, where the residual term $\epsilon_{\mathrm{it}} = \omega_{\mathrm{i}} + \mathrm{v}_{\mathrm{i}} \cdot \mathrm{t} + \mathrm{e}_{\mathrm{it}}$. The researcher is interested in the effect of being married (λ) and the effect of having stayed one additional year in marriage (γ). Suppose that the components in the residual are not observed. Type 1 selection occurs when the person-specific intercept in the residual of the wage determination equation, ω_{i}, is associated with $\mathrm{T}^{\mathrm{Years\ of\ Marriage}}$ or $\mathrm{D}^{\mathrm{Married}}$, and Type 2 selection occurs when the person-specific slope in the residual of the wage determination equation, v_i, is associated with $T^{\text{Years of Marriage}}$ or D^{Married}.

For each type of selection, I further demonstrate directed causal diagrams for four specific cases: (1) no selection; (2) selection into being married; (3) selection of the timing of entry into marriage; (4) selection of the timing of exit from marriage. In the case of no selection, a person's wage could depend on the status of being married and on years of marriage via the parameter of wage growth rate β_i. Years of marriage further depends on the timing of entry into marriage and the timing of exit from marriage. In the case of selection into being married, those could sort into marriage based on person-specific characteristics (U_1) that are simultaneously affect the person's wage throughout the person's life, or based on person-specific characteristics (V_1) that are simultaneously associated with the person's rate of wage growth (β_i).

The latter two cases (bottom two rows in Table 2.A) concern the possibility that individuals who are married for different lengths of time may differ systematically, because the person-specific characteristics that are associated with the timing of entering into marriage (U_2 and V_2 in Table 2.A) or exiting from marriage (U_3 and V_3 in Table 2.A) may simultaneously affect the person's oeveral wage level throughout life and the rate of wage growth. It follows that the observed decline of MWP for women at later years of marriage may be an artifact of the composition of the sample rather than the real decline in the wage return of marriage.

In empirical analysis, not all variables in U_1, U_2, U_3, V_1, V_2, and V_3 are observed in data, and as can be seen in the directed causal diagrams in Table 2.A, failure to control for those unobserved variables means that some of the confounders of the "treatment effect" of being married and years of marriage on wage are left out of the model. Analytic strategies are needed to address these confounding problems. Type 1 selection can be addressed by applying fixed-effect models to longitudinal data so that those person-specific time-invariant unobserved characteristics in the intercept are controlled for (Hausman & Taylor, 1981; Kilbourne, England, & Beron, 1994; Korenman & Neumark, 1991). Some other works use twins or sibling data to control for family-level unobserved heterogeneity (Antonovics & Town, 2004; Isacsson, 2007; Krashinsky, 2004; Neumark & Korenman, 1992). Yet, the validity of this strategy relies on the assumption that the unobserved heterogeneity is equal for twins or siblings. Type 2 selection, however, cannot be ruled out by controlling for the individual fixed effect, because the person-specific slope in the wage equation (i.e. β_i in Table 2.A) remains after accounting for the individual fixed effect (Loughran & Zissimopoulos, 2009; Rodgers & Stratton, 2010). Hence, to further control for the individual differences in wage growth rate, Loughran & Zissimopoulos (2009) adopted a method that removes the individual-specific slope variable by demeaning the first-differenced wage variable. In the Analytical Strategy Section in the main text, I present my strategies to deal with these selection problems.

Table 2.A. A Taxonomy of Selection Problems

	Type 1 Selection: Wage Level Based Selection	Type 2 Selection: Wage Growth Based Selection
No Selection		
Selection into being married		
Selection of the timing of entry into marriage		
Selection of the timing of exit from marriage		

NOTE: β_i represents the person-specific wage growth rate. U_1, U_2, U_3, V_1, V_2, and V_3 represent the confounding variables that simultaneously determine wage and marital status or marriage timing.

Appendix H
Statistics for Sample Restriction

Table 2.B. Statistics for Sample Restriction

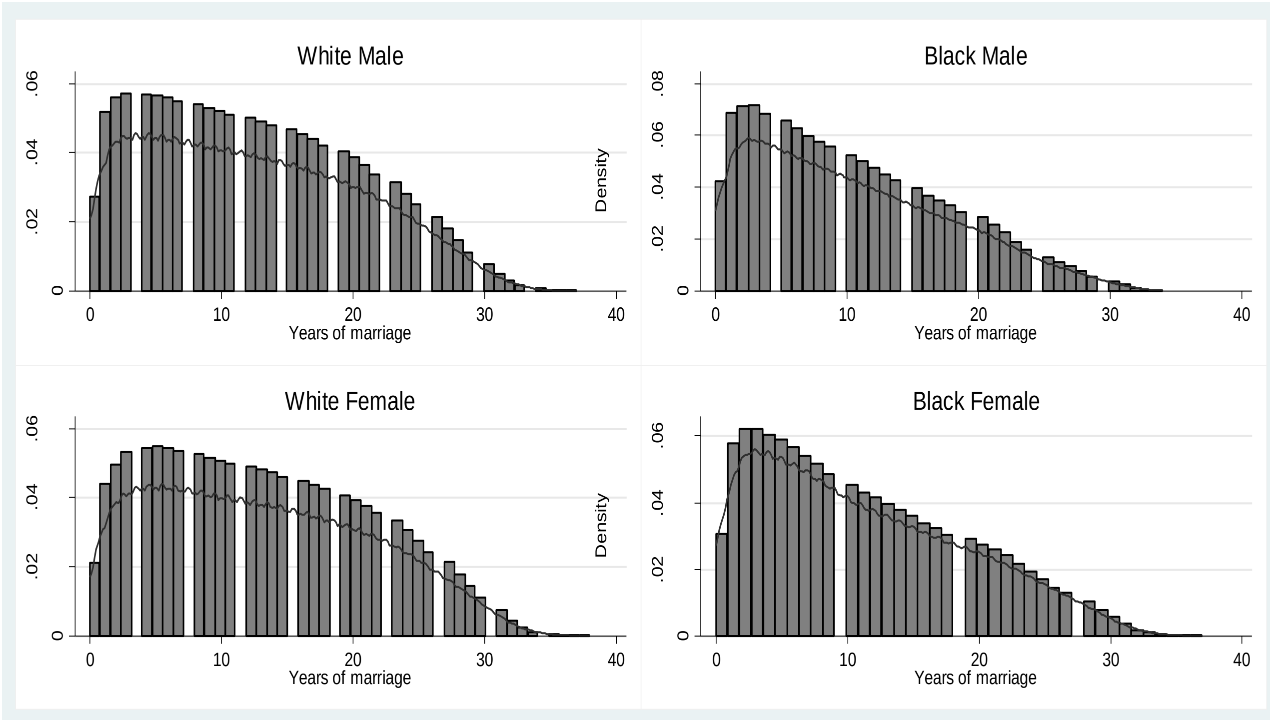
Sample Restriction	White Male		White Female		Black Male		Black Female	
	N	%	N	%	N	%	N	%
All	63992	100.00%	65780	100.00%	32528	100.00%	32853	100.00%
Had no children before 18, and had at least two non-missing wage	44158	69.01%	45769	69.58%	17689	54.38%	15631	47.58%
Non-negative potential experience	35368	55.27%	36860	56.04%	14916	45.86%	12882	39.21%
Non-missing current wage	31667	49.49%	29550	44.92%	12355	37.98%	10294	31.33%
AFM between 18030; cumulative divorce<10	24623	38.48%	20381	30.98%	8104	24.91%	6245	19.01%

NOTE: Data Source: National Longitudinal Survey of Youth 1979-2010, Bureau of Labor Statistics.

Appendix I
Sample Distribution of Years of Marriage and Total Years of Divorced

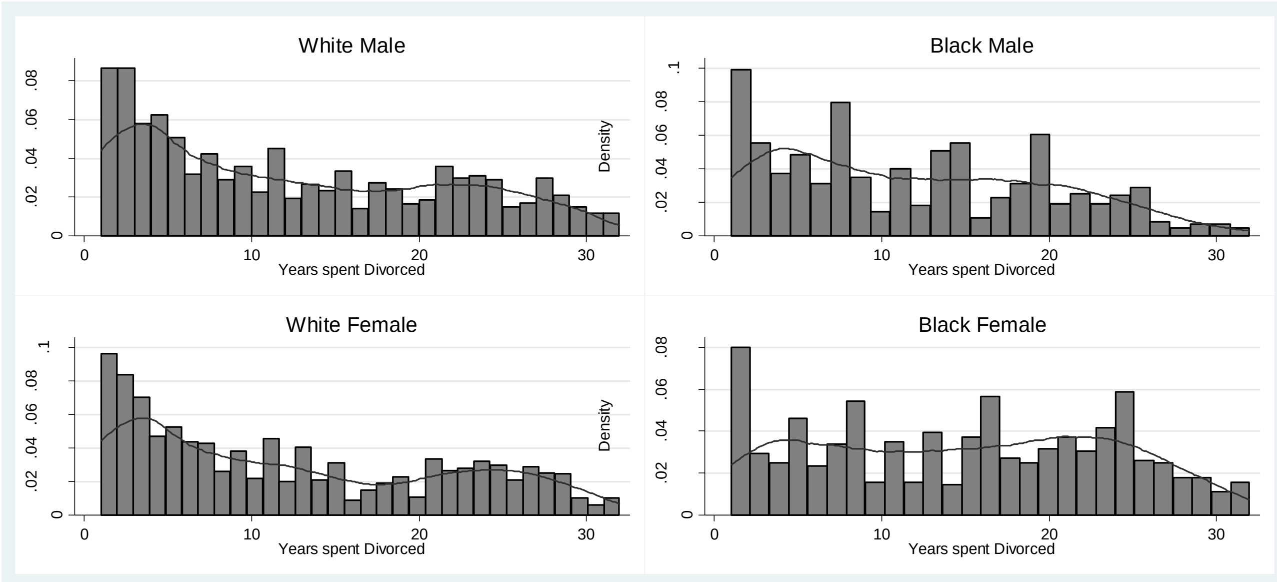
Blacks and Whites differ, not only in the average length of marriage, but also in the shape of distribution of years of marriage and years of divorce. Appendix Figure 2.C1 gives the histogram of years of marriage among those who are married by race and gender. Among Whites, the distribution of years of marriage is more flat across different lengths, while among Blacks, the mass of the distribution is concentrated at the shorter lengths of marriage. The scenario for divorce is the opposite: Appendix Figure 2.C2 gives the distribution of number of years divorced among those who have ever experienced divorce. Among Whites, the mass of the distribution is concentrated at the shorter lengths of divorce spells, while among Blacks, the distribution is more flat across different lengths.

Figure 2.C1 Histogram of Years of Marriage among the Married by Race and Gender



NOTE: Data Source: National Longitudinal Survey of Youth 1979-2010, Bureau of Labor Statistics. Years of marriage is calculated for those who have ever got married in the data.

Figure 2.C2 Histogram of total number of years spent divorced among those who has ever divorced by race and gender



NOTE: Data Source: National Longitudinal Survey of Youth 1979-2010, Bureau of Labor Statistics. Years spent divorced are calculated for those who have experienced at least one year of divorce in the data.

Appendix J
Fixed-effect Models with Different Controls for Selection

Here, I present detailed results from models with different controls for selection. As recognized by prior works, Blacks and Whites may differ significantly in the form and intensity of selectivity in regard to the likelihood and timing of entering, staying in, and exiting from a marriage (Lichter, McLaughlin, Kephart, & Landry, 1992; Manning & Smock, 1995; Wilson, 2012). By separating Black and White samples, my analysis will simultaneously account for the racial differences in the treatment effect as well as the influence of selection. In the analysis, I apply the specification in Equation 1 to the data, yet exclude controls for childbearing or work experience. The full results are given in Appendix Table 2.E. Model (1) - (4) in Appendix Table 2.E excludes controls for selection into and out of marriage based on wage growth rate (i.e. Type-2 selection). Then, I add controls for selection into marriage (i.e. interaction between AFM and potential experience), presented in Model (5)-(8) in Appendix Table 2.D. Lastly, I add controls for selection out of marriage (i.e. interaction between TYD and potential experience), presented in Model (9)-(12) in Appendix Table 2.D. The trajectories of the MWP under the model with no controls for selection, with controls for selection into marriage, and with controls for selection into and out of marriage are presented in Appendix Figure 2.D. The figures suggest that selectivity based on wage growth (i.e. Type-2 selection) plays a greater role among men among women. Among Whites, selection into marriage has little effect on the estimated wage effect of marriage, while selection out of marriage based on wage growth causes an overestimation of the wage effect of marriage. Among Blacks, selection into marriage causes an underestimation of the wage effect of marriage, and selection out of marriage causes an overestimation of the wage effect of marriage. This suggests that both White and Black men with faster wage growth tend to stay longer in marriage, and Black men with faster wage growth tend to get married later.

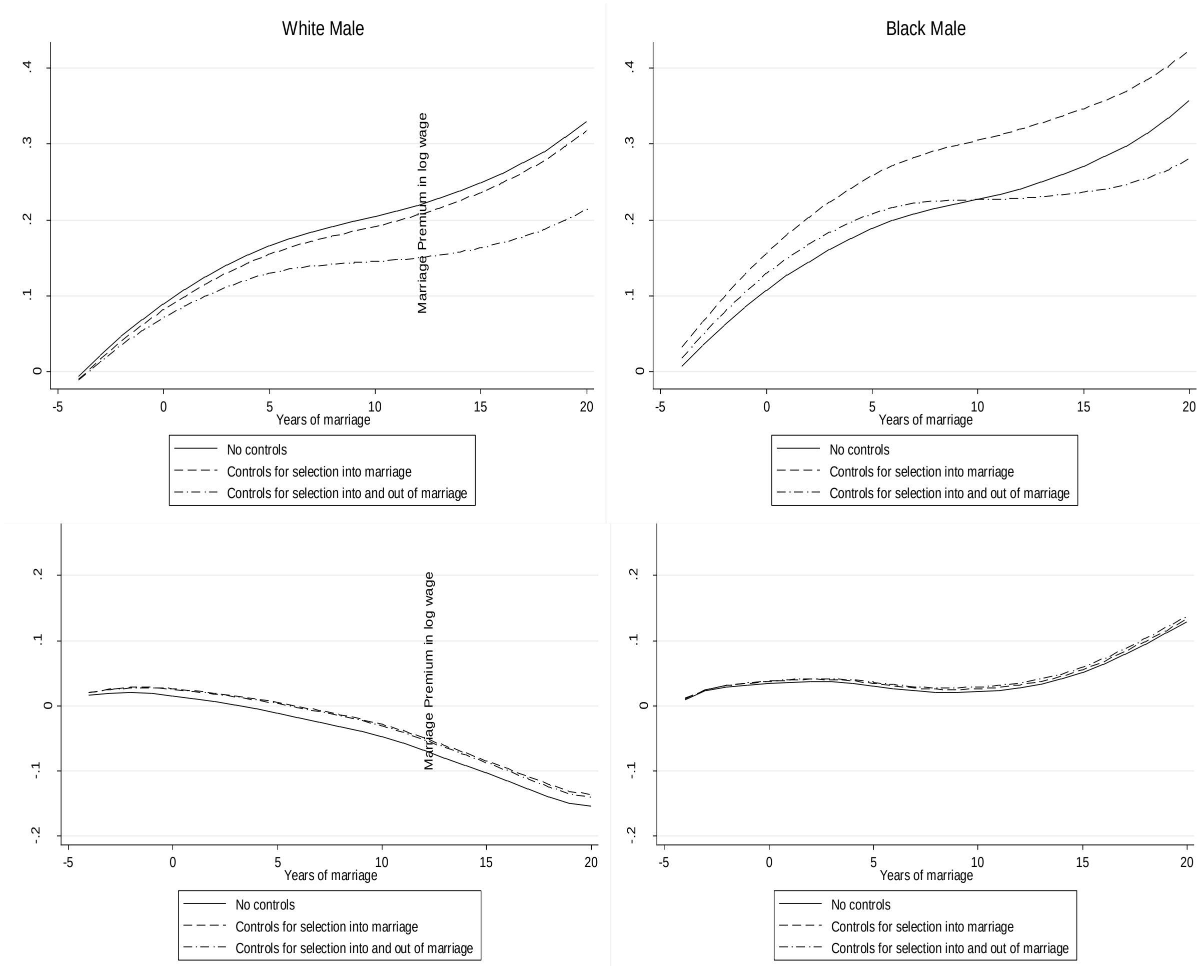
Table 2.D Coefficients on Covariates in Fixed-effect Models Predicting Log Hourly Wage , Comparing Models with Different Controls for Selection into and out of Marriage.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	No Controls for Selection				With Controls for Selection into Marriage				With Controls for Selection out of Marriage			
	White male	White Female	Black Male	Black Female	White male	White Female	Black Male	Black Female	White male	White Female	Black Male	Black Female
Potential experience	0.0351***	0.0451***	0.0238**	0.0506***	0.0342***	0.0463***	0.0313*	0.0511***	0.0436***	0.0467***	0.0459***	0.0506***
	(0.0047)	(0.0058)	(0.0074)	(0.0075)	(0.0074)	(0.0093)	(0.0128)	(0.0138)	(0.0079)	(0.0100)	(0.0124)	(0.0141)
Squared potential experience	-0.0007***	-0.0009***	-0.0005*	-0.0011***	-0.0008***	-0.0008***	-0.0003	-0.0011**	-0.0007***	-0.0008***	-0.0004†	-0.0011**
	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0004)	(0.0002)	(0.0002)	(0.0002)	(0.0004)
Dummy for Divorced	0.1073*	-0.0041	0.1029	0.0298	0.0952	0.0133	0.1753*	0.0341	0.0838	0.0121	0.1549†	0.0350
	(0.0504)	(0.0606)	(0.0726)	(0.0648)	(0.0611)	(0.0774)	(0.0784)	(0.1027)	(0.0609)	(0.0787)	(0.0792)	(0.1046)
Some college × experience	0.0015	-0.0053†	-0.0022	-0.0063†	0.0012	-0.0049	-0.0007	-0.0062	0.0014	-0.0049	-0.0020	-0.0061
	(0.0026)	(0.0028)	(0.0044)	(0.0034)	(0.0027)	(0.0030)	(0.0044)	(0.0043)	(0.0027)	(0.0031)	(0.0043)	(0.0044)
College and above × experience	0.0072*	-0.0262***	-0.0023	-0.0192**	0.0067†	-0.0255***	0.0008	-0.0189*	0.0069†	-0.0256***	-0.0015	-0.0189*
	(0.0029)	(0.0037)	(0.0060)	(0.0073)	(0.0037)	(0.0046)	(0.0065)	(0.0084)	(0.0036)	(0.0047)	(0.0065)	(0.0085)
Age at first marriage × experience					0.0001	-0.0001	-0.0006	-0.0000	-0.0001	-0.0001	-0.0007	-0.0000
					(0.0004)	(0.0006)	(0.0006)	(0.0009)	(0.0004)	(0.0006)	(0.0006)	(0.0009)
Total years spent divorced × experience									-0.0006**	-0.0000	-0.0008***	0.0000
									(0.0002)	(0.0002)	(0.0002)	(0.0003)
Dummies for Years of Marriage?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	2.2088***	2.0762***	2.0759***	1.8398***	2.2130***	2.0681***	2.0531***	1.8379***	2.2139***	2.0685***	2.0558***	1.8378***
	(0.0258)	(0.0340)	(0.0374)	(0.0396)	(0.0275)	(0.0448)	(0.0386)	(0.0561)	(0.0274)	(0.0451)	(0.0381)	(0.0562)

R-squared	0.1349	0.0426	0.1043	0.0885	0.1349	0.0426	0.1046	0.0885	0.1358	0.0426	0.1088	0.0885
# of person-year observations	24,623	20,381	8,104	6,245	24,623	20,381	8,104	6,245	24,623	20,381	8,104	6,245
# of respondents	1,907	1,739	591	505	1,907	1,739	591	505	1,907	1,739	591	505

NOTE: Data Source: National Longitudinal Survey of Youth 1979-2010, Bureau of Labor Statistics. Standard errors are presented in parentheses. *** p<0.001; ** p<0.01; * p<0.05; † p<0.1. Being married means that the person is married and his/her spouse is physically present; the reference category is being never married. The models also include a dummy for a person being either divorced or married but separated from their spouse. The models control for potential experience and its square term. Other baseline controlling variables include and the interactions between educational attainment (coded as high school and below, college educated, and beyond college education) with potential experience. All analyses are weighted.

