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Life Course Trajectories and Wealth Accumulation in the United States: Comparing Late Baby Boomers and Early Millennials

Rob J. Gruijters¹, Zachary Van Winkle², Anette E. Fasang³

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¹ REAL Centre, Faculty of Education, University of Cambridge: rjg85@cam.ac.uk

² Centre de Recherche sur les Inégalités Sociales (CRIS), Science Po

³ Department of Social Sciences, Humboldt Universität zu Berlin

Abstract

Millennials are often assumed to be economically worse off than previous generations, partially due to more precarious employment and unstable family lives. The older Millennials are now approaching middle age, when they can be expected to settle into relatively stable life trajectories - a good time to take stock of these claims. Using sequence analysis and unconditional quantile decomposition, we analyze the work and family trajectories of late Baby Boomers (born 1957-1964) and early Millennials (born 1980-84) from age 18 to 35, and relate them to wealth holdings at age 35. Cohort differences in wealth change across the distribution: the poorest Millennials have less wealth than their Baby Boomer counterparts, but the wealthiest Millennials have more. Millennials are less likely to enter high-status occupations and are more likely to work in low-skilled service jobs. Changes in family trajectories are even more pronounced, with a strong decline of traditional early marriage and parenthood. Contrary to expectations, these compositional changes in life course trajectories cannot account for the increase in wealth inequality. Instead, the distribution of wealth has become more unequal because the economic returns to typical middle-class trajectories have increased, while the returns to typical working-class trajectories have stagnated or declined.

Key words: Work-family life courses, Wealth inequality, Cohort comparison, Sequence Analysis, Quantile decomposition, National Longitudinal Survey of Youth (NLSY)

Introduction

Millennials are widely seen as the 'Precarious Generation', bearing the brunt of increasing inequality and instability in American society (Bessant, Farthing, and Watts 2017; Hacker 2008). Their experience is often juxtaposed to that of their parents' generation, the Baby Boomers, who are generally perceived as an economically privileged generation. A major concern, among scholars as well as the general public, is that the combination of insecure employment and a prolonged transition to adulthood prevents Millennials from obtaining economic security in the form of wealth and home ownership (Ingraham 2019; Leonhardt 2019; Thompson 2018). As a result, it has been suggested that they are “the first generation that is worse off than their parents” (Leatherby 2017)—posing a major challenge to the American Dream narrative of steadily improving opportunity and prosperity (Chetty et al. 2017).

The popular claim that Millennials are doing worse than the Baby Boomers at the same stage in their lives might be misleading, for two main reasons. First, the Baby Boomers—and especially the ‘late’ Baby Boomers, who are the focus of this study—also came of age in a time of major economic upheaval and adverse labor market conditions. Considering their economic prospects, Easterlin et al. (1993) observed that “the prevailing sentiment in scholarly circles and the media appears to be pessimistic” (p. 497). Second, generational comparisons of this kind tend to overlook within-cohort differentiation, thus creating an artificial impression of generational homogeneity (Dannefer 1987; Lersch, Schulz, and Leckie 2020). Instead of focusing on the average or ‘normative’ experience of each birth cohort, we consider it more fruitful to study intra-cohort patterns of life course diversity, and their association with household wealth (net worth).

The purpose of this study is therefore to compare early⁴ Millennials' work and family life courses in young adulthood—from age 18 to 35—to those of the late¹ Baby Boomers, and to assess the relationship between these life course trajectories and wealth accumulation in each cohort. Specifically, we address four questions:

1. How does the distribution of household wealth at age 35 differ between Millennials and Baby Boomers?
2. How do early work and family trajectories differ between Millennials and Baby Boomers?
3. How do the wealth returns to different work and family trajectories vary between Millennials and Baby Boomers?
4. To what extent can cohort differences in household wealth be attributed to changes in work and family life courses?