Figure 2.D Estimated Wage Premium by Years of Marriage by Race and Gender, with Different Controls for Selection into and out of Marriage (Lowess Smoothed)

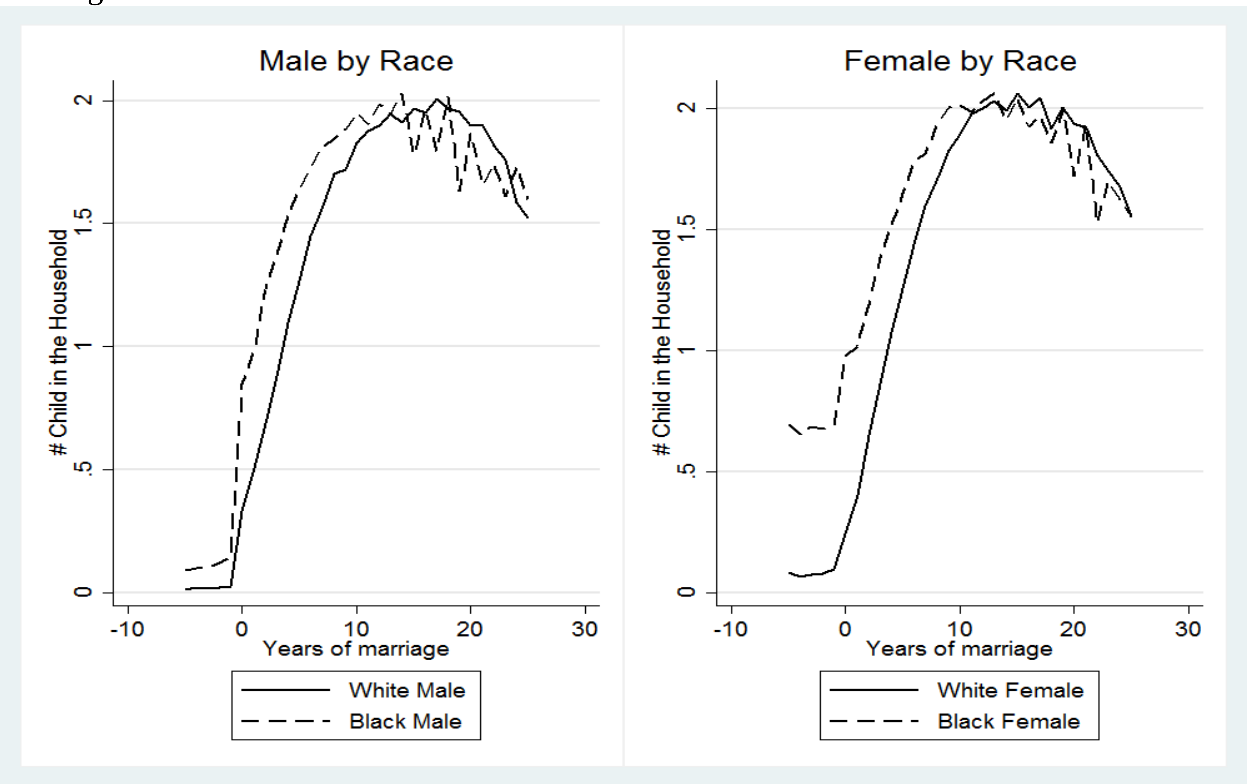


NOTE: Data Source: National Longitudinal Survey of Youth 1979-2010, Bureau of Labor Statistics. The models also include a dummy for a person being either divorced or married but separated from their spouse. The models control for selection into marriage by including the interaction between age at first marriage and potential experience, and control for selection out pf marriage by including the interaction between total years of divorce and potential experience. The models control for potential experience and its square term. Other baseline controlling variables include and the interactions between educational attainment (coded as high school and below, college educated, and beyond college education) with potential experience.

Appendix K

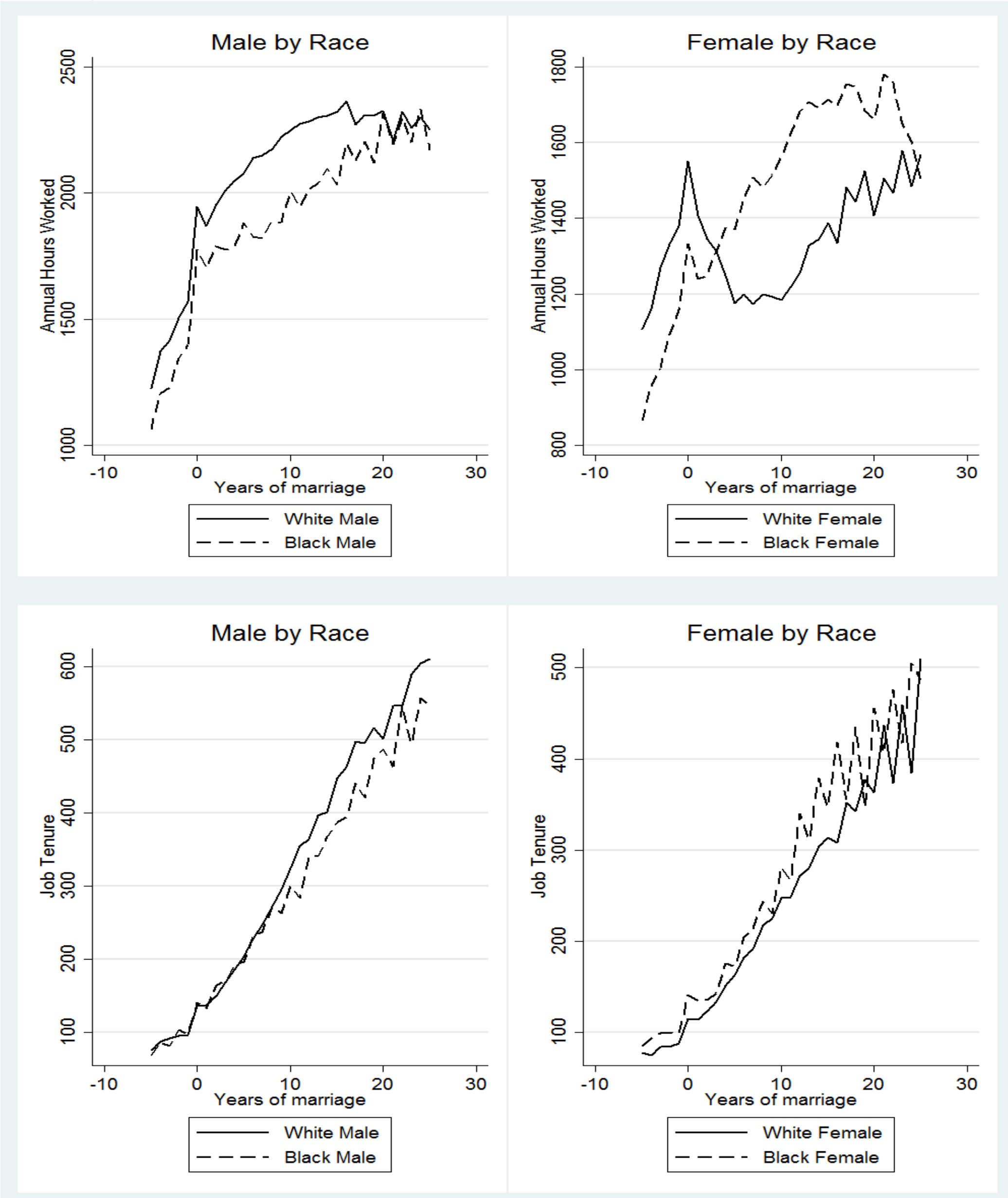
Descriptive Trajectories of the Number of Children in the Household and Measured Work Experience

Figure 2.E1 Descriptive Trajectories of the Number of Child(ren) in the Household by Years of Marriage



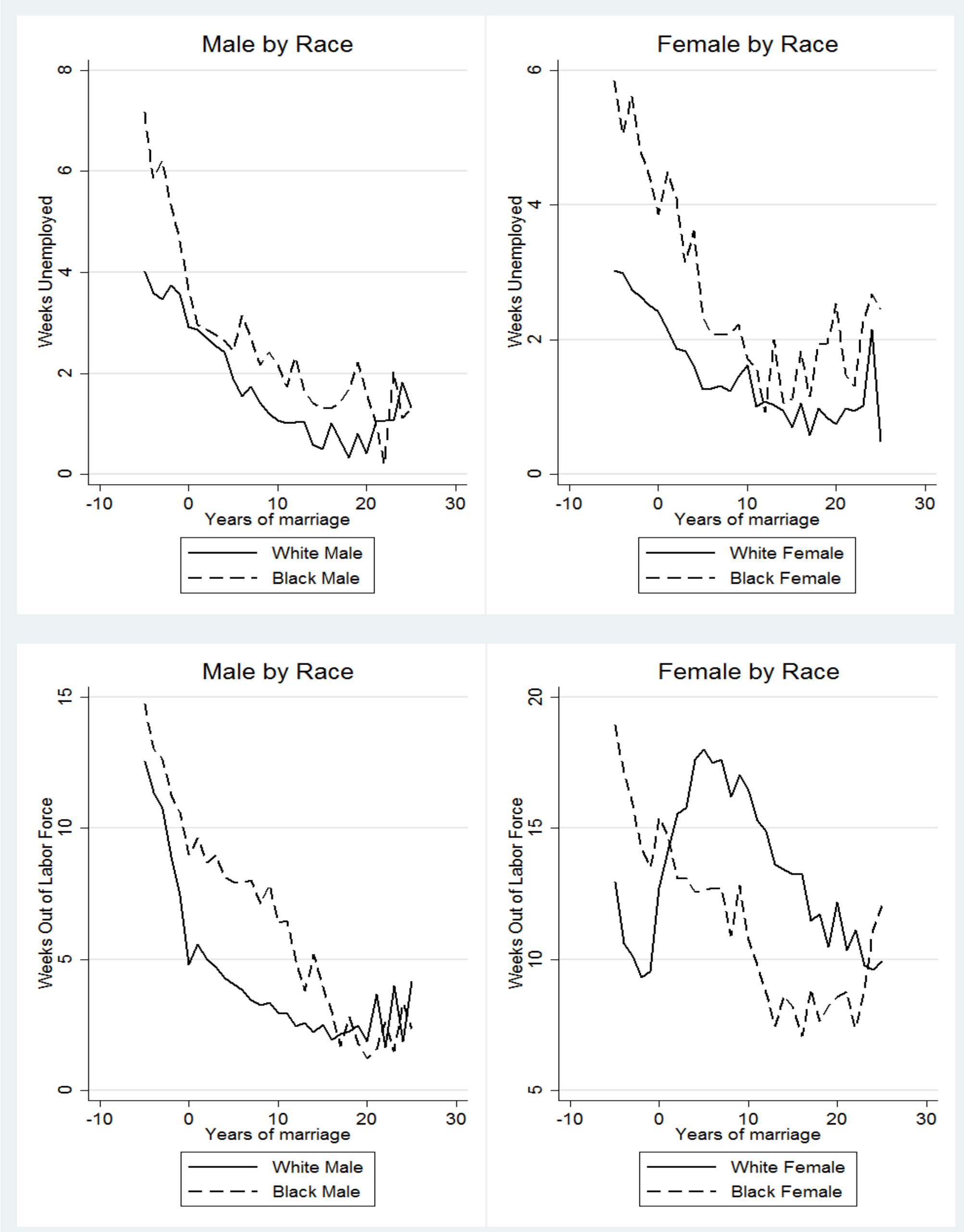
NOTE: Data Source: National Longitudinal Survey of Youth 1979-2010, Bureau of Labor Statistics.

Figure 2.E2 Descriptive Trajectories of Annual Hours Worked and Job Tenure by Years of Marriage



NOTE: Data Source: National Longitudinal Survey of Youth 1979-2010, Bureau of Labor Statistics.

Figure 2.E3 Descriptive Trajectories of Annual Weeks Unemployed and Annual Weeks out of the Labor Force by Years of Marriage



NOTE: Data Source: National Longitudinal Survey of Youth 1979-2010, Bureau of Labor Statistics.

Appendix L
Coefficients in Fixed-effect Models with Different Controls for Mechanisms

Table 2.F1 Coefficients on Covariates in Fixed-effect Models Predicting Log Hourly Wage , Comparing Models with Different Controls for Medication Mechanisms (With and Without Controls for Childbearing)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Baseline Model, No Controls				Baseline Model + Controls for Childbearing			
	White Male	White Female	Black Male	Black Female	White Male	White Female	Black Male	Black Female
Potential experience	0.0436***	0.0467***	0.0459***	0.0506***	0.0430***	0.0500***	0.0449***	0.0560***
	(0.0079)	(0.0100)	(0.0124)	(0.0141)	(0.0079)	(0.0099)	(0.0125)	(0.0141)
Squared potential experience	-0.0007***	-0.0008***	-0.0004†	-0.0011**	-0.0007***	-0.0012***	-0.0004	-0.0012**
	(0.0002)	(0.0002)	(0.0002)	(0.0004)	(0.0002)	(0.0002)	(0.0002)	(0.0004)
Dummy for Divorced	0.0838	0.0121	0.1549†	0.0350	-0.0267	-0.0374	0.0082	-0.0694†
	(0.0609)	(0.0787)	(0.0792)	(0.1046)	(0.0309)	(0.0381)	(0.0370)	(0.0393)
Some college × experience	0.0014	-0.0049	-0.0020	-0.0061	0.0013	-0.0076*	-0.0018	-0.0064
	(0.0027)	(0.0031)	(0.0043)	(0.0044)	(0.0027)	(0.0031)	(0.0043)	(0.0045)
College and above × experience	0.0069†	-0.0256***	-0.0015	-0.0189*	0.0065†	-0.0283***	-0.0016	-0.0197*
	(0.0036)	(0.0047)	(0.0065)	(0.0085)	(0.0037)	(0.0048)	(0.0064)	(0.0087)
Age at first marriage × experience	-0.0001	-0.0001	-0.0007	-0.0000	-0.0001	0.0004	-0.0007	-0.0000
	(0.0004)	(0.0006)	(0.0006)	(0.0009)	(0.0004)	(0.0006)	(0.0006)	(0.0009)
Total years spent divorced ×	-0.0006**	-0.0000	-0.0008***	0.0000	-0.0005**	-0.0001	-0.0008***	-0.0000
	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0003)

experience								
Number of child(ren)					0.0162	-0.0071	0.0192	-0.0032
					(0.0192)	(0.0172)	(0.0191)	(0.0222)
Number of child(ren) × Married					-0.0120	-0.0428*	-0.0198	-0.0441*
					(0.0193)	(0.0176)	(0.0219)	(0.0188)
Youngest child age 0-6					0.0427**	-0.0266	0.0368†	0.0075
					(0.0147)	(0.0203)	(0.0207)	(0.0261)
Youngest child age 7-12					0.0014	-0.1066***	0.0411†	-0.0048
					(0.0206)	(0.0274)	(0.0246)	(0.0306)
Youngest child age 13-18					0.0100	-0.0638*	0.0047	0.0096
					(0.0246)	(0.0322)	(0.0335)	(0.0365)
Dummies for Years of Marriage?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	2.2139***	2.0685***	2.0558***	1.8378***	2.2157***	2.1027***	2.0551***	1.8317***
	(0.0274)	(0.0451)	(0.0381)	(0.0562)	(0.0274)	(0.0461)	(0.0385)	(0.0583)
R-squared	0.1358	0.0426	0.1088	0.0885	0.1369	0.0476	0.1102	0.0917
# of person-year observations	24,623	20,381	8,104	6,245	24,623	20,381	8,104	6,245
# of respondents	1,907	1,739	591	505	1,907	1,739	591	505

NOTE: Data Source: National Longitudinal Survey of Youth 1979-2010, Bureau of Labor Statistics. Standard errors are presented in parentheses. *** p<0.001; ** p<0.01; * p<0.05; † p<0.1.

Table 2.F2 Coefficients on Covariates in Fixed-effect Models Predicting Log Hourly Wage , Comparing Models with Different Controls for Medication Mechanisms (With and Without Controls for Work Experience)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Baseline model + Controls for work experience				Baseline model + Controls for work experience + Controls for childbearing			
	White Male	White Female	Black Male	Black Female	White Male	White Female	Black Male	Black Female
Potential experience	0.0556***	0.0610***	0.0486***	0.0434**	0.0553***	0.0626***	0.0476***	0.0470***
	(0.0086)	(0.0102)	(0.0123)	(0.0139)	(0.0086)	(0.0102)	(0.0122)	(0.0139)
Squared potential experience	-0.0007***	-0.0006**	-0.0004†	-0.0008*	-0.0007***	-0.0009***	-0.0004	-0.0009*
	(0.0002)	(0.0002)	(0.0002)	(0.0004)	(0.0002)	(0.0002)	(0.0002)	(0.0004)
Dummy for Divorced	0.0839	0.0439	0.0633	-0.0020	-0.0196	0.0083	-0.0110	-0.0781†
	(0.0713)	(0.0788)	(0.0796)	(0.0945)	(0.0379)	(0.0395)	(0.0419)	(0.0420)
Age at first marriage × experience	-0.0001	-0.0002	-0.0002	0.0006	-0.0000	0.0001	-0.0002	0.0005
	(0.0005)	(0.0005)	(0.0007)	(0.0008)	(0.0005)	(0.0006)	(0.0006)	(0.0008)
Total years spent divorced × experience	-0.0002	0.0000	-0.0006**	-0.0001	-0.0002	-0.0000	-0.0006**	-0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Some college × experience	0.0005	-0.0050†	-0.0049	-0.0077†	0.0003	-0.0067*	-0.0047	-0.0075†
	(0.0026)	(0.0029)	(0.0039)	(0.0042)	(0.0026)	(0.0029)	(0.0040)	(0.0043)
College and above × experience	0.0042	-0.0245***	-0.0040	-0.0152*	0.0038	-0.0262***	-0.0039	-0.0155†
	(0.0037)	(0.0045)	(0.0061)	(0.0077)	(0.0037)	(0.0046)	(0.0060)	(0.0079)

Number of child(ren)					0.0088	0.0084	0.0279	0.0068
					(0.0207)	(0.0176)	(0.0178)	(0.0225)
Number of child(ren) × Married					0.0002	-0.0362*	-0.0244	-0.0423*
					(0.0206)	(0.0184)	(0.0206)	(0.0179)
Youngest child age 0-6					0.0235	-0.0204	0.0269	-0.0050
					(0.0144)	(0.0201)	(0.0217)	(0.0285)
Youngest child age 7-12					-0.0234	-0.0948***	0.0226	0.0033
					(0.0200)	(0.0275)	(0.0255)	(0.0312)
Youngest child age 13-18					-0.0069	-0.0426	0.0157	0.0295
					(0.0240)	(0.0309)	(0.0318)	(0.0329)
Job tenure	0.0003***	0.0006***	0.0005***	0.0006***	0.0003***	0.0006***	0.0005***	0.0006***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Job tenure × experience	-0.0000*	-0.0000***	-0.0000**	-0.0000**	-0.0000*	-0.0000***	-0.0000*	-0.0000**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Total hours worked in the previous year	0.0000	0.0000**	0.0000*	0.0001*	0.0000	0.0000**	0.0000*	0.0001*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Total hours worked in the previous year × experience	-0.0000***	-0.0000***	-0.0000**	-0.0000†	-0.0000***	-0.0000***	-0.0000**	-0.0000†
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

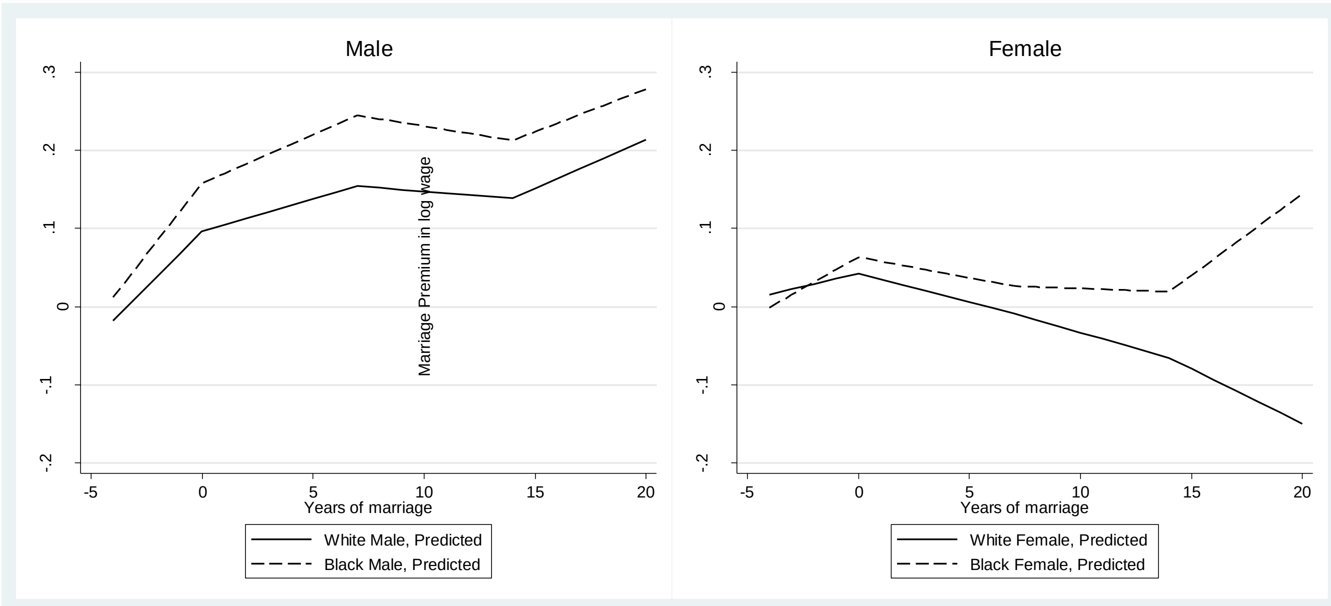
# of weeks unemployed in the previous year	-0.0016	-0.0011	-0.0025†	-0.0028	-0.0015	-0.0009	-0.0026†	-0.0029
	(0.0011)	(0.0017)	(0.0013)	(0.0019)	(0.0011)	(0.0017)	(0.0013)	(0.0019)
# of weeks out of labor force in the previous year	-0.0002	0.0014	0.0007	-0.0044*	-0.0001	0.0014	0.0007	-0.0043*
	(0.0013)	(0.0011)	(0.0023)	(0.0017)	(0.0013)	(0.0011)	(0.0023)	(0.0017)
# of weeks unemployed in the previous year × experience	-0.0002†	-0.0002	-0.0001	-0.0001	-0.0002†	-0.0002	-0.0001	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
# of weeks out of labor force in the previous year × experience	-0.0004***	-0.0004***	-0.0003†	-0.0000	-0.0004***	-0.0004***	-0.0003†	-0.0000
	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)
Cumulative # of weeks unemployed	-0.0019***	-0.0021**	-0.0014**	-0.0010†	-0.0019***	-0.0022**	-0.0013**	-0.0010†
	(0.0003)	(0.0007)	(0.0004)	(0.0005)	(0.0003)	(0.0007)	(0.0004)	(0.0005)
Cumulative # of weeks out of labor force	-0.0008**	-0.0008***	-0.0007*	-0.0005*	-0.0008**	-0.0008***	-0.0007*	-0.0004†
	(0.0003)	(0.0001)	(0.0003)	(0.0002)	(0.0003)	(0.0001)	(0.0003)	(0.0002)
Dummies for Years of Marriage?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Constant	2.1638***	2.1446***	2.1339***	1.7434***	2.1574***	2.1773***	2.0938***	1.7197***
	(0.0913)	(0.1912)	(0.0726)	(0.1403)	(0.0898)	(0.1896)	(0.0771)	(0.1377)
R-squared	0.1829	0.1076	0.1725	0.1663	0.1837	0.1102	0.1737	0.1687
# of person-year observations	21,320	17,346	6,917	5,234	21,320	17,346	6,917	5,234
# respondents	1,872	1,694	581	497	1,872	1,694	581	497

NOTE: Data Source: National Longitudinal Survey of Youth 1979-2010, Bureau of Labor Statistics. Standard errors are presented in parentheses. *** p<0.001; ** p<0.01; * p<0.05; † p<0.1.