The importance of wealth an almost universally aspired marker of success and social status can hardly be overstated (Keister 2005). Moreover, wealth is associated with a range of desirable life outcomes for individuals and their descendants, including happiness, health, and longevity (Benton and Keister 2017; Pfeffer 2018; Senik 2014). It also serves an important insurance function, in the absence of a comprehensive social safety net (Killewald, Pfeffer, and Schachner 2017; Shapiro 2017; Western et al. 2012). Conversely, indebtedness and the lack of economic security contribute to family instability, social conflict, and other individual and societal problems (Desmond 2016; Savage 2021; Western et al. 2012).

⁴ The NLSY birth cohorts included in our study do not cover their entire generation, as it is typically defined (Fry 2018). Specifically, we look at the late Baby Boomers (born 1957-1964, also known as the 'Generation Jones') and the early Millennials (born 1980-84). For the sake of readability, we will refer to these cohorts as 'Millennials' and 'Baby Boomers' throughout.

Increases in wealth inequality over the past few decades have been well documented (Piketty 2014; Wolff 2017). Growth in aggregate wealth has been concentrated at the top of the distribution, with stagnant or even declining wealth for most of the population. The increasing gap between the rich and the poor is one of the most pressing challenges of our time, and has galvanized major social movements, including Occupy Wall Street and Bernie Sanders' presidential campaigns. We complement the predominant macro-perspective in the wealth literature with a micro-level analysis of individual life course trajectories and wealth outcomes across the two birth cohorts.

We ascribe to a holistic life course perspective that conceptualizes work and family lives as longitudinal processes, rather than as point-in-time characteristics (Abbott 2005). Highly detailed prospective data from the 1979 National Longitudinal Survey of Youth (NLSY79 - the 'Baby Boomers') and the NLSY97 (the 'Millennials') allow us to reconstruct work and family life courses from age 18 to 35. We then use sequence and cluster analysis to generate a typology of early work and family trajectories in each cohort. We are particularly interested in assessing whether and how generational shifts in typical work and family trajectories as well as changes in the economic returns to these trajectories relate to generational differences in household wealth and wealth inequality. For example, Millennials might accumulate less wealth because they have a higher likelihood to experience unstable, low wage employment and family lives of serial cohabitation and separation that already led to lower wealth accumulation among the Baby Boomers. In this case, Millennials would acquire less wealth because their life trajectories are less conducive to wealth accumulation (a compositional effect). However, it may also be the case that the same work and family life courses—such as blue-collar employment combined with stable marriage and parenthood—are associated with different levels of wealth accumulation for Millennials compared to Baby Boomers (a returns effect).

Our core finding is that, even though there were substantial compositional shifts in work and family trajectories between the two cohorts, these did not explain the observed increase in wealth inequality. Instead, wealth inequality increased because the returns to high-status work trajectories have increased, while the returns to low-status trajectories have stagnated or declined. The findings challenge prevailing narratives about a general decline in economic wellbeing across generations; and highlight the importance of considering within-cohort heterogeneity. These findings suggest that policies affecting the returns to life course trajectories—such as tax and transfer policies—are most likely to curb the trend towards increasing wealth inequality.

In the following sections, we first briefly review trends in average wealth holdings and wealth inequality across birth cohorts in the US. Next, we introduce our life course approach to wealth differences across birth cohorts. We then describe three major macro-structural changes in American society, and discuss how they may have contributed to changes in the composition of and returns to work-family trajectories.

Wealth Differences between Baby Boomers and Millennials

Our first research question relates to differences in the distribution of household wealth at the beginning of mid-life (age 35) for Millennials and Baby Boomers. Unlike income, wealth reflects not just the economic situation at a point in time but the cumulative flows up to that point, including consumption, transfers and income from labor and capital. It is therefore particularly well-suited as an indicator of both past and future economic wellbeing (Spilerman 2000). Although trends in wealth inequality have been studied for many years, public and academic interest in the topic has been particularly pronounced in recent years, in part because of Piketty's *Capital in the Twenty-*

First Century (2014). Piketty and others have documented a sharp increase in wealth inequality in the US over the past few decades, with strong increases at the top and stagnation at the bottom (Piketty 2014; Saez and Zucman 2016). The FED Survey of Consumer Finances showed that real mean US household wealth almost doubled between 1989 and 2016, from 353,000 to 689,000⁵. Median wealth increased only marginally during the same period, however: from 87,000 to 97,000. Meanwhile, household wealth at the 90th percentile increased from 686,000 to 1,187,000, and household wealth at the 10th percentile consistently hovered around zero.

Increases in wealth inequality are driven by a number of factors. Piketty (2014) highlighted the increasing returns on capital relative to labor, while Wolff (2017) emphasized differences in rates of return on different types of assets, notably housing wealth—which is predominant among the middle class—and financial assets, which are more common among the rich. Increasing wage inequality is another leading cause of increasing wealth disparities (Piketty and Saez 2003; Wolff 2017). Acemoglu & Autor (2011:1056) document a steadily increasing gap in the real wages of workers with different levels of education, starting in the early 1970s. This pattern is driven by a decline in the real wages of less-educated workers, particularly men without a college degree, in combination with rapid increases at the top of the wage distribution. The Great Recession of 2008 led to a further increase in wealth inequality (Pfeffer, Danziger, and Schoeni 2013).

The importance of Piketty and related economists' work can hardly be overstated, but the aggregate cross-sectional picture they present has its limitations. Cohort differences in wealth do not necessarily follow changes in the aggregate distribution of wealth. There are indications that wealth gaps between older and younger households have increased (Wolff 2017), but we know little about

⁵ Calculations by authors, data derived from <https://sda.berkeley.edu/sdaweb/analysis/?dataset=scfcomb>

the extent to which wealth inequality has changed across birth cohorts. More importantly, cross-sectional wealth records do not allow us to link wealth outcomes to social origins, life course trajectories, and other micro-level factors that give rise to differences in wealth. Sociologists, on the other hand, have studied the individual channels through which individuals accumulate wealth or debts, such as earnings from employment and investments, via partnering and family formation, or through inheritance and gifts from parents and other family members (e.g. Keister 2000; Killewald et al. 2017; Lersch, Jacob, and Hank 2017; Spilerman and Wolff 2012).

Birth cohorts may differ in their ability to generate wealth because they vary in their initial endowments, because of shifts in typical life trajectories, or because of changes in the returns to those trajectories. In this study, we will concentrate on changes in two major domains: work and family life. In particular, we seek to assess which work and family trajectories are conducive to wealth accumulation, and the extent to which this might explain cohort differences in the distribution of wealth. By comparing the life trajectories and wealth holdings of Millennials and Baby Boomers at the same age, we complement the economic story about changes in the aggregate distribution of wealth with a detailed sociological account of cohort change in individual work and family life courses and its implications for economic opportunity and inequality. In the following two sections, we present our theoretical framework and review the evidence on compositional change in work-family life courses and changes in the economic returns to those life courses.

A Life Course Approach to Wealth Differences across Birth Cohorts

Our approach to cohort change in wealth accumulation is based on three integral principles of the life course paradigm: 1) comparing birth cohorts as a way of studying social change, 2) intra-cohort

differentiation and inequality, and 3) an emphasis on life courses as longitudinal, sequenced trajectories (Elder 1975; Fasang and Mayer 2020). Below, we relate each of these principles to our study.