Appendix M
Sensitivity Analysis 1: Linear Spline Specification and Test for Significance of Changes in MWP

Figure 2.G Estimated MWP by Years of Marriage by Gender and Race, Using Linear Spline Functions



NOTE: Data Source: National Longitudinal Survey of Youth 1979-2010, Bureau of Labor Statistics. Estimation and prediction are based on the coefficients on the dummies for years of marriage as presented in the baseline model of the total effect of marriage, with no controls for childbearing and work experience.

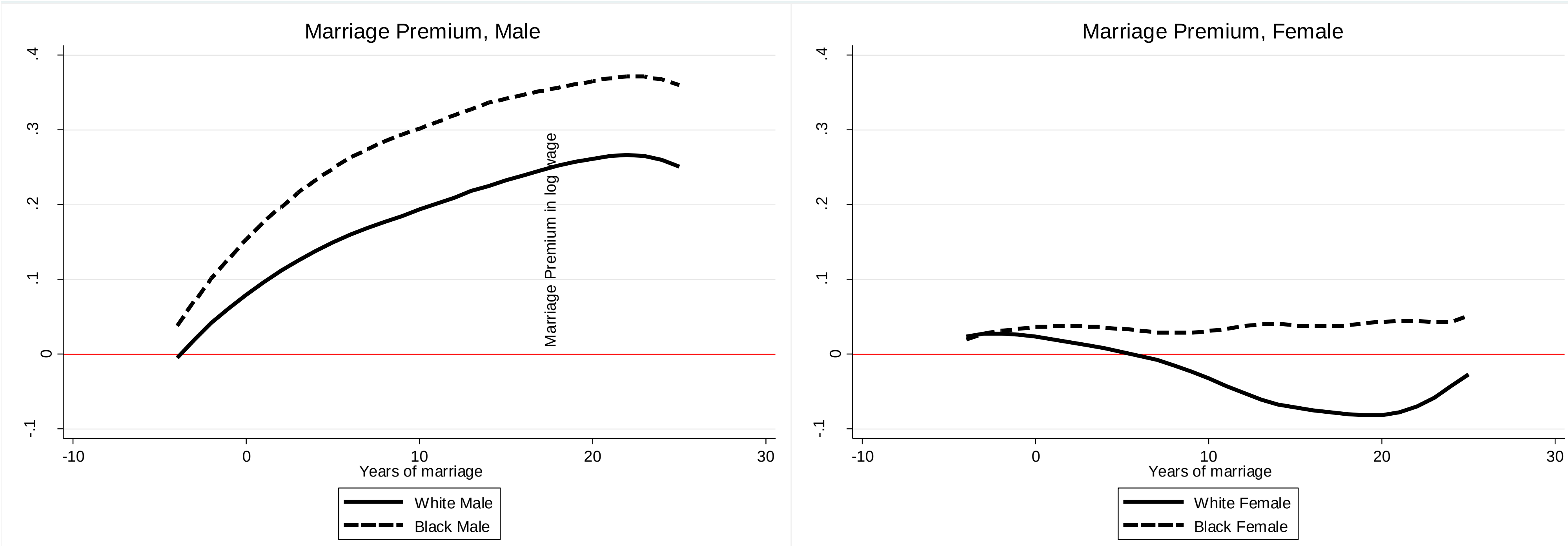
Table 2.G Test for Significance of Changes in MWP by Linear Splines

	(1)	(2)	(3)	(4)
	White Male	Black male	White Female	Black Female
Spline1 (-4-0)	0.0284***	0.0366***	0.00678	0.0161†
	(3.93)	(5.32)	(0.65)	(1.96)
Spline2 (1-7)	0.00832*	0.0124***	-0.00733	-0.00530
	(2.47)	(3.86)	(-1.50)	(-1.39)
Spline3 (8-14)	-0.00225	-0.00457	-0.00810†	-0.00102
	(-0.70)	(-1.49)	(-1.73)	(-0.28)
Spline4 (15-20)	0.0125*	0.0110*	-0.0140*	0.0209***
	(2.83)	(2.60)	(-2.18)	(4.17)
Constant	0.0957***	0.158***	0.0423†	0.0632**
	(6.19)	(10.73)	(1.88)	(3.60)
N	25	25	25	25

NOTE: Data Source: National Longitudinal Survey of Youth 1979-2010, Bureau of Labor Statistics. Standard errors are presented in parentheses. *** p<0.001; ** p<0.01; * p<0.05; † p<0.1. Estimation is based on the coefficients on the dummies for years of marriage as presented in the baseline model of the total effect of marriage, with no controls for childbearing and work experience.

Appendix N
Sensitivity Analysis 2: Alternative Control for Selection out of Marriage

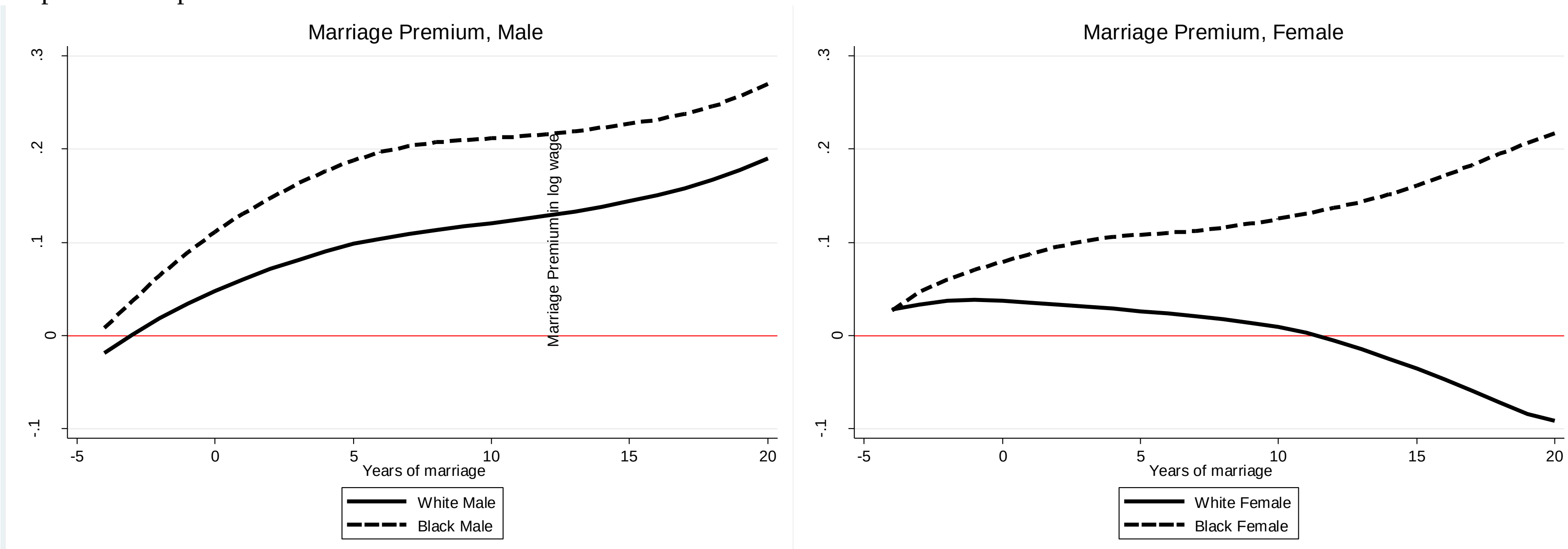
Figure 2.H Selection-adjusted marriage premium in total effect model, with selection out of marriage controlled for by interacting the proportion of total years in sample spent divorced and potential experience



NOTE: Data Source: National Longitudinal Survey of Youth 1979-2010, Bureau of Labor Statistics. The models also include a dummy for a person being either divorced or married but separated from their spouse. The models control for selection into marriage by including the interaction between age at first marriage and potential experience, and control for selection out of marriage by including the interaction between the *proportion* total years of divorce among all years in the sample and potential experience. The models control for potential experience and its square term. Other baseline controlling variables include and the interactions between educational attainment (coded as high school and below, college educated, and beyond college education) with potential experience.

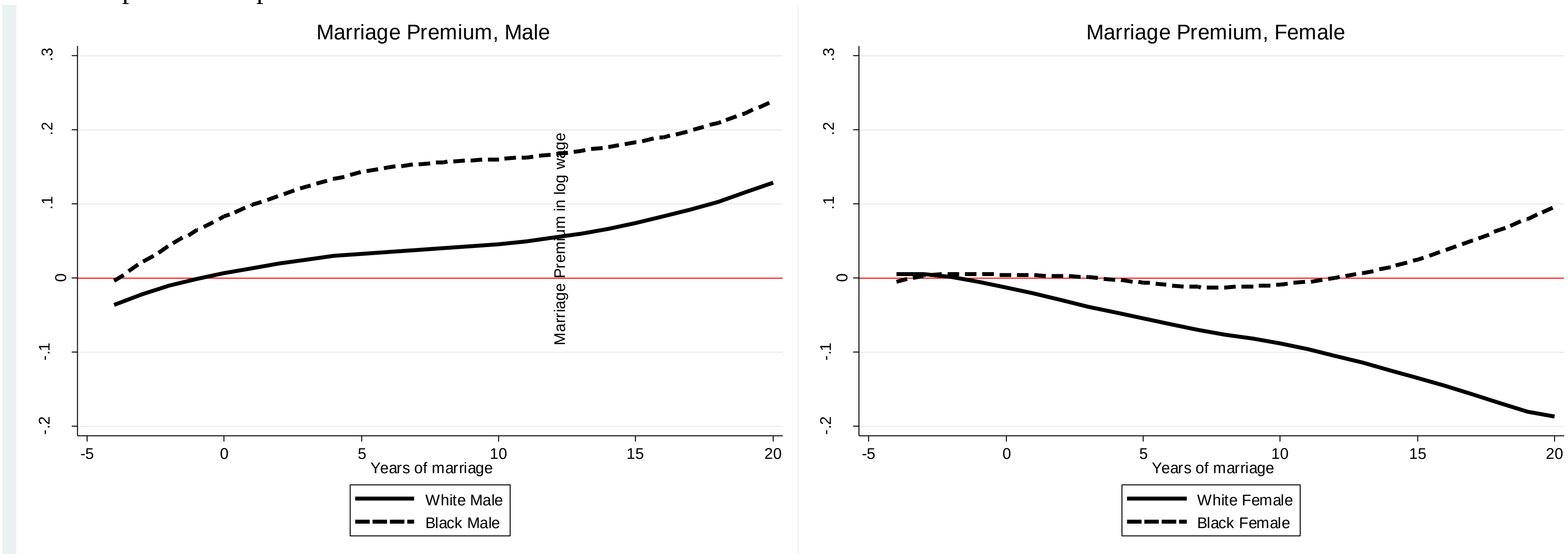
Appendix O
Sensitivity Analysis 3: Alternative Specifications for Potential Experience

Figure 2.I1. Selection-adjusted marriage premium in total effect model, with logarithm of potential experience included as control for potential experience.



NOTE: Data Source: National Longitudinal Survey of Youth 1979-2010, Bureau of Labor Statistics. The models also include a dummy for a person being either divorced or married but separated from their spouse. Control for potential experience is done by including the logarithm of potential experience in the independent variable in the fixed-effect models. The models control for selection into marriage by including the interaction between age at first marriage and potential experience, and control for selection out of marriage by including the interaction between the *proportion* total years of divorce among all years in the sample and potential experience. Other baseline controlling variables include and the interactions between educational attainment (coded as high school and below, college educated, and beyond college education) with potential experience.

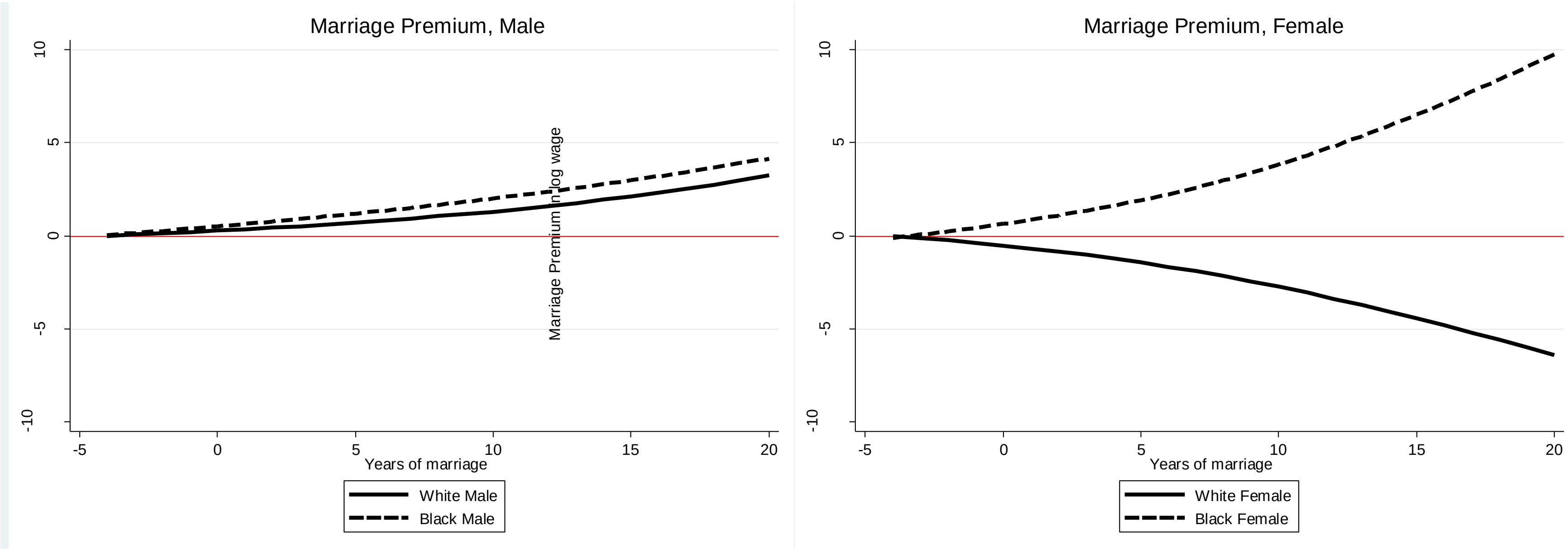
Figure 2.I2. Selection-adjusted marriage premium in total effect model, with linear splines of potential experience included as control for potential experience.



NOTE: Data Source: National Longitudinal Survey of Youth 1979-2010, Bureau of Labor Statistics. The models also include a dummy for a person being either divorced or married but separated from their spouse. Control for potential experience is done by including five linear splines of potential experience (splines separated by knots of 5, 10, 15, and 20 years of potential experience) in the independent variable in the fixed-effect models. The models control for selection into marriage by including the interaction between age at first marriage and potential experience, and control for selection out of marriage by including the interaction between total years of divorce among all years in the sample and potential experience. Other baseline controlling variables include and the interactions between educational attainment (coded as high school and below, college educated, and beyond college education) with potential experience.

Appendix P
Sensitivity Analysis 4: Restricting to First Marriage and Childless Years

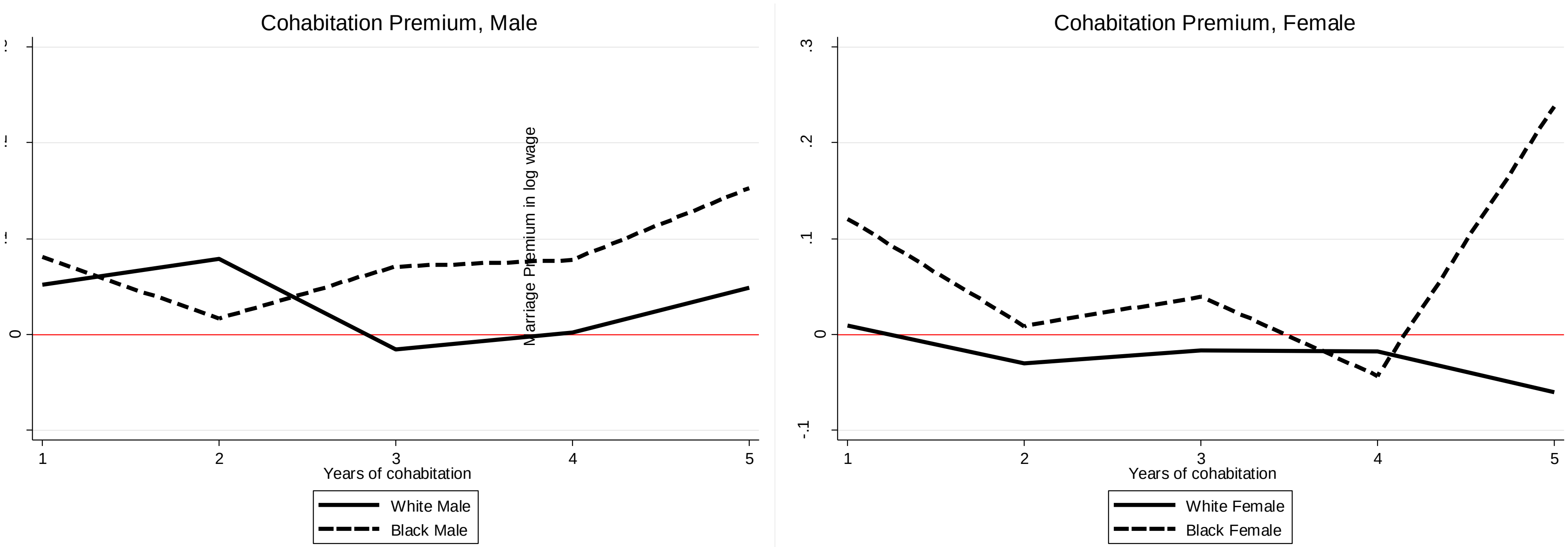
Figure 2.J. Selection-adjusted marriage premium in total effect model, with sample restricted to first marriage, childless years



NOTE: Data Source: National Longitudinal Survey of Youth 1979-2010, Bureau of Labor Statistics. The models also include a dummy for a person being either divorced or married but separated from their spouse. Control for potential experience is done by including a linear and square term in the independent variable in the fixed-effect models. The models control for selection into marriage by including the interaction between age at first marriage and potential experience, control for selection out of marriage by including the interaction between the *proportion* total years of divorce among all years in the sample and potential experience, and control for selection of childbearing is by the interaction between age at first birth and potential experience. Other baseline controlling variables include and the interactions between educational attainment (coded as high school and below, college educated, and beyond college education) with potential experience.