The first principle emphasizes the unique experience of each birth cohort as it comes of age in a particular historical period (Elder, Kirkpatrick Johnson, and Crosnoe 2003; Mayer 2009). Macro-structural change differentiates cohorts from one another, and thus “the comparison of their careers becomes a way to study change” (Ryder 1965:844). Because of their similar age and historical experience, cohorts are the appropriate *location* within which to study structural inequality and its change over time. As they age, birth cohorts pass through varying socio-historical opportunity structures, which may provide favorable or unfavorable conditions for wealth accumulation. Studying successive birth cohorts at the same time in their lives not only improves our understanding of historical change, but also provides a window into the future: as older cohorts are gradually replaced by younger ones, the attitudes and characteristics of the younger cohort become increasingly dominant. The cohort perspective is particularly important when analyzing stock variables such as wealth, which accumulate with age. Yet, to date only a few studies on wealth inequality use a cohort approach (Crystal, Shea, and Reyes 2017; Keister, Benton, and Moody 2019), and none link cohort wealth outcomes to longitudinal life course data.

The second principle emphasizes intra-cohort differentiation and its implications for inequality (Cheng 2015; Elder and George 2016). Cross-cohort comparisons based on measures of central tendency, such as average wealth holdings, can be misleading if cohorts are highly differentiated (Dannefer 1987). Baby Boomers and Millennials do not constitute homogenous social groups: differences in socio-economic family backgrounds, life courses, and opportunities for wealth

accumulation are generally larger within than between cohorts (van Winkle and Fasang 2017). Well-known processes of cumulative advantage and disadvantage tend to increase within-cohort inequality over time (DiPrete and Eirich 2006). This ‘Matthew effect’ is particularly pronounced in the case of wealth, because wealth itself begets more wealth in the form of asset appreciation, dividends, and other returns. Between-group variation in initial wealth holdings or parental transfers may therefore translate into large differences later in life. In this study, we look at household wealth holdings at age 35, which reflect the degree of differentiation in wealth accumulation that has occurred within cohorts up to that point (Cheng 2021). Moreover, we link wealth to individual life course trajectories to assess not only how much wealth outcomes vary within cohorts, but also who ends up where in the distribution. By combining this intra-cohort approach with the cross-cohort comparison outlined above, we assess how the nature of within cohort differentiation changes over time. For example, Millennials might have a lower prevalence of certain trajectories (for example, stable middle-class employment combined with early marriage and parenthood) but the wealth returns to such trajectories might have stayed the same or even increased.

The third principle refers to a holistic view of human lives as longitudinal patterns of interconnected stages (Elder and Rockwell 1979). In the life course tradition, individual work and family lives are often conceived as trajectories: temporal sequences of categorical states and the transitions between them (Elder 1985; Spilerman 1977). For example, a work trajectory might consist of a sequence of different jobs, perhaps interspersed with time in training, parental leave, or unemployment. Trajectories can be characterized by the presence or absence of certain states, but also by their timing, duration, and temporal sequencing. Work and family trajectories mutually support or constrain each other over the life course, and both are conditioned by social origins

(Fasang and Aisenbrey 2022). The holistic, processual perspective embodied in the concept of trajectories is often contrasted to the ‘snapshot’ approach that looks at individual outcomes and characteristics at a single point in time (Abbott 2016). In this study, we argue that cohorts can be characterized by the *composition* or relative prevalence of typical trajectories: for example, precarious employment trajectories and non-standard family lives are often seen as emblematic of the Millennial cohorts. At the same time, the second principle (see above) highlights within-cohort heterogeneity in life course trajectories, and turns attention to potentially differential *wealth returns* to similar life courses for different birth cohorts.

Theoretical explanations for the wealth returns to different work and family trajectories can be divided into four different categories: treatment, facilitation, selection, and discrimination (Jalovaara and Fasang 2020; Petersen, Penner, and Høgsnes 2014). These four mechanisms tend to work in the same direction, contributing to the Matthew effect described above. *Treatment mechanisms* relate to the direct wealth-enhancing effects of work and family life courses. Work trajectories affect wealth accumulation through the economic rewards and opportunities for career progression associated with different occupations (Spilerman 1977). Family life courses affect wealth accumulation directly through partnering and the financial implications of certain family states and transitions—such as costly divorce suits or the expenses involved in raising children. Family trajectories also shape consumption behavior and possibilities to pool resources and benefit from economies of scale. Hacker (2008) argues that unstable life course trajectories characterized by frequent transitions are particularly detrimental to economic security and wealth accumulation. *Facilitation* occurs when wealth enables transitions or provides access to certain trajectories, or, conversely, when pathways are blocked or complicated by a lack of wealth. An example are parental wealth transfers to pay for higher education, which in turn facilitates access to graduate-

level occupations. In the family domain, pervasive social norms see wealth—often in the form of homeownership—as a precondition for marriage and childbearing: the ‘marriage bar’ (Cherlin 2020). Facilitation-based mechanisms highlight that the relationship between life course trajectories, earnings and associated wealth accumulation is reciprocal and mutually constitutive (Jalovaara and Fasang 2020). *Selection*-based explanations posit that differential returns to work and family trajectories arise in part because of the ways in which people are sorted into those trajectories. Cognitive and non-cognitive abilities, social origins, and individual preferences are important determinants of individual life courses and are also relevant for wealth accumulation. Finally, *discrimination* occurs when employers, parents and others exhibit bias against or in favor of certain life course trajectories in ways that are relevant to wealth accumulation. For example, parents may reward or punish their children’s life choices through financial transfers, and welfare benefits can (dis)incentivize marriage, cohabitation, and childbearing. Employer discrimination is often expressed in gendered and racialized ways (Pedulla 2020). In our study, the combination of treatment, facilitation, selection, and discrimination is likely to produce strong associations between life course trajectories and wealth, although it is not possible to empirically disentangle the four mechanisms over the life course⁶.

In summary, our conceptual framework suggests that cohort-specific opportunity structures favor stronger or weaker processes of intra-cohort differentiation across early adult life courses, which shape the distribution of household wealth at a given age for different birth cohorts. Cohort differences in historical opportunity structures can affect the link between life course patterns and

⁶ Because wealth is a stock variable, it is often difficult—both conceptually and empirically—to distinguish between its sources (Spilerman 2000). For example, imagine an individual who is admitted to an elite university because of their test scores (selection). A parental wealth transfer enables them to take up the offer (facilitation), as a result of which they acquire a well-paid job (treatment). It is not obvious to which of the three channels their subsequent wealth accumulation should be attributed.

wealth in two important ways. First, they might affect the prevalence of certain life course trajectories—for example, blue-collar careers—that have a specific association with wealth. This process creates cohort differences in the distribution of wealth through the *compositional change of life courses* without changing the wealth returns to specific life course trajectories. Second, structural differences may affect the mechanisms of treatment, facilitation, selection, and discrimination that link life course trajectories and wealth, thereby changing the levels of wealth accumulation associated with specific work and family trajectories within each cohort. These *changes in wealth returns to life courses* would create cohort differences in the distribution of wealth even if the underlying composition of life courses remained the same. By linking individual life course trajectories to cohort wealth outcomes, our conceptual framework provides a micro-level foundation for macro-level changes in inequality (see also Cheng 2015).

We compare two birth cohorts, observed from ages 18 to 35 (see Figure 1). The first cohort, born 1957-1964, forms part of the late ‘Baby Boomer’ generation, while the second cohort consists of early ‘Millennials’. Baby Boomers and Millennials have come to symbolize the generational divide in popular discourse (Ingraham 2019; Leonhardt 2019; Lorenz 2019). Our findings therewith speak to contemporary debates about generational justice and economic inequality in the United States. The focus on young adulthood—the period between age 18 and 35—was chosen because the early Millennials have only recently turned 35. More importantly, however, the period up to age 35 is often considered the most crucial phase in the adult life course (Billari 2001). It is a "demographically dense" time in which most of life's major transitions take place, including the transition from school to work, leaving the parental home, and starting a family (Billari 2001; Rindfuss 1991). By the start of mid-life (around age 35) the often turbulent life courses of early adulthood have solidified into relatively stable categories, which reproduce themselves though

well-known processes of path dependency and cumulative (dis)advantage (Dannefer 2003). Inequalities emerging in the early life course therefore lay the foundation for future socio-economic stratification.