Appendix Q
Sensitivity Analysis 5: Replicating the Analysis on Cohabitation History

Figure 2.K. Estimated cohabitation premium in total effect model



NOTE: Data Source: National Longitudinal Survey of Youth 1979-2010, Bureau of Labor Statistics. The analytic sample contains individuals who are never-married. Cohabitation premium is defined as the wage difference between those with k years of cohabitation and those who are not cohabiting. The fixed-effect models control for potential experience and its square term. Other baseline controlling variables include the interactions between educational attainment (coded as high school and below, college educated, and beyond college education) with potential experience.

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Chapter 4 Risk-Sharing in the Family: Within-couple Inter-temporal Responsiveness in Labor Market Activities

INTRODUCTION

Family has long been regarded by sociologists as the core structural unit in the stratification system. Recently, the theoretical orientation of family research has undergone three major reforms. The first is the shift from the unitary perspective, which describes a family's socioeconomic position by the attainment of the male household head (Goldthorpe, Llewellyn, & Payne, 1980; Sewell & Hauser, 1975), towards the individualistic perspective that recognizes the autonomy of every individual member, particularly every woman (Drobnic & Blossfeld, 2001; Sorensen & McLanahan, 1987; Sweeney, 2002). The second is the shift from the static perspective, which emphasizes the cross-sectional variations in socioeconomic status that are linked to the intergenerational transmission of advantage (Blau & Duncan, 1967; Hout, 1984; Sewell & Hauser, 1975), towards the life course perspective, which emphasizes the intragenerational mobility of life conditions (DiPrete, 1981, 2002; Rosenfeld, 1992; Sørensen, 1975; Warren, Sheridan, & Hauser, 2002; Western, Bloome, Sosnaud, & Tach, 2012). The third is the shift from construing the family as a resource-sharing institution, in which family members share resources that are crucial for their well-being (Coleman, 1988; Duncan & Brooks‐Gunn, 2000; Sara McLanahan, 2004), towards viewing the family as a risk-sharing institution, in which family members adjust their behaviors according to each others’ so as to buffer against external uncertainties that affect total well-being of the family (Cooper, 2014; DiPrete, 2002; Western et al., 2012).

These three theoretical shifts have strongly influenced family stratification research in recent years, in part because they align well with two ongoing empirical trends in US society. The first trend is rising female labor participation (Drobnic & Blossfeld, 2001; Goldin, 2002; McCall & Percheski, 2010; Pencavel, 2006; Sweeney, 2002), which highlights the importance of female household members’ contributions to the family’s financial resources as well as the growing role females play in the family’s decision making. The second is the growing significance of economic insecurity and instability (Gottschalk & Moffitt, 2009; Hacker & Jacobs, 2008; Kalleberg, 2009; Western et al., 2012), which makes it necessary for social institutions such as the family to function as a “safety net” that buffers against external risks to its members (DiPrete & McManus, 2000; Western et al., 2012). In addition, potential empirical investigations are made possible by the ongoing effort in data collection to obtain more detailed information on individual-level, long-term longitudinal data (Cheng, 2014; Elder Jr & Giele, 2009). Individual-level data, as opposed to household-level measures, allows the researcher to gauge the behaviors of specific individual family members. The long-term longitudinal design allows the researcher to link outcomes of individual persons into trajectories or sequences of life, which then facilitates the investigation of within-person changes over the lifetime.

Despite the growing significance of these theoretical shifts in family research, their empirical applications have just started to accrue and remain far from adequate. The current literature suffers from two major limitations. First, in examining the implications of risks to families and their individual members, prior works often characterize risks by the occurrence of adverse events (i.e. “negative shocks”), such as job displacement (Brand & Thomas, 2014; DiPrete, 1981; Lundberg, 1985; Stephens Jr, 2001) and family dissolution (Cherlin, Chase-Lansdale, & McRae, 1998; Smock, Manning, & Gupta, 1999). These discrete events, however, represent only a very small and particular share of individuals’ experiences in their social and economic lives. A family may experience substantial year-to-year fluctuations in well-being even absent these events. Second, while existing works have started to move from cross-sectional observations towards longitudinal analysis, prior longitudinal analyses often draw on data that cover a short period of time ranging from a few months to less than five years (e.g. Juhn & Potter, 2007; Lundberg, 1985; Pencavel, 2006; Spletzer, 1997). Since individuals may vary considerably in their timing of many important life course transitions such as job mobility and childbearing, limiting the analysis to a short time period may ignore a sizable share of changes in labor market activities that occurred outside of the observation window.

This paper aims to cross-fertilize these three theoretical shifts in family research through an in-depth examination of the case of within-couple inter-temporal responsiveness in labor supply among married couples. Specifically, I define the within-couple inter-temporal responsiveness as the temporal adjustments in one’s labor supply according to the spouses’ labor market activities. These adjustments will occur, for example, when the wife increases her level of labor force participation after the husband experiences low earnings, or when the husband works more than normal hours after the wife retreats from the labor market. I argue that such within-couple inter-temporal responsiveness, if found to be true, will serve as empirical evidence that the individualistic, life course, and risk-sharing perspectives are better suited for contemporary family research than the unitary, static, and resource-sharing perspectives.

First of all, within-couple inter-temporal responsiveness in labor supply stems from the individualistic perspective, because to study how individual family members respond to each other, we should first recognize individual family members as independent, goal-oriented agents that interact with each other in decisions about their labor market behaviors. Second, the inter-temporal nature of these within-couple dynamics points to the significance of the life course perspective, because these temporal changes in individual behaviors and corresponding inter-temporal adjustments unfold gradually over the life course. And most importantly, within-couple inter-temporal responsiveness provides an excellent case for the function of the family as a risk-sharing institution. On the one hand, marriage is one of the most common forms of family formation. And since the husband and wife commit to providing financial support for each other, they likely consider their spouses' labor market activities in making their own labor market decisions. On the other hand, given the dominant pattern of marital age homogamy, it is more common for the husband and wife to be at similar life course stages than for other family relations such as parents and children. Hence, married couples are likely to share similar life experiences, such as the birth of a child, as well as similar domestic responsibilities, such as taking care of their parents and in-laws. These similarities make it likely and possible for the husband and wife to maintain economic stability through collaboration. For example, if the husband experiences a drop in his wage, the wife may change from a part-time job to a full-time job, or work more hours in order to compensate for the husband's lost earnings. As such, individuals connected by family ties are able to protect themselves against economic insecurity and instability.

I then conduct an empirical analysis to investigate the existence of, and heterogeneity in, the responsiveness of the individual's labor force participation to his or her spouse's labor market activities. My key outcome measures include a continuous indicator of the total number of hours a person works annually, a categorical indicator of the total number of hours a person works, and categorical indicators of the person's work status: not working, working part-time, working full-time, or working overtime. My key independent variables are the spouse's one-year-lagged labor market outcomes, including annual earnings, total number of hours worked, and hourly wage. I adopt several identification strategies to aid the causal interpretation of the analysis: I first employ fixed-effect models to control for the couple-specific fixed effect, then use time-varying covariate controls to net out potential confounders such as childbearing and family size, and lastly use the individual's own lagged labor force participation variable to block out the influence of time-varying unobserved variables. My analysis accounts for two dimensions of responsiveness heterogeneity. Hypothesizing that the persisting gender roles in the family may lead to greater responsiveness of women than of men to spouses' outcomes, I examine within-couple responsiveness for males and females separately and test for gender differences in the degree of responsiveness. Hypothesizing that the presence of a greater number of children, and a young child in particular, may increase the necessity of a stable income flow to the family, I test whether such responsiveness is associated with parenthood status.

Applying these models to the National Longitudinal Survey of Youth 1979 data, I show that the wife tends to adjust her labor supply according to the labor market outcomes of her husband, such that if the husband earns less annual income, works fewer hours, or receives a lower hourly wage, the wife is likely to increase the amount of hours she works annually or to transition from lower-labor-supply to higher-labor-supply work status. However, no such behavior is found for the husband. In addition, the wife's responsiveness in labor supply is greater when there is a young child present in the household. These findings provide evidence of within-family risk-sharing in the real world and point to the importance of considering gender and childbearing when studying such risk-sharing behaviors.

Finally, I conclude by suggesting that the case of within-couple inter-temporal responsiveness points to new directions of family research that align well with the individualistic, life course, and risk-sharing perspectives. Drawing on the empirical results, I will discuss the case of within-couple inter-temporal responsiveness in the context of four lines of sociological inquiries: (1) the functions of family in the contemporary society; (2) the dimension of "risk" in social inequality; (3) the proper unit of analysis in stratification theories; (4) gender in the family.

THREE THEORETICAL SHIFTS IN FAMILY RESEARCH

Scholarly understandings of the nature and functions of family in the modern society are strongly influenced by what theoretical perspectives we adopt. And the popularity and pertinence of these perspectives in the research literature evolve with time. In recent decades theoretical orientations on family research have undergone three major transformations: (1) from unitary to individualistic, (2) from static to life course, and (3) from resource-sharing to risk-sharing. This section discusses these theoretical shifts, focusing particularly on how they may be brought in to understand within-family dynamics in the contemporary society.

From the Unitary towards the Individualistic Perspective

It is a long-standing tradition for stratification research to consider the family as the primary unit of stratification, yet, the issue of how to best describe the position of a family in the stratification system has been constantly questioned and debated. It was once the common practice for stratification research to adopt the unitary perspective, relying on the fundamental assumption that the socio-economic position of a family can be sufficiently captured by the attainment of the male household head (Erikson, Goldthorpe, & Portocarero, 1979; Erikson, 1984; Goldthorpe, 1983). This unitary perspective on family is also consistent with what functionalists sees as a "functional necessity," as it facilitates the assignment of the offspring to proper social status (Giddens, Duneier, Appelbaum, & Carr, 2000; Parsons, 1953).

A sizable literature has challenged the assumptions underlying the unitary perspective, arguing instead that with the rise of married women's labor market participation, the socioeconomic standing of a family can no longer be reduced to the standing of the male household head (Acker, 1973; DiPrete, 2002; Sorensen & McLanahan, 1987; Sørensen, 1994). Observing that the traditional nuclear family in which the wife completely depends on the husband has been declining, Acker (1973) posited that women's position in the total social structure will become a more legitimate sociological problem. Two decades later, Annemette Sørensen (1994) further developed arguments that while the empirical evidence is to some extent in favor of the conventional approach, there seem to be sufficient grounds for recommending the incorporation of women's outcomes in stratification studies, given the changes that have taken place in women's economic roles.

These changes in the labor market and the family continued into the current era, when the dominant patterns of American families have transitions from the male bread-earner families to the prevalence of dual-earner families, accompanied by the decline of gender wage gap in the labor market (Drobnic & Blossfeld, 2001; Goldin, 1994, 2002; Moen, 1992; Sayer, Casper, & Cohen, 2004). In the traditional male-headed family, the amount of financial resources available to the family depends primarily on the earnings of the husband. However, with a growing number of women working in the labor market and taking higher-paying jobs, the wife could also play an important role in maintaining the family's total financial resources and economic stability (Goldin, 2002; McCall & Percheski, 2010).

The growing importance of women in the family implies that the unitary perspective may be problematic, as it often reduces a family's economic standing to the household head (Goldthorpe, 1983). One natural solution to this problem is to add women's earnings to the calculation of the family's economic standing. For example, Wright (1989) amended the unitary perspective by decomposing a family's standing into "the totality of direct and mediated class relations" (Wright, 1989, pp. 41). However, I argue that such amendment is still questionable, because it atomizes each individual in the family and thus fails to fully acknowledge the mode of relations and interactions between the individuals. In fact, one key implication of the growing significance of women's economic contribution is that it enables women to engage more equally in negotiations and collaborations with their spouse in their decisions on labor market behaviors. As a result, the family operates as a social environment that hosts constant and dynamic interactions, responses, and adjustments among its members.

Finally, despite the growing significance of women's earnings as an important source of family income, the within-family dynamics remain far from gender-neutral. As numerous studies have indicated, the gender revolution in the labor market is far from complete, as women are still segregated in lower-paying occupations (England, 2005; Petersen & Morgan, 1995; Don Tomaskovic-Devey & Skaggs, 2002), earning lower wages (Goldin, 2002; Tomaskovic-Devey & Skaggs, 2002), and facing substantial barriers to their career advancement (DiPrete & Soule, 1988; Fernandez-Mateo, 2009; Petersen & Saporta, 2004). Meanwhile, gendered norms and display in the family continues to impact the distribution of power and responsibilities in the family (Bittman, England, Sayer, Folbre, & Matheson, 2003; England, 2010; West &

Zimmerman, 2009). In their interpretation of these facts, the unitary and individualistic perspectives differ substantially. Works like Erikson & Goldthorpe (1992), for example, interpreted the finding that employed married women's class identification is more closely associated with their spouse's class than with their own as evidence that the unitary perspective is more preferable. By contrast, I argue that the stalled gender revolution at home and at home indeed endorses the significance, rather than the irrelevance, of the individualistic perspective, for two reasons. First, since gender is fundamentally an attribute attached to the individual, the attention to gender asymmetry in within-family behaviors actually accords with the emphasis of the individualistic perspective. Second, studying within-family interactions through gender lens implies that treating family as a unitary entity runs the peril of overlooking the nuanced *interactions* among individual members within the family, particularly the within-family interactions that develops around gender roles.

From the Static towards the Life Course Perspective

As discussed above, the individualistic approach establishes the individual family members as independent, goal-oriented social actors of interest. Yet, the question remains as to whether individual outcomes are better described as permanent or changing. The conventional intergenerational attainment literature follows from the static perspective, as it often describes a person's socioeconomic attainment by the person's education or occupation which are fixed throughout the adult life (P. M. Blau & Duncan, 1967; Hout, 1984; Sewell & Hauser, 1975). Later works, however, brought up the importance of the intragenerational mobility process that affects the trajectory of attainment over the life course (Cheng, 2014; DiPrete & Eirich, 2006; Sørensen, 1975; Warren et al., 2002). They have explored extensively the patterns by which the individual’s trajectory develops from earlier to later life stages (Elder, Johnson, & Crosnoe, 2003; Elder, 1985; Fernandez-Mateo, 2009; Willson, Shuey, & Elder, 2007). As a whole, these later works invoked the life course perspective in stratification and family research.

Two implications of the life course perspective could bear on the nature and function of the family in the contemporary world. The first concerns between-person associations in life course trajectories. In its most basic form, the between-person connection can be described as “similarity” or “homogamy. For example, a sizable literature has demonstrated that life course trajectories tend to be similar for individuals sharing the same social attributes such as gender, education, and race (Cheng, 2014; Elman & ORand, 2004; Fernandez-Mateo, 2009; Tomaskovic-Devey, Thomas, & Johnson, 2005). Yet, such accounts of the statistical resemblance between individual life course trajectories come from the researcher’s, or the outsider’s point of view. Missing from this line of works is whether and how a person’s life course trajectory can interact directly with the life course trajectories of other family members. In other words, the life course trajectories of family members may be interdependent, not only because these members share the same living conditions, but also because they could engage in constant within-family exchanges, adjustments, and collaborations over the lifetime. These interactions give rise to the co-movements, responsiveness, and interdependence of family members’ trajectories in the long run.

The second implication is the conceptualization of life course risks. In the extreme case of a stable society where individuals can perfectly predict or insure against future fluctuations in well-being, taking the life course perspective is almost equivalent to portraying the person’s exact life course trajectory. However, such a stable society does not exist, as the unanticipated fluctuations are always part and parcel of socioeconomic attainment in the modern society

(Cheng, 2014; DiPrete, 2002; Sorenson, 2000). As DiPrete (2002, pp.273) described, “even common “transitory” fluctuations in income may not be adequately anticipated by many people.” This brings up the importance of considering the concept of “risk” when we study the individual life course. Sorenson (2000), for example, established the concept of living conditions, and argued that there are substantial class differences in the level of uncertainty in living conditions. DiPrete (2002) follows up Sorenson’s argument and further illustrated that life conditions cannot adequately be defined at the individual level, because the living conditions of individuals depend on how the impact of past life course risks is shared by the household. Following this argument, the incorporation of life course risks into the life course perspective in family research makes it imperative to further consider the function of family in insuring against these risks, which will be the core argument in the next theoretical shift to follow.

From the Resource-sharing towards the Risk-sharing Perspective

The preceding paragraphs established the importance of incorporating individuals’ life trajectories and life course risks in the study of family. However, my discussion above did not explicitly address why and how family members would act to buffer against these life course risks. This leads us to the third theoretical shift in family research: the shift from viewing the family as a resource-sharing institution towards a risk-sharing institution.

Family is, first and foremost, a social unit in which individuals pool and share their resources. A sizable body of research has shown that these family resources are crucial determinants for demographic transitions such as marriage and childbearing (Michael & Tuma, 1985; Schneider, 2011), the achievement of offspring (Coleman, 1988; Duncan & Brooks-Gunn, 2000; Sara McLanahan, 2004), and individual attitudes (Dominitz & Manski, 1996; McHugh, Gober, &

Reid, 1990; Sorenson, 2000). This resource-sharing perspective has been the central focus of intergenerational mobility research and status attainment research.

And yet, if family operates merely as a resources-sharing unit, then it can be reduced to no more than the aggregate of atomized individuals. It then follows that the well-being of the family can be easily summarized by adding up the amount of resource available to each family member. This assertion is problematic, because it downplays the importance of family ties as social relations that hold them as a group. As Annemette Sørensen (1994) pointed out, "Research on those aspects of the stratification or class system that are linked to the pooling of resources and the sharing of living conditions clearly must consider the interdependence among the members of the group that shares resources and living conditions. This group is usually the family."

More importantly, the interdependence among family members could operate as a social mechanism through which the life course risks to the family can be reduced. It is particularly fitting to discuss this mechanism against the backdrop of the recent growth of economic instability and insecurity in contemporary American society (Gottschalk & Moffitt, 2009; Hacker, 2008; Karen, Douglas, & Daniel, 2012). Economic instability causes unstableness of family financial resources and limits the family's short-term consumption, particularly in years of unexpected low income (Osberg & Sharpe, 2002; Western et al., 2012). In extreme cases, economic instability may even pose risks of severe financial difficulty or poverty (Gottschalk, Moffitt, Katz, & Dickens, 1994; Hacker & Jacobs, 2008). Fluctuations and uncertainties are incurred by individual wage-earners in the labor market, but when these individuals combine into families and relate to each other in their daily lives, they may be able to jointly mitigate the external risks with other family members through their dynamic interactions. For example, within-family risk pooling may take place when a perceived decrease in the earnings of one family member is followed by a compensatory increase in the earnings of another family member, or when an increase in the labor force participation of one family member is responded by a retreat from the labor market of another family member. As a result, these family members enjoy more stable financial resources, and thus are better-off with these within-family interactions than if they had acted as unrelated and isolated individuals. This in turn signifies the family as a meaningful social institution which functions above and beyond isolated individuals.

Accompanying this empirical trend of growing economic insecurity is the emerging stratification literature that explicitly underscores the function of family as a risk-sharing institution in the stratification system. DiPrete (2002) illustrated that when faced with life course risks for downward mobility, individuals, when formed into a household, have "the opportunity for rapid recovery provided by counter-mobility events such as reemployment, upward occupational mobility, or remarriage" (pp.278). Similarly, Western et al. (2012) described risk pooling that smoothes incomes over time as a collective endeavor in which household and family ties could play a crucial role in insuring against income instability. Western, Bloome, & Percheski (2008) showed empirical patterns consistent with this risk-sharing argument that the within-group variance in log income – an indicator of the economic volatility of the household – is lowest for two-parent families with a working mother.[64] These works point to the importance of considering the family, as opposed to the individual, as the key stratification units, because the collaborations among family members to buffer against risks clearly demonstrate some collective

[64] Another line of works suggest that family members may offset transitory earnings fluctuations by adjusting their consumption or by self-insuring through family savings (e.g. Dynarski et al. 1997; Guariglia and Kim 2004; Guiso, Jappelli, and Terlizzese 1992; Morduch 1995). While consumption adjustment and savings are effective mechanisms to reduce the negative consequences of economic instability, they typically occur *after* earnings are obtained from the labor market. But because insecurity in earnings takes place first and foremost in the labor market, I emphasize that family members may adjust their career decisions according to the past labor market outcomes of another family member, *before* they resort to any post-earnings insurance strategies such as consumption adjustment or savings.

protective power that goes beyond isolated individuals (DiPrete, 2002; Western et al., 2012).