Macro-Structural Change and the Polarization of Work-Family Life Courses

In this section, we briefly explain the main structural changes that differentiate our two birth cohorts, and discuss how they may have contributed to shifts in the *composition* of work and family trajectories, as well as changes in *wealth returns* to specific life trajectories across cohorts. We distinguish between three broad categories of macro-structural trends: economic restructuring, ideational change and the Second Demographic Transition, and social policy and tax reforms. We show that each of these trends contributed to the polarization of work-family life courses through 1) increasing the prevalence of precarious, economically disadvantaged trajectories, and 2) diverging economic returns to stable middle-class trajectories and precarious working-class trajectories.

Economic Restructuring

De-industrialization, skill-biased technological change and the rise of the service economy have fundamentally reshaped the American occupational structure over the last few decades. De-industrialization and de-unionization led to a decline in secure and well-paying blue-collar jobs, as manufacturing work was increasingly automated or offshored to low-income countries. Especially since the 1980s there has been a rapid growth in low-paid service occupations and a relative decline in mid-level administrative and production jobs, which have been particularly affected by

automation and computerization (Acemoglu and Autor 2011; Autor, Katz, and Kearney 2006). At the same time, this skill-biased technological change increased the economic returns to specific skillsets, such as computer programming. In combination, these trends fueled a polarization between ‘good’ and ‘bad’ jobs, with rising wage inequality (Acemoglu and Autor 2011; Kalleberg 2009). Dwyer (2013) found that care work in particular has contributed to job polarization among women. Economic restructuring also contributed to the precarization and fragmentation of employment careers. The prevalence of unstable 'alternative work arrangements'—which includes agency workers, freelancers and other forms of non-standard work—has increased, especially among new labor market entrants (Katz and Krueger 2019). Precarious and fragmented early careers can lead to lower wealth outcomes because they complicate economic planning, affect hiring decisions, and impose a financial and psychological toll on families (Hacker 2008; Pedulla 2020).

Economic restructuring was accompanied by repeated periods of economic recession (see Figure 1). The late Baby Boomers, who are the focus of this study, entered the labor market when the oil crises of the mid-1970s and early 1980s accelerated the decline of manufacturing, and service jobs started to outpace manufacturing jobs. In contrast, the early Millennials experienced extended periods of economic growth in their childhood and early adulthood, which abruptly ended with the financial crisis in 2008. The deep recession that followed, and the subsequent slow economic recovery and wage stagnation, severely impaired Millennials’ labor market prospects during this important career stage.

In terms of *compositional life course change*, economic restructuring likely reduced stable manual careers among Millennials, while increasing the prevalence of precarious service work. Increasing economic insecurity, rising student debt, the increased cost of housing and the impact of the Great

Recession also impacted Millennials' family trajectories. Returning to or remaining in the parental home for extended periods of time became more prevalent, and there has been a pronounced decline in marriage (Smith, Crosnoe, and Chao 2016; Smock and Schwartz 2020). Skill-biased technological change and precarization had negative implications for workers without advanced degrees—especially women and ethnic minorities—but benefited many college educated workers (Dwyer 2013; Pedulla 2020). Economic restructuring therefore contributed to the polarization of the *economic returns to life course trajectories*, eroding the wealth returns to typical low-skilled careers, while increasing the returns to high-skilled careers.