AN EMPIRICAL CASE: WITHIN-COUPLE INTER-TEMPORAL RESPONSIVENESS

Why This Case?

The previous section has discussed the development of three theoretical shifts in family research. Whether these theoretical shifts are useful in sociological research depends on whether they could be matched to patterns and cases in social reality. As mentioned earlier, current empirical studies of the dynamics in the family have not well-matched the growing significance of these theoretical shifts, for two major reasons. First, risks to the family are often characterized by the occurrence of adverse events, such as job displacement (Brand & Thomas, 2014; DiPrete, 1981; Lundberg, 1985; Stephens Jr, 2001) and family dissolution (Cherlin et al., 1998; Smock et al., 1999). DiPrete (2002), for example, called attention to the implications of these discrete events and their socioeconomic consequences to the life course mobility of individuals and families. However, while the author recognizes that the consequences of these discrete events could be related to fluctuations in the socioeconomic standings, the analyses are essentially events-centered, revealing little about whether these fluctuations, by themselves, have implications for the behaviors of household members. The next key step of such life course mobility analysis is to move towards the analysis of year-to-year fluctuations in economic well-being that are defined and measured continuously.

Second, the growing availability of longitudinal data has prompted recent studies on family and work to move from cross-sectional observations towards longitudinal analysis. Yet, previous longitudinal analyses tend to rely on data that cover only a short period of time ranging from a few months to less than five years (e.g. Juhn & Potter, 2007; Lundberg, 1985, 1988; Pencavel, 2006; Spletzer, 1997). While these works are important first steps in our scholarly inquiries, such short-term analysis suffers from two major limitations. On the one hand, individuals may vary considerably in their timing of many important life course transitions, such as job mobility and childbearing (Fuller, 2008; Hynes & Clarkberg, 2005; Looze, 2014). A short time period may only capture a small and very limited share of these life transitions, missing a sizable share of observations of life course transitions occurring outside of the observation window. On the other hand, the statistical efficiency of the estimation of inter-temporal associations relies critically on the amount of variation over time versus the amount of between-person variation. A short observation period could make the estimation subject to more measurement error, as within the period there may not be enough observations for each person to precisely estimate and rule out the influence of the person's fixed effect.

To address these two limitations, this paper focuses on the within-couple inter-temporal responsiveness in labor supply over the long-term marital life course as an empirical case that integrates and illustrates the importance of the three theoretical shifts. My conceptualization of the within-couple inter-temporal responsiveness describes the phenomenon in which one adjusts one's labor force participation according to the spouses' labor market outcomes, including annual earnings, hourly wage, and amount of hours worked annually, so as to reduce the external fluctuations in their wellbeing. Here, by focusing on *within-couple* changes, I rule out from my conceptualization the spousal associations due to marital sorting (Lundberg, 1988); and by focusing on *inter-temporal* responsiveness, I highlight the dynamic within-couple adjustments that occur gradually over the long-term marital life course.

How does this empirical case engage the three theoretical shifts? Figure 9 provides a conceptual illustration of how the within-couple inter-temporal associations can be viewed through the lenses of three theoretical shifts discussed in the previous section.[65] The top two graphs show that the unitary perspective characterizes the family as a stratification unit dominated by the male household head and his wife, whereas the individualistic perspective conceptualizes the family as two equal and interacting individuals. The middle two graphs show that the static and life course perspective considers the lives of the husband and wife differently: the former treats the husband and wife as playing two fixed roles and marginalizes the variable of time, while the latter extends the focus of analysis from "dots" to "trajectories" that unfold gradually over the life course.

Finally, the bottom two graphs of Figure 9 show how the within-couple inter-temporal responsiveness accords with the transition from the resource-sharing perspective to the risk-sharing perspective. Under the resource-sharing perspective, the family is a simple aggregate of the life course trajectories of the husband and wife, and the two spouses are assumed to journey through their life courses without interactions between their life course trajectories. The risk-sharing perspective, by contrast, recognizes the dynamic, inter-temporal associations in the husband and wife's life course trajectories that are needed for reduce thing overall income flows to the family. These inter-temporal associations are indicated by the arrows coming back and forth between the husband and wife's life trajectories in the bottom-right graph. Under this risk-sharing perspective, the grouping of individuals by marriage is meaningful, not just because the spouses choose to share resources over a period of time, but also because they

[65] It would be interesting, particularly in the new era, to consider the dynamics of same-sex couples. But for simplicity, I focus on heterogeneity couples in the current study.

could engage in the dynamic cooperation between themselves over their marital life course.

Relation to Existing Theories

Next, I discuss my conceptualization of within-couple inter-temporal responsiveness in relation to several existing theories on marriage and family. First, there are important distinctions between my conceptualization of within-couple inter-temporal responsiveness and Becker's specialization theory. The specialization theory sees marriage as a social institution in which the husband and wife makes the joint decision to specialize in different divisions of labor (Becker, 1991; Hersch & Stratton, 2000; Kenny, 1983; Waite & Gallagher, 2002). As such, the specialization theory involves the interactions and joint decisions between the husband and wife, which is consistent with the individualistic perspective in family research. Yet, it implicitly assumes that, once the couple has decided on a specialization scheme, they will be no uncertainties or fluctuations in their labor market activities and outcomes. In other words, the specialization theory ignores the temporal changes – particularly those undesirable changes – that occur over the marital life course, as well as the inter-temporal responsiveness to these changes. This explains a sharp difference in prediction from my analysis and that from Becker's theory: Becker's theory predicts the function of family as a social institution will decline because women's enhanced position in the labor market renders household specialization less valuable, while by contrast, I predict that the increase in women's labor force participation makes it more possible for them to act responsively to their husband's labor market outcomes and therefore strengthens the role of the family as a risk-sharing institution.

Another important distinction between specialization theory and my conceptualization of within-family risk-sharing behaviors is that they assume different mechanisms for the association between the husband and wife's labor market activities. The specialization theory implies a negative association between the husband and the wife's labor force participation after getting married, because it predicts that men will allocate more time in the labor market and women in the family. Hence, after controlling for men's work hours, men's hourly wage rate – a measure of productivity rather than time allocation – should not affect women's labor force participation. If, however, married couples adjust their labor force participation not just as an act of household specialization, but also as a dynamic strategy to defend against earnings uncertainty, then we should expect that women's labor force participation will respond negatively to their spouse's hourly wage, even after the spouse's labor force participation is controlled for. This distinction makes it possible for my analysis to test whether within-couple risk-sharing behaviors exist in addition to conventionally household specialization.

Second, my conceptualization of within-couple inter-temporal responsiveness can be seen as a more general form of the added-worker effect. The "added-worker effect" literature describes the phenomenon in which the wife increases her labor market participation in the event of her husband's unemployment, so as to provide a "spousal safety net" that compensates for the forgone earnings (Lundberg, 1985; Stephens, 2001). Yet, works following this perspective tend to focus on the impact of an adverse event, such as involuntary job loss, on the behavior of other family members (DiPrete & McManus, 2000; Heckman & MaCurdy, 1980; Stephens Jr, 2001). The occurrence of these particular adverse events, however, represents only a very small and particular share of individuals' experiences in their social and economic life. Instead, my analysis asks a more general question about whether, even in absence of the occurrence of adverse events, married couples collaborate by acting responsively to each other's labor market outcomes so as to reduce economic instability and insecurity.

Third, my conceptualization of within-couple responsiveness engages the growing literature on the deinstitutionalization of marriage and the need to consider alternative bases for modern marriage (Amato, 2004; Burgess & Cottrell, 1939; Burgess & Locke, 1945; Cherlin, 2004; Coontz, 2004; Lauer & Yodanis, 2010). Burgess & Cottrell (1939) observed the weakening institutional basis of marriage and the emergence of companionate marriage. Following this line of argument, Cherlin (2004) further discussed the transition from companionate marriage to individualized marriage beginning in the American society in the 1960s. The marker of the individualized marriage is the declining influence of social norms on family and personal life and the rise of self-development, negotiations, communications and openness within marriage (Cancian, 1990; Cherlin, 2004). One important implication of this deinstitutionalization view on marriage is that, individuals nowadays form marriage, not just because social values told them to, but more importantly, because they choose to share life with each other in their separate yet mutual pursuit of personal interests and rewards. If we consider more stable income flows and lower economic insecurity as part of the mutual interests that individuals pursue in marriage, then the within-couple inter-temporal responsiveness can be seen as a manifestation of the actions taken by the husband and wife to realize the value and enhance the quality of their individualized marriage.

HETEROGENEITY IN THE DEGREE OF RESPONSIVENESS

My earlier discussion in the theoretical section points to the importance of considering the heterogeneity in the degree of responsiveness within married couples. One important implications of the individualistic perspective is that personal attributes may affect modes of interactions with other family members. Meanwhile, central to the life course perspective is the notion that individuals' behaviors are contingent on the context of the life cycle (Elder, 1985; Mayer, 2009).[66] Following these perspectives, analysis in this paper further considers two sociologically-meaningful dimensions of heterogeneity in degree of responsiveness.

Gender and Degree of Inter-temporal Responsiveness

First, I argue that the within-couple decision-making process may turn out to be a locale where gender roles in the family are manifested, strengthened and even reproduced. While women's labor market participation has increased in recent years, due to the persistence of the gendered division of labor within married couples, the husband may continue to be considered the primary income earner in the family and the wife the secondary source of family income, or the "added worker" to the family (Bianchi, Sayer, Milkie, & Robinson, 2012; Goldin, 1994; Jacobs & Gerson, 2004; Lundberg, 1985). This could happen when the traditional gender role persists in the family domain and has an impact on the division of responsibilities between the husband and wife (Cooke, 2006; Cotter, Hermsen, & Vanneman, 2011; Hochschild & Machung, 1989; West & Zimmerman, 1987), or when barriers to women's entry and promotion continue to operate in the workplace (England, 2010; Tomaskovic-Devey & Skaggs, 2002; Yang & Aldrich, 2014), which can discourage women from prioritizing their careers. By contrast, for men, behaviors in the family and in the labor market can be viewed as symbols for their masculinity, a phenomenon commonly referred to as "doing gender" or "gender display" (Bianchi, Milkie, Sayer, & Robinson, 2000; Goffman, 2007; West & Zimmerman, 1987). As an act of "doing gender", men

[66] Waite (1980), for example, illustrated that in making decisions on labor market participation, wives tend to weigh factors differently at different life cycle stages.

may not always reduce their labor force participation when their spouse's earnings are higher, so as to display their masculinity by maintaining their status as the primary breadwinner in the family. If this is the case, one may expect the wife's labor force participation to be more malleable in response to the financial situation of the family than the husband's, a finding that is suggested by earlier works (Cha, 2010; Devereux, 2004; Hyslop, 2001; Pencavel, 2006).

To address the heterogeneity by gender, my analysis will examine the degree of responsiveness for men and women separately:

Hypothesis 1A (men): Men increase (reduce) their labor supply when their wives earn lower (higher) income, lower (higher) wages, or work less (more) hours.

Hypothesis 1B (women): Women increase (reduce) their labor supply when their husbands earn lower (higher) income, lower (higher) wages, or work less (more) hours.

I then test whether the gender difference in the degree of responsiveness is non-zero:

Hypothesis 2 (gender difference): The degree of labor force participation responsiveness to the spouse's labor market activities is greater among women than among men.

Parenthood and Degree of Inter-temporal Responsiveness

Indicators of parenthood status may work as a moderator of the effects of spousal labor market outcomes on the individual's labor market activities. Because economic instability, especially the implied risks of poverty, is particularly harmful for the well-being of children (Brooks-Gunn & Duncan, 1997; Duncan & Brooks-Gunn, 2000; McLoyd, 1998), the demand for maintaining a stable income flow and offsetting hazards of family poverty is greater when the wellbeing of the children is taken into consideration in the parent's labor market decisions. Lundberg (1988), for example, found that husbands and wives without pre-school children act like separate individuals, and the negative association in the husband and wife's labor force participation occurs only to couples with more than one pre-school child. Lehrer (1999) also showed that the husband's income depresses female employment most strongly when preschoolers are present in the home. Moreover, given that the economic costs associated with raising children have risen in recent years (Casper & O'Connell, 1995; England & Folbre, 1999), financial difficulties in child-raising are usually beyond what can be solved by borrowing money from elsewhere in short term, and thus maintaining a substantial amount of financial resources in the family is particularly important to couples with children in the household. Therefore, I expect the degree of responsiveness in the couple's labor market activities to be greater for couples with children, particularly those with a young child. Using number of children and age of the youngest child as indicators of parenthood status, my analysis will test the following two hypotheses:

> *Hypothesis 3 (number of children): The degree of inter-temporal responsiveness is higher with the presence of a greater number of children in the household.*
>
> *Hypothesis 4 (age of youngest child): The degree of inter-temporal responsiveness is higher with the presence of a younger child in the household.*

RESEARCH DESIGN

Timeline of Analysis

My analysis of within-couple inter-temporal responsiveness relies on data that contain multiple observations for each person. For each person, I focus on the years of his or her first marriage to ensure homogeneity in the nature of marriage. I first line up the married couple's experiences in the order of time. Then, for each couple-year observation, I use the spouse's labor market activities in the previous year (L_{t-1}^{sp}) and the respondent's own labor market activities in the previous year (L_{t-1}^{own}) to predict the respondent's own labor market activities in the current year (L_t^{own}). This specification requires that (1) the two individuals should stay married in both time *t-1* and *t*, and (2) no missing information in L_{t-1}^{sp}, L_{t-1}^{own} and L_t^{own}. By way of demonstration, Figure 10 visualizes the timeline of one hypothetical individual respondent, Respondent R. Respondent R enters the labor market at time point zero, and the numbers in the figure counts the number of years since Respondent R's labor market entry. A circled number means that none of L_{t-1}^{sp}, L_{t-1}^{own} and L_t^{own} is missing, at a non-circled number means that information is missing at this person-year or couple-year. At time 2, Respondent R got married, for the first time in his or her life, to Spouse S. The marriage lasted seven years, until they divorced at time 9. During their marriage, as indicated by the circled numbers, information is available for Respondent R at 2, 3, 4, 7, 8, and 9 years of labor market experience, and available for Spouse S at 2, 3, 6, 7, 8, and 9 years of labor market experience. The arrows in the figure, leading from L_{t-1}^{sp} or L_{t-1}^{own} to L_t^{own}, represent the couple-year observations that will be used in my model estimation. For example, Time 2 is not used as the outcome time point, because this is the year when the couple got married, and thus L_{t-1}^{sp} and L_{t-1}^{own} are not defined prior to this year. Time 7 is not used as the outcome time point, because L_{t-1}^{own} is missing.[67] After the 9th time point, the two persons got divorced, and thus what happened afterwards will not be included in my analysis.

Alternative Mechanisms and Identification Strategies

The theoretical arguments point to the possibility and importance of risk-sharing within married

[67] The fixed-effect model, however, is flexible with missing data and unbalanced spacing of observations across different individuals.

couples. This risk-sharing behavior should be manifested as the negative "treatment effect" of the spouse's labor market outcomes (e.g. earnings, work hours, and hourly wage) on the respondent's own labor force participation. However, in the empirical analysis, the identification of such treatment effects requires the exclusion of several alternative mechanisms by which a husband-wife association in labor market activities may also be induced. Below, I discuss each of the four possible alternative mechanisms and introduce my identification strategies. Table 2 presents a list of alternative mechanisms, along with their corresponding type of confounding effect in statistical language, examples, illustration with directed acyclic graphs (DAG hereafter), and my identification strategies.

The first alternative mechanism is marital sorting on fixed individual attributes, which typically induces a positive cross-sectional association in labor market activities among married couples because individuals with similar traits tend to marry each other (Hout, 1982; Mare, 1991; Schwartz, 2010). The DAG in the first row of Table 9 provides a visual illustration of the confounding effect of marital sorting. *S* represents the couple's shared time-invariant attributes, such as education, race, or family background. For example, *S* could represent the husband and the wife's average level of education. Because individuals tend to marry individuals of the same educational attainment, and given that, in general, educational attainment positively affects the individual's labor force participation at any time point, *S* will positively affect L_{t-1}^{sp}, L_{t-1}^{own} and L_t^{own}. A spurious and positive association between L_{t-1}^{sp} and L_t^{own} will be induced if we do not rule out this confounding effect of *S*. I rule out the influence of marital sorting on individual attributes by adopting the fixed-effect model to control for the individual-specific and couple-specific fixed characteristics, so that the estimated associations between the husband and wife's work hours or wages are entirely due to *inter-temporal variations* within couples, rather than the cross-sectional associations in their labor market activities.

Second, the husband and wife may share similar career trajectories, which could induce spurious associations. For example, the husband and wife may have the same educational attainment, and because individuals with higher educational attainment tend to experience faster career progress (Elman & O'Rand, 2004), the couple's labor market trajectories may move in a similar direction, not because they purposefully adjust their labor market activities, but because their career trajectories tend to follow similar trends. The second row of Table 9 illustrates this confounding effect of trajectory-induced husband-wife association. Such spurious association is not ruled out by the fixed-effect model, because the fixed-effect model only deals with the confounding due to couple's fixed attributes that affect earnings constantly over time. To account for such trajectory-induced spurious association, my fixed-effect models will include controls for the husband-wife association in wage growth rate due to their similarities in educational attainment, cognitive ability, and race.

The third alternative mechanism is the spurious association in the couple's labor market activities induced by their mutual association with observed time-varying confounding variables, such as parenthood status, family size, and total family income. Take parenthood status for example. The specialization theory predicts that married men tend to specialize in market labor while married women specialize in domestic labor. It is thus implied that when demand for domestic responsibilities increases due to events such as childbearing, household specialization will be intensified, resulting in the husband's increasing his labor force participation and the wife incurring a reduction her labor force participation. This in turn induces a "spurious" negative association in the couple's labor market activities. The DAG in the third row of Table 9 illustrates this confounding effect. The graph shows that the observed time-varying confounders, represented by $OTVC_{t-1}$, affect L_{t-1}^{sp}, L_{t-1}^{own} and L_t^{own} simultaneously and induce a “spurious” within-couple inter-temporal association. My analysis addresses this problem by explicitly controlling for these potential time-varying confounders. These controls include number of children in the household, age of youngest child in the household, family size, and the total income to the family.

Lastly, unobserved time-varying confounders may exist to induce spurious within-couple associations. These unobserved confounders may include the changing values towards family and work that affect the behaviors of the husband and wife simultaneously, and the unobserved shocks to the household that induce both the husband and wife to alter their behaviors. To address this problem, I include the respondent’s own labor force participation at time *t-1*, L_{t-1}^{own}. This strategy is visualized in the DAG at the last row of Table 1. Controlling for L_{t-1}^{own} blocks out the confounding effect of unobserved time-varying confounders on the effect of L_{t-1}^{sp} on L^{own} by blocking the path of their effects on L_t^{own} that works through L_{t-1}^{sp}. This identification strategy requires the assumption that given the respondent’s own labor force participation at time *t-1*, the unobserved time-varying confounders are independent of the respondent’s own labor market activities at time *t*. This identification assumption can be formalized as: $\mathrm{UTVC}_{t-1} \perp \mathrm{L}_t^{\mathrm{own}} \mid \mathrm{L}_{t-1}^{\mathrm{own}}$.

DATA, MEASURES, AND MODELS

Data

This study uses the National Longitudinal Survey of Youth 1979 data (NLSY79 hereinafter), a longitudinal study that follows a nationally representative sample of 12,686 young people aged

14 to 22 when they were first surveyed in 1979. These individuals were interviewed annually through 1994 and biennially thereafter. The major advantage of the NLSY79 dataset for the purpose of this study is that it provides rich information about the temporal variations of individuals' labor market experiences, as well as family domain transitions, which stretch across more than 30 years within a cohort of population. The analytic sample consists of an average of 5.8-6.5 couple-year observations per respondent, with a maximum of 22 couple-year observations per respondent. As discussed earlier, sufficient within-couple long-term temporal variation is crucial for modeling and estimating the within-couple inter-temporal associations in labor market activities.[68] My analysis draws on all currently available waves (1979-2010) of the NLSY79 data. The sample is weighted in the analysis.

In the NLSY79 data, when a spouse is present, the respondent will be asked about information on the spouse's work-related experiences and outcomes. Cautioning that individuals may behave in different ways in first and later marriages, I restrict the analytic sample to the couple-years pertaining to the individual's first marriage so as to retain relatively homogeneous marriage experiences. Because I focus on the respondent's years in first marriage, the NLSY79 respondent's married person years are equivalent to couple years, and for simplicity, the rest of this paper will refer to the unit of analysis as couple years.