Ideational Change and the Second Demographic Transition

The Second Demographic Transition (SDT) describes a decline in marriage, delayed fertility, and increasing separation and family complexity (Lesthaeghe 2010). It is typically attributed to a shift towards post-materialist values of self-autonomy and self-actualization since the 1970s, although increasing economic insecurity is also likely to play a role (Norris and Inglehart 2019). Changing gender norms and the feminist movement contributed to the decline of the 'male breadwinner' model and increased female labor force participation between our study cohorts (Blau, Brinton, and Grusky 2006). Increased labor market participation and delayed fertility have improved women's economic prospect and financial independence. Women are also more likely to enter the professions and other high-status occupations, although high levels of occupational gender segregation and substantial gender wage gaps persist and a trend towards more gender equality has stalled since the 1990s (Blau, Brummund, and Liu 2013). The SDT prompted concerns about 'diverging destinies' between children growing up with married, dual-earner parents, and those

who have unmarried parents that hold low-paying jobs and have unstable family lives (McLanahan 2004).

Concerning *compositional life course change*, it has been argued that, because of the shift towards post-materialist values, Millennials are less inclined to pursue the most high-paying careers (Twenge 2010). Parallel socio-demographic changes suggest a decline in the stable marriage-based family trajectories that are most conducive to wealth accumulation, and an increase in the complex family lives associated with economic hardship: unstable marriage, separation and re-partnering, and unmarried parenthood (Killewald and Bryan 2018; Lersch 2017; Smock and Schwartz 2020). In terms of *economic returns*, the polarization described in the ‘diverging destinies’ literature likely contributes to rising wealth inequality among the Millennial cohort. A smaller group of increasingly positively selected, dual-earner couples enjoy increased wealth returns, while the capacity to accumulate wealth remains limited for unstable and complex families, as well as for single-earners (Cherlin 2020; McLanahan and Percheski 2008). Overall, ideational shifts and changing family demographics suggest lower and more unequal net worth for Millennial compared to Baby Boomer households.

Social Policy and Tax Reforms

The late Baby Boomer cohort reached age 35 just before the 1996 welfare reform (see Figure 1), when federal social policy still guaranteed a minimum level of aid to those in poverty. The 1996 Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA) eliminated the entitlement status of welfare, established time limits on receiving aid, and imposed compulsory work requirements. Welfare eligibility ended after two years, regardless of employment status, and a lifetime limit of five years was set on assistance (Iceland 2013:126). Early adult life courses of

the Millennial cohort were therefore less secured against economic hardship by welfare benefits and more economically dependent on work.

Moreover, the effective US tax rate has become substantially less progressive over the last few decades (Saez and Zucman 2019) and key labor market institutions such as union laws and minimum wage regulations have become gradually more disadvantageous for low-wage workers. While payroll taxes and health insurance premiums increased, the wealthy benefited from a steep decline in capital taxes, as well as expanded opportunities for tax evasion. In contrast, the value of the real minimum wage has declined almost continuously since the early 1980s, which is seen as a major contributor to increasing wage inequality, especially at the lower end of the distribution (Autor, Katz, and Kearney 2008). Finally, the increasing cost of college implies that many Millennials started their employment careers with a large amount of debt.

The activating elements of the 1996 welfare reform reduced the prevalence of extended periods out of the labor force among Millennials compared to Baby Boomers, a *compositional change* in life courses that could be beneficial to wealth accumulation for the Millennials. Yet, higher employment rates after the 1996 reform mainly reflected low-paying, unstable jobs, and a rise of the working poor (Lichter and Jayakody 2002). The combination of tax and labor market reforms outlined above also contributed to diverging *economic returns* to low-wage, working class trajectories and high-wage, middle class trajectories across cohorts. These reforms were particularly beneficial for those fortunate enough to inherit or acquire assets, but disadvantageous to those who derived their primary income from wages or social transfers.