Measures

I use two key dependent variables to describe the respondent's labor market activities. The first is a categorical indicator of work status, which contains four mutually exclusive categories: (1)

[68] Yet, because of the dataset's relatively homogeneity in the range of birth years, one should take caution when generalizing results based on this dataset to other cohorts.

non-working; (2) working part-time (less than 35 hours per week); (3) working normal hours (35 to 50 hours per week); and (4) working overtime (more than 50 hours per week). The second is the logarithm of annual work hours, which is the total amount of hours worked by the respondent in the calendar year. The categorical indicators reflect individuals' adjustment in labor force participation by changing their work statuses, while the continuous indicators reflects their adjustment in work hours in greater granularity (Damaske, 2011; Lundberg, 1985).

The key independent variables include the logarithm of the spouse's total annual income (including income from salaries, wages, and business income), the logarithm of the spouse's annual hours worked and the logarithm of spouse's hourly wage of the most current or primary job for the individual in the previous year. From 1994, the NLSY79 survey schedule changed from annually to every other year, and in cases where a one-year lag is missing, I assume that the labor market activities remain unchanged from the previous year (i.e. two-year lag).[69] The independent variable is lagged by one year for two reasons. First, methodologically speaking, the concurrent labor market experiences of the individual and the spouse are more likely to be confounded by other unobserved time-varying confounders, while using a one-year lagged predictor can reduce such confounding problem, that is, the effects of spousal variables can be assumed to follow a causal direction (Cha, 2010). Second, the organization of the real labor market makes it not likely that one can adjust his or her work hours or change between work statuses instantaneously. Thus, it usually takes some time for the responsiveness to spouse's labor market activities to actualize, which gives us another reason to specify a one-year lag of the

[69] Two robustness checks are conducted in this respect. First, I replaced the one-year lag in the main analysis with the different lengths of lags; Second, I restricted my analysis to pre-1994 years when the NLSY79 interviews are conducted every year. Results are consistent with my main findings, and are available upon request to the author.

independent variables of labor market activities.[70]

Note that for each couple-year observation, I choose to use the spouse's labor market activities to predict the NLSY79 respondent's own labor market activities, but do not use the NLSY79 respondent's labor market activities to predict the spouse's labor market activities. This is because of two concerns. The first is a concern with measurement. The NLSY79 data measures the respondent's and his or her spouse's earnings and work hours differently: the respondent self-reports his or her own labor market activities, while the spouse's labor market information is proxy-reported by the respondent. Hence, in addition to the common measurement error shared by these two self-reported measures, the measures for the spouse's labor market activities are also subject to an additional proxy reporting bias. Such differences in the sources of variation in these two different measures makes it problematic to treat the respondent and spouse's information as symmetric and draw statistical inferences from them as if they were the same dependent variable.[71] Therefore, my analysis consistently uses the respondent self-reported experiences as dependent variables, but not the other way round. The second is a concern with survey design. The nature of the NLSY79 data as a longitudinal individual-based survey means that more detailed covariates, such as cognitive test scores and race/ethnicity, are available for the respondents than for their spouses. Hence, treating the respondent's earnings and work hours as the dependent variable will allow me to control for other important covariates

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70 Appendix Figure 3.A demonstrates the relationship between L_{t-1}^{sp}, L_{t-1}^{own}, and L_t^{own}, as well as the measures for each of these three key indicators.

71 Appendix Table 3.B1 gives the mean and variances of hourly wage, annual work hours, and annual income for the respondent and spouse by age and gender. some interesting discrepancies in the self- and proxy-reported information can be seen from the numbers in Appendix Table 3.A1. For example, consistent across all three age groups, female respondents report lower average hours worked per year as well as hourly wage than what was reported by male respondents of their female spouses. Thus, at lease descriptively, labor market experiences for the respondent and the spouse should be better treated as different measures.

of the respondents, such as age, race and educational attainment, which are crucial for the statistical inference drawn from the models.

Meanwhile, I measure the continuous dependent and independent variables by the logarithm scale, so that the estimated coefficients on these independent variables can be interpreted by the percentage change in the dependent variable caused by the percentage change in the independent variable.[72] In other words, the scale of measurement of these variables will not affect the results. The scale-free feature of this specification is particularly favorable, because it makes it possible to compare the estimated coefficients for different gender or parenthood status groups who are likely to differ in their level of labor force participation or hourly wage.

Other covariates to be incorporated into the models include the linear and square terms of age, race, highest grade completed, standardized cognitive test score (i.e. AFQT score), number of children in the household and age of the youngest child in the household. The respondent's own annual work hours and hourly wage in the previous period are also included in the models. The inclusion of the respondent's own annual work hours is crucial for the identification of within-couple responsiveness, as I will explain in the next section.

Model Specifications

The first set of fixed-effect models assess whether the respondent's likelihood of working in a certain category of work status is affected by the spouse's annual income. Specifically, I first code the indictor of work status (denoted by *S*) as 1 if the individual is not working, as 2 if the individual is working part-time, 3 if the individual is working normal hours, and 4 if the

[72] For example, the coefficient on log spousal annual work hours in predicting the respondent's log hourly wage will indicate the percentage change in the respondent's hourly wage caused by a percentage change in the spouse's annual work hours.

individual is working overtime. The greater the value of S, the more hours the individual works per week. Then, I predict the respondent's probability of working (i.e. $(S \geq 2|S \geq 1)$), probability of working at least normal hours given that the respondent is working (i.e. $P(S \geq 3|S \geq 2)$, and the probability of working overtime as opposed to working normal hours given that respondent is working at least normal hours (i.e. P($(S \geq 4|S \geq 3)$). Formally, the fixed-effect logistic regression model for $P(S \geq s+1 \mid S \geq s)$, is written as follows:

Eq.3.1: $logit(P(S \geq s+1 \mid S \geq s))$

$= \alpha_0 + \alpha_1 age_{it} + \alpha_3 age_{it}^2$	Baseline and age effect
$+ \sum_{j=1}^{J} \beta_j L_{t-1,j}^{own}$	Controlling for own activities
$+ \sum_{k=1}^{K} \gamma_k L_{t-1,k}^{sp}$	Responses to spouse's activities
$+ \sum_{m=1}^{M} \theta_m X_{itm}$	Time-varying controls
$+\mu_i$	Individual fixed effect
$+\omega_{it}$	Residual

In Eq. 1, the linear and quadratic terms of age captures the individual's general trend of change in labor market activities over the life cycle. The set of $L_{t-1,j}^{own}{}'s$ and $L_{t-1,k}^{sp}{}'s$ represent measures for the labor market activities of the respondent and the spouse, as discussed earlier. The set of $X_{itm}{}'s$ includes time-varying controls, including the interaction terms between age and race, between age and education, and between age and cognitive test score, as well as time-varying variables such as parenthood status, family size, and family total income. μ_i captures the respondent's fixed characteristics. The key coefficients of interest in this equation are the $\theta's$, which represents the effect of the spouse's labor market activities on the respondent's likelihood of being in different work statuses. For example, a negative value of the

θ coefficient on the spouse's annual work hours or hourly wage in the equation where *s=1* will suggest that individuals are less likely to be working as opposed to non-working in response to a greater level of labor force participation or a higher level of hourly wage of their spouse.

The second set of fixed-effect models predict the respondent's logarithm of annual work hours at time *t*, denoted by $Hour_t^{own}$, as follows:

Eq.3.2	$Hour_{\mathrm{t}}^{own} = \delta_0 + \delta_1 age_{it} + \delta_2 age_{it}^2$	Baseline and age effect
	$+ \sum_{j=1}^{J} \psi_{\mathrm{j}} \mathrm{L}_{\mathrm{t-1,j}}^{own}$	Controlling for own activities
	$+ \sum_{k=1}^{K} \phi_{\mathrm{k}} \mathrm{L}_{\mathrm{t-1,k}}^{sp}$	Responses to spouse's activities
	$+ \sum_{m=1}^{M} \lambda_{\mathrm{m}} \mathrm{X}_{\mathrm{itm}}$	Time-varying controls
	$+\eta_i$	Couple-specific fixed effect
	$+\epsilon_{it}$	Residual

The independent variables and their coefficients in Eq. 2 are similar to those in Eq. 1 and explanations are provided following each set of independent variables in the above. The key coefficients of interest in this equation are the ϕs, which indicates the effect of the spouse's labor market activities on the respondent's annual work hours. Recall that as illustrated earlier, when annual income, annual work hours, and hourly wage are included as the dependent or independent variables, they are measured under the log scale. Therefore, the ϕs can be interpreted as the *percentage change* in the respondent's own annual work hours caused by a *percentage change* in the spouse's annual income, annual work hours or hourly wage.

The fixed-effect models specified in Eq. 1 and Eq. 2 will first be applied to the NLSY79 male and female sample separately to test Hypotheses 1A and 1B. Then, I will test the gender differences in the degree of responsiveness (i.e. Hypothesis 2) by applying the models to the male-female pooled sample and interact the independent variables with gender. Lastly, I will test Hypotheses 3 and 4 by conducting another set of analyses with the interactions between the number of children in the household and the age of youngest child with L_{t-1}^{sp} to assess the heterogeneity in within-couple inter-temporal responsiveness by parenthood status.

EMPIRICAL RESULTS

Descriptive Statistics

Table 10 compares the weighted descriptive statistics of these covariates for the total NLSY79 sample and my analytic sample, which is restricted to individuals' first marriages. My analytic sample takes up about 1/3 the size of the total NLSY79 sample. The table suggests that compared to all respondents in the NLSY79 dataset, the analytic sample contained slightly more females than males, and more whites and less blacks. The analytic sample has higher average age than the total sample, mainly because of its exclusion of young-age unmarried person-years. The level of schooling and the cognitive test score are higher for the analytic sample. As for parenthood status, the analytic sample, who are all married, has a higher number of children in the household; and conditional on having at least one child in the household, the age of the youngest child is slightly lower in the analytic sample. As for labor market activities, the analytic sample contains person-years in which the individual works more hours and receive higher hourly wages than the total sample average. In addition to individual-level covariates, the analysis also controls for family size and total family income in the previous year.

Responsiveness to Spouse's Annual Income

I start with assessing the effect of the spouse's annual earnings on the individual's work status, annual work hours, and hourly wage. I apply Eq. 1 and Eq. 2 to the data, with L_{t-1}^{sp} measured by one single variable: log annual income of the spouse ($\log(Inc_{t-1}^{sp})$). Columns (1)-(6) in the upper panel of Table 11 give the estimated coefficients on spouse's annual income in predicting the likelihood of working instead of not working, of working at least normal hours instead of working part-time, and of working overtime instead of working normal hours. The reported coefficients are log odds ratios. A positive coefficient means that spouse's annual income increases the possibility of being in a work status, and a negative coefficient means the opposite. Hypotheses 1A and 1B imply that the coefficients should be negative for men and women, respectively. For the male sample, the results show that contrary to our expectation of a negative association between own labor force participation and spousal annual income, the likelihood of working instead of not working for a husband increases with the annual income of his spouse. One possible explanation is that the norms of traditional gender roles still works in the family, so that when the wife is earning higher income, men become more likely to work instead of staying home, so as to maintain his identity as a breadwinner in the family. However, the spouse's annual income has no statistically significant effect on men's likelihood of working at least normal hours instead of working part-time, or their likelihood of working overtime instead of working normal hours. For the female sample, the results indicate statistically significant negative responses in their labor force participation to their spouse's annual income, in terms of the wife's likelihood of working instead of non-working, and in terms of her likelihood of working at least normal hours instead of working part-time. This implies that when the income earned by the spouse is lower, the wife tends to move to work status embodying greater work hours in order to maintain a more stable income flow to the family. Interestingly, the degree of women's negative responsiveness in labor supply is greatest when we compare the likelihood of working at least normal hours to the likelihood of working part-time. They are more likely to pull back from working at least normal hours to working part-time at time t when their husband earns higher annual income at time $t-1$. This means that women's flexibility of adjusting their labor supply according to their spouse's annual income when they are deciding between working part-time and working normal hours.

I next turn to the effect of spouse's annual income on the respondent's annual work hours. The coefficients, shown in Columns (7) and (8) in the upper panel of Table 11, show that both men and women respond negatively to their spouse's labor force participation. The coefficient is statistically significant for both genders, yet the absolute value of the coefficient for women is five times as large as that for men. In the model that controls for parenthood status additively, given a one percent increase in the spouse's annual income, the women's labor force participation will be reduced by about 0.05 percent, while the men's labor force participation will be reduced by about 0.01 percent. Again, consistent with the findings for work status, this suggests that the labor force participation of women is more responsive to their husband's annual income than that of men to their wife's annual income.

Is the gender difference in the responsiveness in labor supply with regard to spouse's annual income statistically significant? To test this, I run the above models in the male-female pooled sample, with interactions between the independent variables and the dummy for being female. The statistical significance of the coefficient on the interaction terms, therefore, indicates whether the gender difference in the degree of inter-temporal responsive is statistically significant. Table 12 summarizes the empirical results. An estimate with p value ≤ 0.05 will be marked as statistically significant. The table shows that women's greater degree of inter-temporal responsiveness is statistically significant in terms of the likelihood of working versus not-working, and in terms of their adjustment in the continuously measured annual work hours.

Responsiveness to Spouse's Annual Work Hours and Hourly Wage

The preceding analysis focuses on spouse's annual income as one holistic measure of the economic resources brought into the family by the spouses. Next, I break down spouse's annual income into two separate components: (1) annual work hours, which represent the time input in the labor market; and (2) hourly wage, which represent the rate of pay the spouse could receive for one hour of market labor. That is, in Eq. 1 and Eq. 2, the independent variable L_{t-1}^{sp} is measured by two separate variables: log annual work hours of the spouse (log($Hour_{t-1}^{sp}$)) and log hourly wage (log($Wage_{t-1}^{sp}$)). I break down annual income into annual work hours and hourly wage for two reasons. First, as discussed earlier, if the observed inter-temporal association is purely a result of changes in household specialization, we may expect the spouse's work hours to affect the respondent's labor force participation, but may not expect the spouse's hourly wage to affect the respondent's labor force participation. So if significant responsiveness is detected with regard to the spouse's hourly wage, it will stand as evidence that this due to the couple's risk-sharing behaviors rather than pure household specialization. Second, breaking down the sources of annual income allows for the possibility that the two sources of annual income differently.

Columns (1)-(6) in the lower panel of Table 12 presents the effect of the spouse's annual work hours and hourly wage on the respondent's likelihood of working in different work statuses.

Consistent with our findings about the effect of the spouse's annual income, none of the coefficients on the spouse's annual work hours and hourly wage is significant in the male sample, meaning that males' work status does not respond significantly to their spouse's work hours or wage. The coefficients are negatively significant for females for the likelihood of working instead of not working, and the likelihood of working at least normal hours instead of working part-time. Moreover, in both cases, women's labor force participation is responsive to their spouse's labor force participation and rate of pay, yet the responsiveness in men's labor force participation is not statistically significant. [73] This is also true when the respondent's labor force participation is measured using a continuous measure: Columns (7) and (8) in Table 11 show that a one percent increase in the spouse's annual work hours at time $t-1$ will cause about 0.01 percent decrease in men's annual work hours, and about a 0.06 percent decrease in women's annual work hours at time t. A one percent increase in the spouse's hourly wage at time $t-1$ will cause about a 0.01 percent (statistically insignificant) decrease in men's annual work hours, and about a 0.07 percent decrease in women's annual work hours at time t. Significance tests shown in Table 12 suggest that the gender difference in the degree of responsiveness in annual work hours is statistically significant.

In sum, my findings lend little support to Hypothesis 1A, as men's labor force participation appears to be unaffected by their spouse's labor market outcomes. I find strong support to Hypothesis 1B, that is, women exhibit substantial negative inter-temporal responsiveness to their spouse's annual income, annual work hours, and hourly wage. Moreover, the results support Hypothesis 2, as the estimated coefficients for the degree of inter-temporal responsiveness are significantly greater among women than among men. Overall, these findings are consistent with

[73] This difference is comparable because the two measures are logged and thus scale-free.

my expectations that although women have become an important source of household income, they act responsively to their husband's labor market outcomes in making their labor supply decisions.

Heterogeneity in Within-couple Responsiveness by Parenthood Status

Next, I examine whether the degree and pattern of within-couple responsiveness vary by two measures for parenthood status: (1) number of children in the household; (2) the age of youngest child in the household. To do so, in Eq.3.1 and Eq.3.2, I include the interactions between parenthood status and L_{t-1}^{sp}. Table 13 gives the results from the models with the spouse's annual income as the key predictor, and Table 14 gives the results from the models with the spouse's annual work hours and hourly wage as key predictors. The estimated coefficients from these two tables show similar patterns: In both the male and female samples, a greater number of children in the household does not seem to affect the degree of responsiveness. Yet, it turns out that women's degree of responsiveness to their spouse's annual income and hourly wage depends on the age of the youngest child in the household: When deciding between working part-time or working at least normal hours, having a youngest child in the 0-6 and 7-12 age groups makes women's labor force participation more responsive to their spouse's earnings and wage, but having a youngest child aged above 12 does not. The results are consistent with those from earlier studies that found that the presence of young-age children intensifies the wife's responsiveness to the husband's earnings capability (Lehrer, 1999; Lundberg, 1985). The heterogeneity by parenthood status supports my expectation that having a child increases the cost of economic insecurity, and thus raises the necessity for risk-sharing in the family.

Figure 11 and Figure 12 display the point estimates and 95% confidence intervals for the effect of spouse's annual income (Figure 11) and spouse's hourly wage (Figure 12) at time $t-1$ on the respondent's likelihood of working at least normal hours versus working part-time at time t. The figures show that for men, the coefficients for responsiveness are close to zero, and none of these coefficients are statistically distinguishable from zero, regardless of the number of children and the age of youngest child. For women, the coefficients are not significant, and very small, when there is no child in the household, or when the age of the youngest child is over 12 years old. The number of children in the household does not affect the degree of women's inter-temporal responsiveness. By contrast, having a younger-age child in the household increases the degree of responsiveness: When the youngest child in the household is below 12, women's negative inter-temporal responsiveness to their spouse's annual income and hourly wage is statistically significant.[74] Overall, among women, the analysis on the heterogeneity by parenthood does not support Hypothesis 3 about the moderating effect of the number of children, but does support Hypothesis 4 about the moderating effect of the age of youngest child. Neither Hypothesis is supported among men.

DISCUSSIONS AND CONCLUSIONS: FAMILY RESEARCH RECONSIDERED

I started this paper with an overview and discussion of three recent shifts in theoretical orientation in family research: from the unitary to individualistic perspective, from the static to life course perspective, and from the resource-sharing perspective to the risk-sharing perspective. Then, I set out to focus on the case of within-couple inter-temporal responsiveness in labor

[74] There is no statistical difference in the degree of responsiveness, however, between women with a youngest child in the 0-6 or 7-12 age groups.

supply as an empirical case that combines and illustrates these theoretical shifts. Applying fixed effect models with lagged independent variables to the NLSY79 data, I found that, conditional on the couple's fixed characteristics and observed time-varying variables, married women's labor force participation in a given year responds negatively to their spouse's annual income, annual work hours, and hourly wage in the previous year. By contrast, no statistically significant inter-temporal responsiveness is found among men, and this gender difference is statistically significant. Moreover, consistent with my expectation that the presence of young child intensifies the need for financial stability, my results show that having a youngest child aged below 12 years old increases women's degree of responsiveness.

I draw on these findings to reconsider theories and practices in family research in several important ways. First, the findings shed light on the functions of family in contemporary society. Sociologists constantly inquire into the multifaceted functions of family as a social institution. Family as an institution plays a functional role in the society, as it draws the boundary for defining how assets and other resources should be assigned, shared, and inherited by offspring (Parsons, 1949). Meanwhile, family plays a key role in individuals' lives, as it provides an environment for its members to share resources (Keister, 2003; Mare, 2011), companionship (Burgess & Locke, 1945; Cherlin, 2004), social support (Schoeni & Ofstedal, 2010; Shanas, 1979) and cultural values (Halaby, 2003; Lareau, 2011). Findings from this paper add to these lines of works by illustrating, with micro-level evidence, a new function of family from a dynamic perspective. Specifically, the inter-temporal responsiveness within married couples illustrates a case in which family members, beyond sharing varying levels of resources, act collectively to insure against external uncertainties through dynamic interactions. As such, a new boundary is drawn between the family environment and extra-family environment: Outside of the family, individuals each face uncertainties and risks, and these risks may not be fully insured through social policies. However, when these individuals are connected by family ties and grouped into families, they may act collectively and responsively in within the family to reduce the impact of these risks. Family, in this sense, serves its function as a risk-sharing institution in the contemporary society. With the growing prevalence of risks, uncertainties, and insecurities in the everyday life of the contemporary society (Beck, 1992; Cooper, 2014; Gottschalk et al., 1994), one may expect that the risk-sharing function of the family will be more important in the present and future than in the past.

Second, the results underscore the dimension of “risk” or “insecurity” in social inequality among different family structures. Prior works have well-documented the inequality in the amount of economic resources (Sara McLanahan, 2004; Western et al., 2008) , quality of living arrangements (Brown, 2004; Spitze, Logan, & Robinson, 1992) , and availability of social and psychological support (McLanahan, Wedemeyer, & Adelberg, 1981) among families with different structures. However, much less research has noticed the inequality in economic insecurity among contemporary families. One notable exception is the work by Western and colleagues (2008), which showed that within-group inequality – an indicator of economic insecurity – is lowest in two-parent families with a working mother, as it is easier for these families to share risks and absorb unexpected income losses. While the authors provide an aggregate-level analysis of the inequality in economic insecurity, my findings of within-couple inter-temporal responsiveness illustrate the micro-level, dynamic mechanisms through which family members insure against such economic insecurity in reality. These findings confirm, with direct evidence, the long-standing conjecture that, the lower economic insecurity faced by dual-earner families on the macro-level is indeed in part the result of risk-sharing actions taken by individuals within the family.

More specifically, the risk-sharing function of family engages the recent debate about whether the gains to marriage continue to exist in the current society. One side of the debate raises questions as to whether marriage continues to be significant in the contemporary society, given the weakening of social norms that push individuals into establishing households through marriage (Amato, 2004; Cherlin, 2004; Lauer & Yodanis, 2010), the declining value of specialization within marriage given rising female labor force participation (Becker, 1991), and the emergence of alternative family forms (Jencks & Peterson, 2001; Sarah McLanahan & Sandefur, 2009; Seltzer, 2000). The other side of the debate maintains that marriage is still beneficial, as it provide a form of *enforceable trust* (Cherlin, 2000, 2004) between the husband and wife in their commitment of a long-term relationship. One expected result of such enforceable trust is that, over the marital life course, family members would have stronger motivation to work together to increase their mutual well-beings, one of them being economic security. Therefore, my finding that married couples act responsively to reduce the fluctuations in their total economic wellbeing underscores the risk-reduction gains of marriage relative to those never-married, single-parent, divorced, or widowed households.

Third, the results speak to the core debate on the proper unit of analysis in stratification research. As the theoretical as well as empirical developments in this study showed, the re-organization among contemporary American families around both male and female income earners means that the individualistic perspective is more useful than the traditional unitary perspective on the family. However, the recognition of individual behaviors in no way means that we should abandon the family as the unit of analysis. Rather, my findings make it evident that in the contemporary social context, individual interactions and decisions continue to be organized around the family ties. These family ties are, in essence, social relations that connect the life course trajectories, as thus the intra-generational mobility processes, of different individual family members to each other. The spousal relations in my analysis, for example, enable family members to achieve the level of economic security that is not achievable had they acted as isolated individuals. Therefore, the interactions and joint decision-making among individual family members strengthen, rather than weaken, the salience of family as a key stratification unit.

And more broadly, the risk-sharing behaviors among individuals connected by family ties may also be found in extended kinship networks. McLanahan and colleagues (1981), for example, illustrated that single mothers may rely on a complex combination of relatives, friends, and spouse-equivalents for social support crucial for their psychological well-being. Mare (2011) also reminded us that the availability of kin outside of the nuclear family means that stratification studies should extend to consider the quantity and quality of a broader range of family relations. My findings engage this line of argument in suggesting that individuals within the network of family ties may provide support for each other through risk-sharing behaviors, and I await future research to extend this line of analysis to examine whether such risk-sharing behaviors could be found among broader kin networks.

Last, it is important to read my results in light of gender in the family. In many facets of the contemporary American society, the gender revolution is far from complete (Blau, Brinton, & Grusky, 2006; England, 2010; Goldin, 2002). Rather, gender roles and gender divisions of labor in the family nowadays play out in more nuanced and complex ways. Previous research, for example, has focused on how men and women behave differently in housework (Bianchi et al., 2012; Gough & Killewald, 2011; Gupta, 2007; Hochschild & Machung, 1989), time use

(Burgard & Ailshire, 2013; Offer & Schneider, 2011), and geographic mobility (Benson, 2014; Bielby & Bielby, 1992). My findings that women adjust their labor force participation according to their spouse's earnings, wages, and work hours to a greater extent than men do suggest that women may still be considered as a "flexible income earner" or an "added worker" in the family, whose labor force participation is largely contingent on how their husband does. This may be due to several mechanisms, such as gender display in the family, women's continued disadvantage in the labor market, and the segregation of women into occupations with more flexible work hours. But at least as a first step along this new line of inquiries, my results indicate that while the risk-sharing behaviors may benefit both the husband and wife, the way in which such risk-sharing is carried out may not be gender-neutral.

Let me conclude by stressing that, my emphasis on the function of family as a risk-sharing institution does not mean to obscure the significance of other social institutions in shaping the economic well-beings of individuals and families. In fact, individuals and household may cope with insecurity through various channels. As DiPrete (2002) pointed out, a country's life course mobility regime must be understood as shaped simultaneously by various factors including the labor market system of occupational mobility, wage distribution mechanisms, as well as social welfare programs that affect the rates and consequences of union formation and dissolution. In addition, a sizable literature shows that adjustments in consumption and savings behaviors may also alleviate the negative impact of income fluctuations (Dynarski, Gruber, Moffitt, & Burtless, 1997; Guariglia & Kim, 2004; Guiso, Jappelli, & Terlizzese, 1992). Furthermore, the way in which the organization of family influences the individual life course may depend critically on the functions and influences of other co-existing institutions. It is indeed illuminating to consider modern families as structure units embedded in the broader social, political, and cultural contexts.

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Figure 9 Conceptual Illustration of Within-couple Inter-temporal Responsiveness under the Three Theoretical Shifts

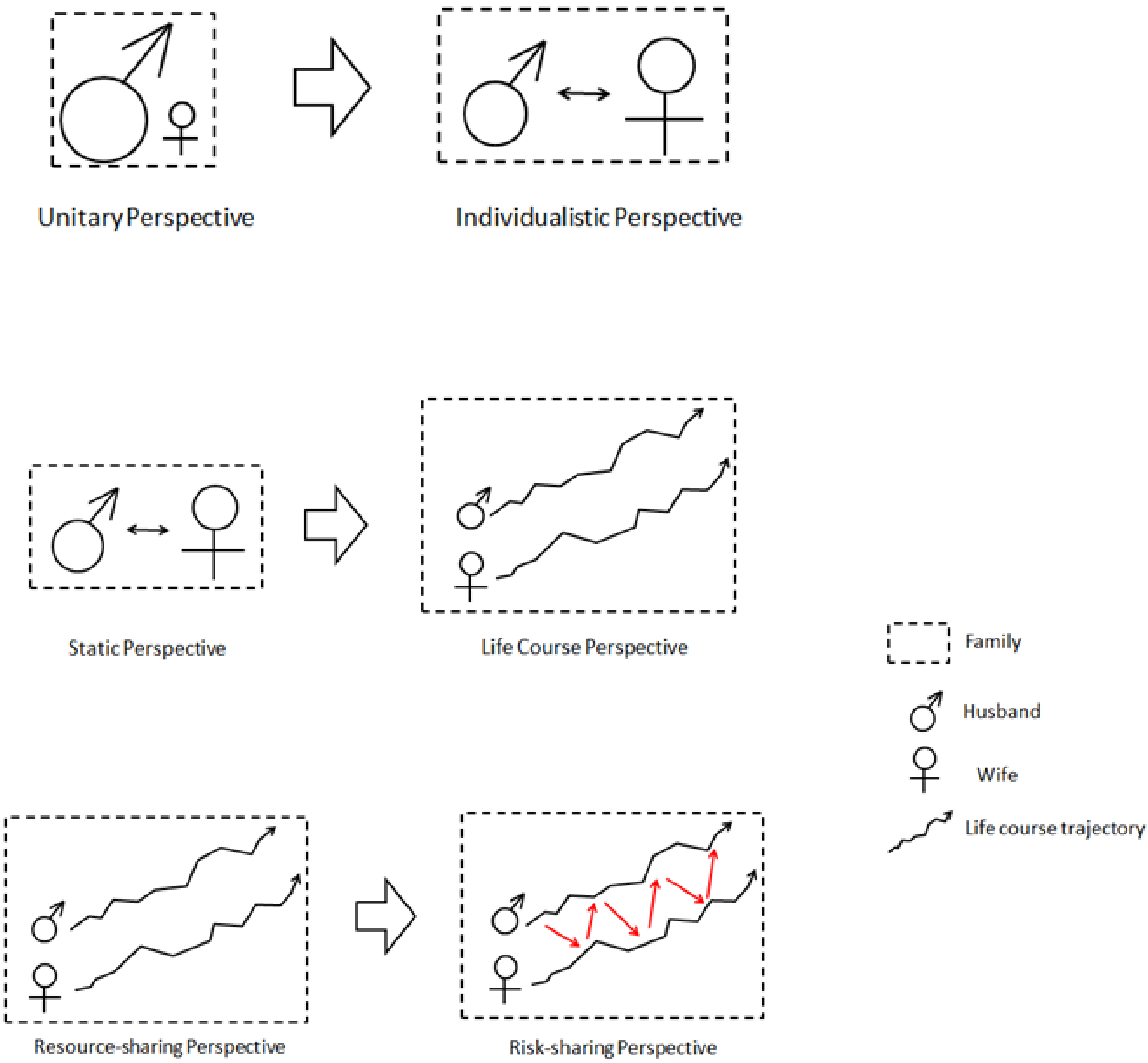


Figure 10 Visualization of the analytic timeline of a hypothetical individual

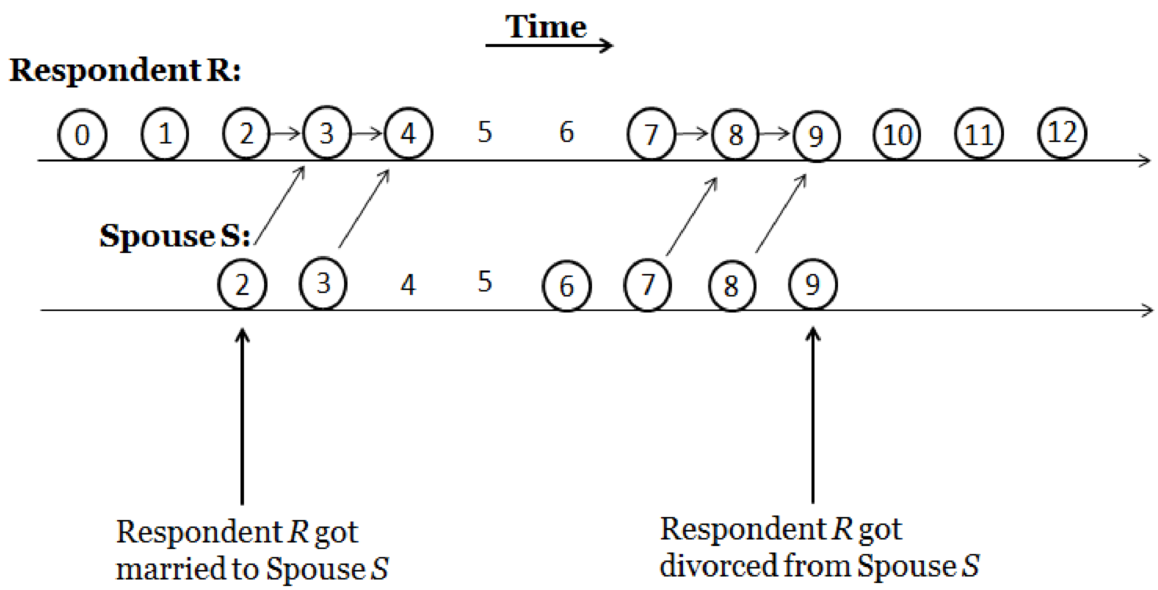


Figure 11 Effect of spouse's annual income on the individual's likelihood of working at least normal hours versus working part-time by number of children and age of youngest child, male and female.

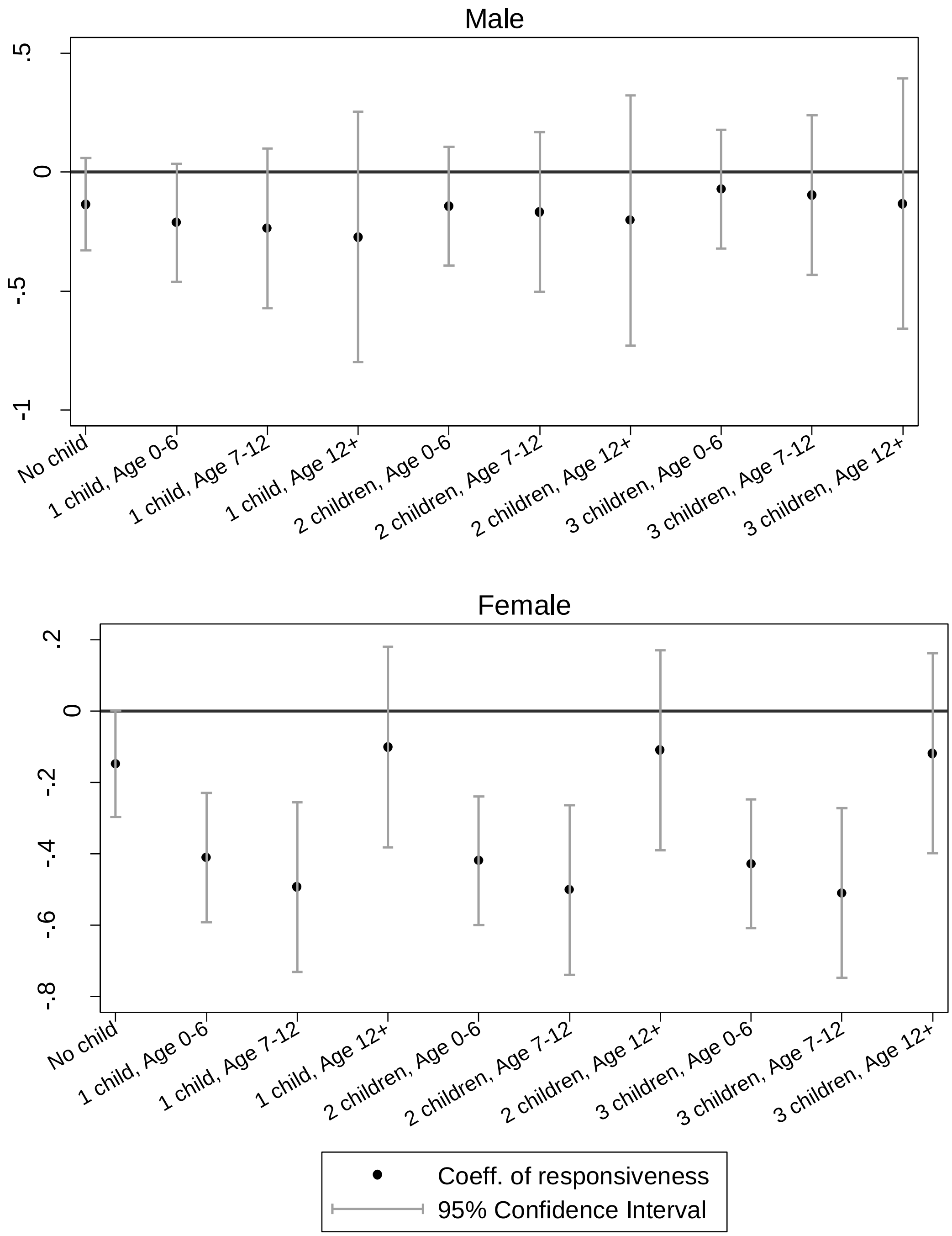


Figure 12 Effect of spouse's hourly wage on the individual's likelihood of working at least normal hours versus working part-time by number of children and age of youngest child, male and female.

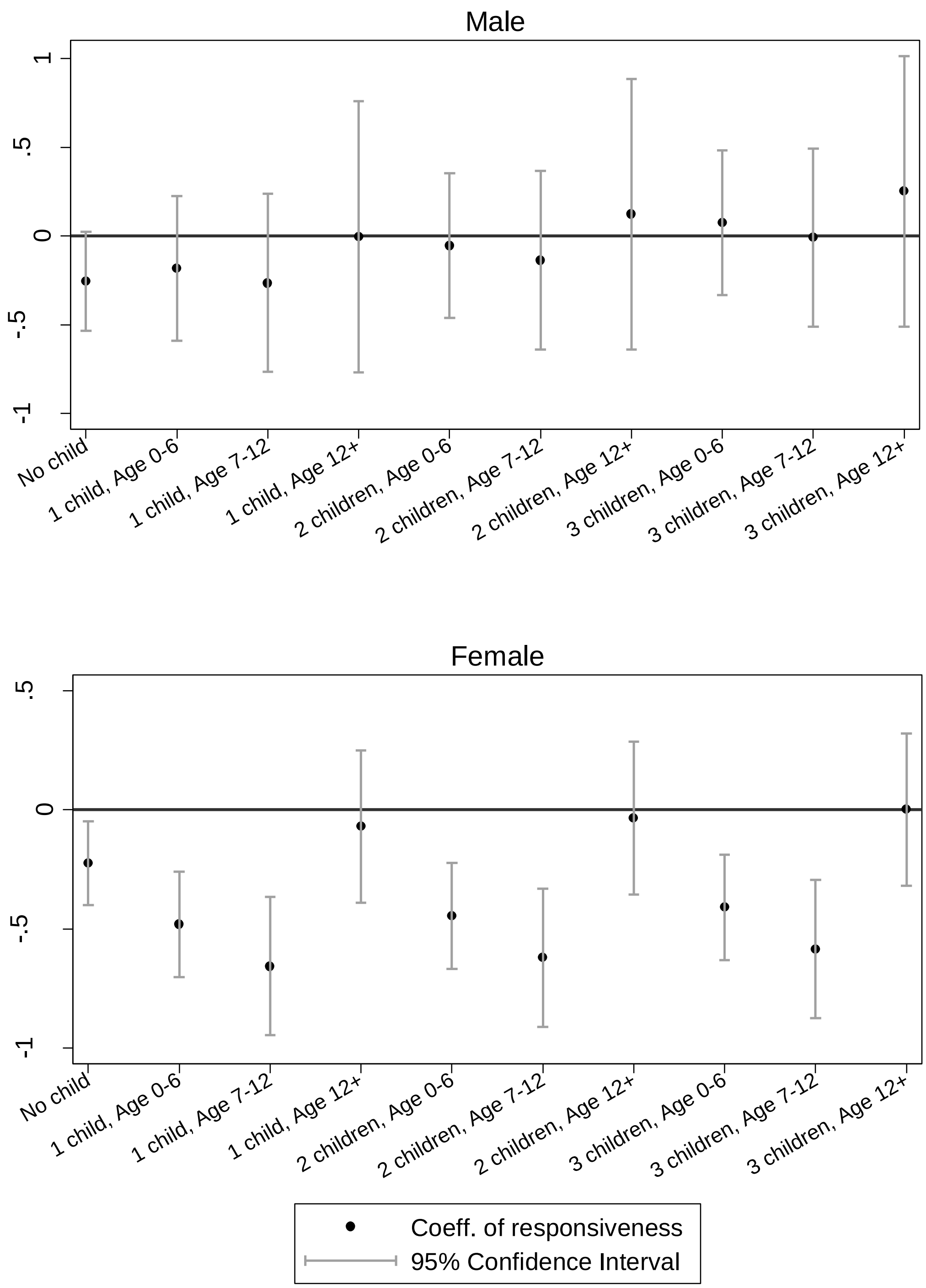
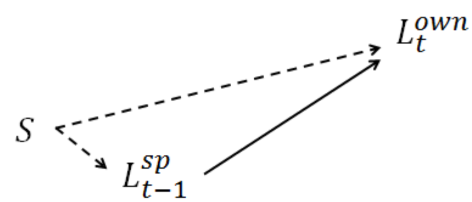
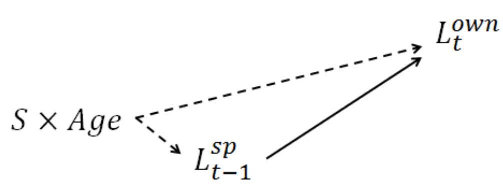
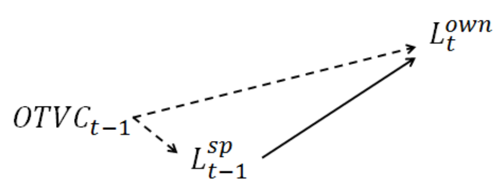
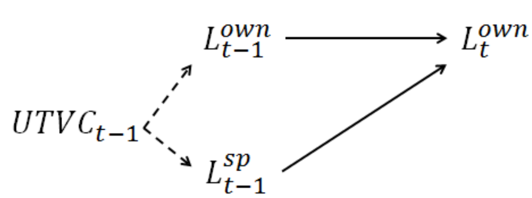


Table 9 Demonstration of alternative mechanisms and identification strategies

Alternative Mechanism	Type of Confounding Effect and Examples	Directed Acyclic Graph	Identification Strategy
Marital sorting on time-invariant attributes	Time-invariant confounder (e.g. marital sorting on education, race, and other unobserved attributes)		Controlling for individual-fixed effects in the fixed-effect model
Mutual trend in career trajectories	Trajectory-induced confounder (e.g. the association between career trajectories with education, cognitive skill, race, gender, etc.)		Controlling for interactions between individual characteristics and age.
Mutual association caused by couple-level events	Observed Time-varying Confounders (e.g. parenthood status, family size, family total income)		Controlling for observed time-varying confounders.
Mutual association with unobserved time-varying variables	Unobserved Time-varying Confounders (e.g., within-couple power dynamics, unobserved events in the family)		Controlling for the respondent's own labor supply and wage at Time *t-1*. (Identifying assumption: $UTVC_{t-1} \perp L_t^{own} \mid L_{t-1}^{own}$)

NOTE
OTVC is short for observed time-varying confounder. UTVC is short for unobserved time-varying confounder

Table 10 Weighted descriptive status for the NLSY79 total sample and my analytic sample

		NLSY79 total sample	Analytic sample
Sex			
	Male	49.47%	47.58%
	Female	50.53%	52.42%
Race			
	Hispanics	6.42%	5.62%
	Black	14.44%	7.65%
	White	79.14%	86.73%
Age			
	Mean	32.08014	34.17089
	S.D.	(9.44)	(8.20)
Highest grade completed			
	Mean	13.00	13.54
	S.D.	(2.47)	(2.52)
Z-score of AFQT test			
	Mean	0.27	0.42
	S.D.	(1.02)	(1.00)
Marital Status			
	Single	32.56%	0%
	Cohabiting	2.61%	0%
	Married	49.61%	100.00%
	Other	15.22%	0%
Number of children in the household			
	0	59.14%	35.12%
	1	13.06%	17.72
	2+	27.80%	47.15%
Age of youngest child			
	<6	46.82%	51.25%
	6---12	32.03%	30.26%
	12--18	21.14%	18.49%
Work Status			
	Non-working	13.66%	13.51%
	Part-time (<35 hours)	20.20%	16.93%
	Normal hours (35-50 hours)	53.75%	55.94%
	Overwork (>50 hours)	12.38%	13.62%
Annual work hours			
	Mean	1571.84	1693.14
	S.D.	(985.14)	(984.59)
Hourly wage			
	Mean	12.90	14.98
	S.D.	(8.89)	(9.85)
N		308242	105652

Table 11 Effects of spousal annual work hours and hourly wage on the individual's likelihood of transition between work status and annual work hours

	Work v.s. Non-work		Normal hours+ v.s. Part-time		Overwork v.s. Normal hours		$\log(\mathrm{Hour}_t^{own})$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Male	Female	Male	Female	Male	Female	Male	Female
Models with spouse's annual income								
$\log(\mathrm{Inc}_{t\text{-}1}^{sp})$	0.167*	-0.179***	-0.126	-0.303***	0.0154	-0.000473	-0.00949*	-0.0537***
	(0.0774)	(0.0539)	(0.0728)	(0.0565)	(0.0393)	(0.0916)	(0.00424)	(0.0132)
N	2903	13486	3915	14054	9599	4825	17643	19559
Models with spouse's annual work hours and hourly wage								
$\log(\mathrm{Hour}_{t\text{-}1}^{sp})$	0.166	-0.204**	-0.121	-0.282***	0.0133	-0.0817	-0.0111*	-0.0578**
	(0.105)	(0.0760)	(0.0930)	(0.0751)	(0.0483)	(0.114)	(0.00495)	(0.0186)
$\log(\mathrm{Wage}_{t\text{-}1}^{sp})$	0.0432	-0.231***	-0.115	-0.350***	0.0439	0.0567	-0.0110	-0.0654***
	(0.107)	(0.0623)	(0.102)	(0.0647)	(0.0566)	(0.104)	(0.00628)	(0.0157)
N	2547	12423	3523	13134	8936	4543	16605	18682

NOTE: Data Source: National Longitudinal Survey of Youth 1979-2010, Bureau of Labor Statistics. Standard errors are presented in parentheses. *** p<0.001; ** p<0.01; * p<0.05.

Table 12 Summary of Empirical Results on the Significance of Inter-temporal Responsiveness and Gender Differences

	Work Status			Annual work hours
	Work v.s. Non-work	Normal hours+ v.s. Part-time	Overwork v.s. Normal hours	
Effect of spouse’s annual income				
Men	No	No	No	Yes
Women	Yes	Yes	No	Yes
Gender diff.	Sig.	N.S.	N.S.	Sig.
Effect of spouse’s annual work hours				
Men	No	No	No	Yes
Women	Yes	Yes	No	Yes
Gender diff.	Sig.	N.S.	N.S.	Sig.
Effect of spouse’s hourly wage				
Men	No	No	No	No
Women	Yes	Yes	No	Yes
Gender diff.	N.S.	Sig.	N.S.	Sig.

NOTE: Data Source: National Longitudinal Survey of Youth 1979-2010, Bureau of Labor Statistics. Standard errors are presented in parentheses. *** p<0.001; ** p<0.01; * p<0.05.

Table 13 Effect of spouse's annual income on the respondent's own labor supply, testing the heterogeneity by parenthood status

	Work v.s. Non-work		Normal hours+ v.s. Part-time		Overwork v.s. Normal hours		$\log(\text{Hour}_{t}^{own})$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Male	Female	Male	Female	Male	Female	Male	Female
$\log(\text{Inc}_{t-1}^{sp})$	0.400***	-0.0573	-0.135	-0.148	0.00383	0.0387	-0.0175**	-0.0432*
	(0.115)	(0.0722)	(0.0990)	(0.0759)	(0.0634)	(0.130)	(0.00659)	(0.0171)
Interactions with number of children in the household								
$\log(\text{Inc}_{t-1}^{sp})$	-0.164*	-0.0120	0.0702	-0.00856	0.0201	-0.0572	0.00238	-0.0233
$\times$ #child	(0.0710)	(0.0305)	(0.0558)	(0.0393)	(0.0323)	(0.0616)	(0.00468)	(0.0139)
Interactions with age of youngest child								
$\log(\text{Inc}_{t-1}^{sp})$	-0.0325	-0.224**	-0.148	-0.254**	-0.0249	-0.00823	0.00795	-0.0125
$\times$ age 0-6	(0.161)	(0.0800)	(0.127)	(0.0921)	(0.0747)	(0.159)	(0.0102)	(0.0296)
$\log(\text{Inc}_{t-1}^{sp}) \times$	0.176	-0.0655	-0.172	-0.336**	-0.0193	0.103	0.00674	0.0115
age 7-12	(0.206)	(0.106)	(0.171)	(0.121)	(0.0963)	(0.171)	(0.0124)	(0.0321)
$\log(\text{Inc}_{t-1}^{sp})$	-0.134	0.168	-0.208	0.0556	-0.0861	0.299	-0.00737	0.111*
$\times$ age 12 +	(0.242)	(0.142)	(0.268)	(0.143)	(0.122)	(0.255)	(0.0137)	(0.0511)
N	2903	13486	3915	14054	9599	4825	17643	19559

NOTE: Data Source: National Longitudinal Survey of Youth 1979-2010, Bureau of Labor Statistics. Standard errors are presented in parentheses. *** $p<0.001$; ** $p<0.01$; * $p<0.05$.

Table 14 Effects of spouse's annual work hours and hourly wage on the respondent's own labor supply, testing the heterogeneity by parenthood status

	Work v.s. Non-work		Normal hours+ v.s. Part-time		Overwork v.s. Normal hours		$\log(Hour_t^{own})$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Male	Female	Male	Female	Male	Female	Male	Female
$\log(Hour_{t-1}^{sp})$	0.503**	-0.203	0.0626	-0.197	0.0840	0.209	-0.0119	-0.0821**
	(0.176)	(0.119)	(0.130)	(0.108)	(0.0891)	(0.194)	(0.00809)	(0.0279)
$\log(Wage_{t-1}^{sp})$	-0.0147	-0.0616	-0.254	-0.224*	-0.0307	0.00432	-0.0333***	-0.0488*
	(0.159)	(0.0896)	(0.142)	(0.0894)	(0.0853)	(0.152)	(0.00978)	(0.0195)
Interactions with number of children in the household								
$\log(Hour_{t-1}^{sp}) \times$ #child	-0.205	-0.0837	-0.0184	-0.0473	0.0313	-0.194*	-0.000713	-0.00420
	(0.108)	(0.0610)	(0.0823)	(0.0662)	(0.0424)	(0.0932)	(0.00481)	(0.0222)
$\log(Wage_{t-1}^{sp}) \times$ #child	-0.0275	-0.00901	0.128	0.0356	-0.0102	-0.0217	0.00288	-0.0354*
	(0.102)	(0.0386)	(0.0843)	(0.0478)	(0.0476)	(0.0769)	(0.00722)	(0.0162)
Interactions with age of youngest child								
$\log(Hour_{t-1}^{sp}) \times$ age 0-6	0.0564	0.174	-0.305	-0.134	-0.150	-0.0483	0.00537	0.0113
	(0.268)	(0.161)	(0.191)	(0.162)	(0.109)	(0.241)	(0.0118)	(0.0486)
$\log(Hour_{t-1}^{sp}) \times$ age 7-12	-0.147	0.248	-0.201	-0.0553	-0.177	0.0754	0.000222	0.0326
	(0.343)	(0.221)	(0.272)	(0.215)	(0.131)	(0.291)	(0.0137)	(0.0519)

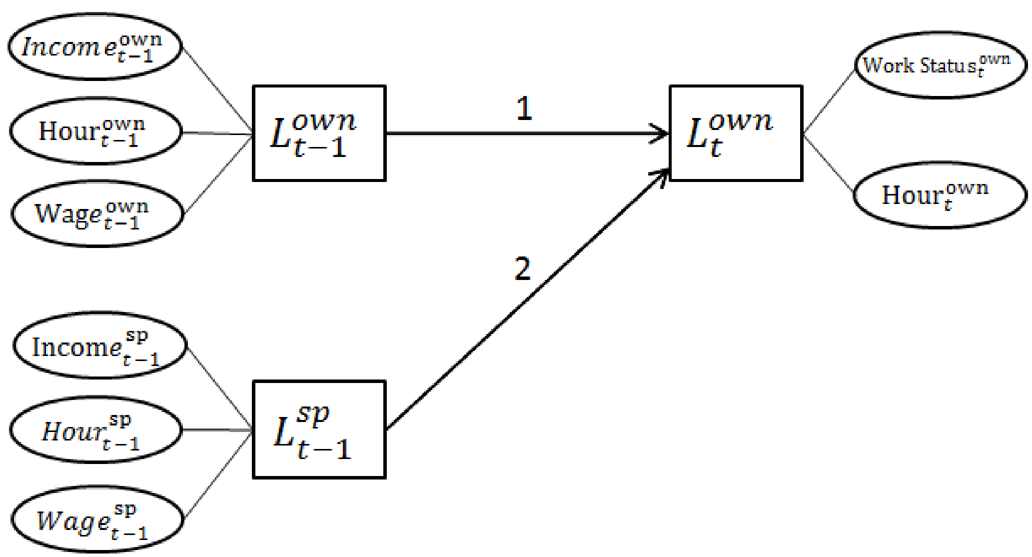
$\log(\text{Hour}^{sp}_{t-1})$ $\times$ age 12 +	-0.539 (0.443)	0.360 (0.273)	-0.820 (0.488)	0.510 (0.268)	-0.212 (0.165)	0.198 (0.360)	-0.00963 (0.0152)	0.156* (0.0682)
$\log(\text{Wage}^{sp}_{t-1})$ $\times$ age 0-6	-0.0367 (0.241)	-0.255* (0.102)	-0.0551 (0.208)	-0.292** (0.113)	0.128 (0.111)	0.0145 (0.201)	0.0286* (0.0141)	-0.00425 (0.0368)
$\log(\text{Wage}^{sp}_{t-1}) \times$ age 7-12	0.613 (0.314)	-0.240 (0.136)	-0.138 (0.256)	-0.467** (0.148)	0.216 (0.143)	0.179 (0.205)	0.0336 (0.0172)	0.0213 (0.0394)
$\log(\text{Wage}^{sp}_{t-1})$ $\times$ age 12 +	0.158 (0.279)	0.134 (0.166)	0.122 (0.389)	0.0118 (0.163)	0.0922 (0.174)	0.318 (0.305)	0.0169 (0.0211)	0.130* (0.0589)
N	2547	12423	3523	13134	8936	4543	16605	18682

NOTE: Data Source: National Longitudinal Survey of Youth 1979-2010, Bureau of Labor Statistics. Standard errors are presented in parentheses. *** p<0.001; ** p<0.01; * p<0.05.

Appendix R

Appendix Figure 3.A demonstrates the relationship between $L^{sp}_{t\text{-}1}$, $L^{own}_{t\text{-}1}$ and L^{own}_{t}, as well as the measures for each of these three key indicators. Path 1 represents the effect of the respondent's own labor market activities in the previous year on those in the current year, and Path 2 represents the effects of the spouse's labor market activities in the previous year on the respondent's labor market activities in the current year. The construction of one-year lag variables is straightforward prior to Year 1993, as the respondents were interviewed every year. Yet, from 1994 afterwards, the NLSY79 data collects information biannually. In consequence, for the observations at or later than year 1994, I have information on the respondent's and his or her spouse's labor market experience at the current period (i.e. at t) and two years ago (i.e. at t-2), but not for the previous year (i.e. t-1). Additional complications for observations after 1994 are added by the fact that in each interview, the respondent's own wage is recorded for the current year while the respondent's annual work hours and the spouse's wage, annual work hours are record for the previous year. The result of this is that depending on the specific model, some of the lag variables will be missing for the previous year but available for two years ago. To address this, whenever the lag variable for the previous year is missing, I assume that the individual's labor market experiences remain unchanged from t-2 to t-1, and thus use the reporting at t-2 as the proxy for the reporting at t-1.

Figure 3.A Illustration of within-couple inter-temporal responsiveness



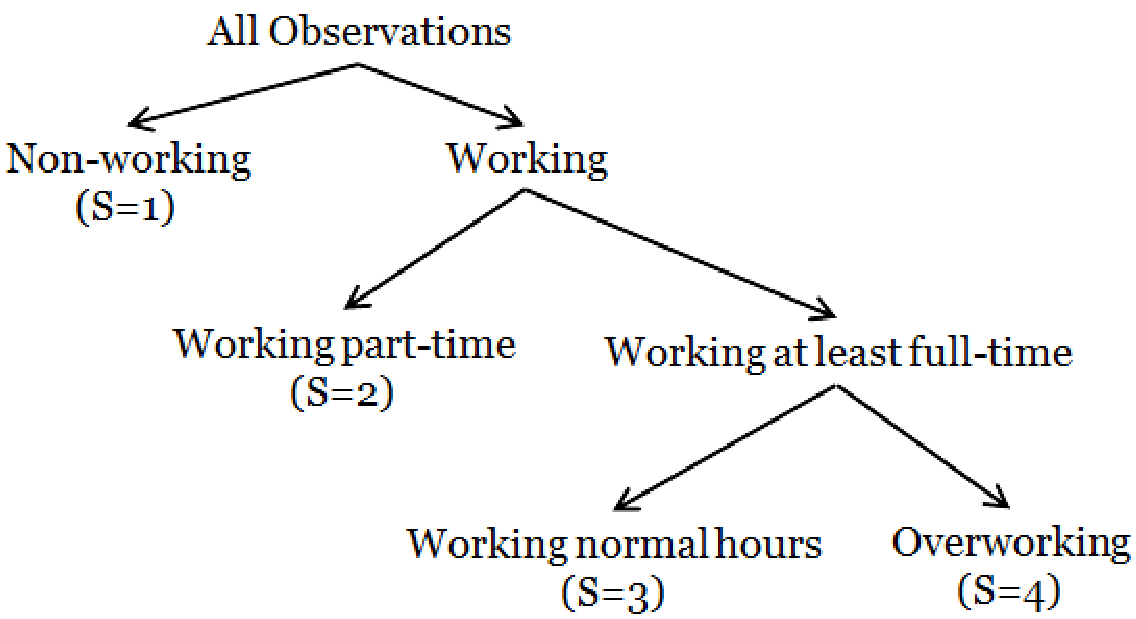
Appendix S

Table 3.B Weighted descriptive statistics of annual income, hourly wage, and annual work hours for the respondent and the spouse

	All age		Age 18-30		Age 31-40		Age 40+	
	Male	Female	Male	Female	Male	Female	Male	Female
$\text{Hours}^{\text{own}}$	2153.30	1294.67	2027.53	1203.07	2283.59	1347.61	2242.59	1498.08
	(827.06)	(936.92)	(851.80)	(912.44)	(767.57)	(955.85)	(817.18)	(942.49)
Hours^{sp}	1557.26	2193.80	1478.45	2137.01	1600.27	2268.13	1700.42	2263.39
	(767.65)	(649.00)	(791.31)	(680.30)	(751.65)	(599.67)	(699.27)	(597.20)
Wage^{own}	17.62	12.23	14.12	10.30	19.35	13.87	22.55	14.92
	(10.48)	(8.31)	(7.68)	(6.54)	(11.10)	(9.28)	(12.01)	(9.57)
Wage^{sp}	14.04	17.51	12.47	16.57	15.09	19.10	16.14	17.89
	(10.25)	(9.68)	(10.56)	(10.60)	(10.05)	(8.57)	(9.14)	(7.69)
Inc^{own}	42574.08	20820.29	33179.78	17200.04	49892.95	24321.25	52266.22	25184.64
	(29316.44)	(19278.24)	(21723.68)	(14774.05)	(32726.99)	(21390.68)	(31972.66)	(23989.53)
Inc^{sp}	20782.25	38238.36	17745.51	34627.51	22381.27	43587.71	23919.73	40041.12
	(16392.57)	(22040.66)	(13343.99)	(21654.79)	(16556.24)	(23077.03)	(19617.04)	(19528.24)

Appendix T

Figure 3.C Demonstration of Transition between Different Work Statuses



Chapter 5 Conclusion and Future Research

Sociological studies on social stratifications are, by nature, studies of differentiation processes in society. Among various differentiation processes, the life course process is one of the most important, as it ties together the development of human life cycle and the influence of social, historical, and institutional contexts. The three papers of my dissertation examined life course inequality from three different angels: (1) the macro-micro linkage, (2) the intersection of gender and race, and (3) the dynamic function of family. Together, these chapters illustrate the possibility and importance of studying social stratification from the life course perspective.

The life course approach to inequality is a major thread tying together the various components of my research agenda. I plan to move forward with three lines of future research. First, whereas my past work focused mainly on one specific cohort of population, my future research will examine whether and how patterns of life course inequality are shaped by historical and social contexts. The LCT framework established in Chapter 2 can be applied to the Panel Study of Income Dynamics data and test whether various mechanisms generating inequality have operated in different ways or exerted different influences for different birth cohorts in the US. Uncovering such intercohort differences will reveal important structural, cultural and demographic processes shaping the trajectories of inequality in the United States. In addition, I will combine micro-level panel data from different countries, such as the US, UK, Germany and China, to conduct a cross-country comparison of the life course patterns of inequality across different social, political, and institutional configurations.

The second line of research, growing out of Chapter 4, focuses on the effect of within-family interactions in life trajectories. Specifically, I will study how an individual's life trajectory responds to the trajectories of his or her parents and grandparents, spouse, children, siblings, and even more remote kin. In conventional stratification research, the characteristics of one's family are often simplified as static measures of "family background." In contrast, my research emphasizes that one's family does not always stay unchanged in the "background." Instead, one's own life trajectory may affect, or be affected by, the trajectories of family members. Such dynamic within-family interactions could cause co-movements of life trajectories among related individuals, enable individuals to insure against potential income risks, shift the distribution of power within the family, or alter the patterns and closeness of social interactions between different family members. Through this research, I hope to show that adopting the life course approach can not only aid our understandings of macrolevel inequality patterns, but also deepen our knowledge about the microlevel dynamic functions of individuals and their families.

The third line of future work involves methodological development. I plan to design quantitative methods for drawing causal inference from complex longitudinal data. I will establish an integrative model for mapping the "sequence space" of life events (e.g., cohabitation, marriage, childbearing, and job changes) to a "life course trajectory" of outcomes (e.g., income, wealth, and health). A satisfactory model should account for two critical issues: (1) how to identify causal effects of time-varying treatments with the presence of time-varying moderators and confounders; (2) how to account for compositional bias due to the selectivity of the timing and duration of life events. The successful solution to these issues lies in drawing a linkage between trajectory-based models (e.g., Sequence Analysis, Latent Class Analysis, Growth Curve Model) and causal models (e.g., Inverse Probability Weighting, Marginal Structural Model). It is my goal to enable such a linkage and build a model that is readily applicable to both simulated and real data.