Summary and Expectations

Taken together, the observed trends in economic restructuring, ideational change, and social policy and taxation suggest adverse compositional life course change and polarizing wealth returns for the early Millennials compared to the late Baby Boomers. We therefore expect higher wealth inequality at age 35 among the Millennials compared to the Baby Boomers (research question 1). Adverse compositional change in life courses for the Millennials (research question 2) will be visible in a higher prevalence of life courses that are less conducive to wealth accumulation, including less marriage, more unpartnered parenthood and family complexity, more low-wage service work and fewer stable careers in manufacturing. A polarization of wealth returns to similar life courses (research question 3), implies that already economically disadvantaged life courses—such as unstable low-skilled employment—among the Baby Boomers will be associated with even lower wealth returns at age 35 among Millennials. At the same time, the economically most advantaged life courses of continuous employment in professional occupations and stable marriage are expected to result in even higher wealth returns among Millennials compared to Baby Boomers. With respect to research question 4 (To what extent can cohort differences in wealth be attributed to changes in work and family life courses?) our empirical analyses for the first time allow to quantify the relative importance of adverse compositional life course change, and shifting economic returns to life courses for differences in wealth holdings at age 35 between Baby Boomers and Millennials.

Method

Data and Sample

We rely on the NLSY79 and NLSY97 to address our research questions. The NLSY79 is a sample of 9,964 individuals born between 1957 and 1964, who were first interviewed in 1979. The NLSY97 sample consists of 8,984 respondents born between 1980 and 1984, who were first interviewed in 1997 and most recently in 2019/20. Both NLSYs collect economic, social, and demographic information on an annual or biannual basis, which allows us to construct detailed family and employment trajectories for each cohort. After accounting for attrition and item non-response, our analytical sample size is 6,681 for the NLSY79 ('Baby Boomers') and 6,062 for the NLSY97 ('Millennials'). All analyses use sampling weights to account for the oversampling of ethnic minority respondents in the NLSY.

Measures

Our main variable of interest is real household wealth (net worth) at age 35: the combined value of all assets, minus debts, adjusted for inflation. Both the NLSY79 and the NLSY97 ask for respondents' main assets and debts at regular intervals. For respondents who are married or living with a partner, the wealth variable also includes the partner's wealth. To ensure comparability across cohorts, we converted all wealth measures to 2020 USD and applied the same topcode (600k). Appendix B provides a detailed description of how we computed the harmonized 'wealth at 35' variable. We also assess differences in wealth components (home equity, financial assets, non-financial assets and debts) and home ownership across cohorts. Homeownership is not only an

important proxy for wealth, but also carries a profound cultural and psychological meaning (Desmond 2016; Pfeffer 2018).

Our key explanatory variables are the respondents' work and family trajectories between age 18 and 35. To this end, we prepare the NLSY's rich annual panel data as a monthly calendar and apply sequence and cluster analysis to empirically identify work and family life course trajectories. We thereby examine "a complex set of life-course trajectories as they actually take place, providing ideal types of trajectories that can be interpreted and analyzed in a meaningful way" (Aassve, Billari, and Piccarreta 2007:371).

For the employment sequences, we distinguish between occupations based on the 9-category Erickson-Goldthorpe-Portacero (EGP) class scheme (Erikson, Goldthorpe, and Portocarero 1979), which is widely regarded as the dominant class scheme in the sociological literature (Breen and Jonsson 2005). Table 1 contains a list of EGP classes, including examples of typical occupations. Appendix A details the crosswalks used to convert NLSY occupational codes to EGP classes. Despite its numerical labels, the EGP scheme does not imply a linear prestige hierarchy of occupations. There is a clear prestige ranking, however, within the non-manual classes (I to IIIb), where we can distinguish between high-status white-collar classes (EGP I and II, the 'salarariat'), and lower status service occupations (EGP IIIa and IIIb). A similar hierarchy exists among the manual classes (V to VII), where class V (supervisors and technicians) represent the most high-status technical occupations, and VII (unskilled manual workers) the lowest. Classes IIIb (lower service), VI (skilled manual workers) and VII (unskilled manual workers) are typically considered working class jobs (Morgan 2017). In addition to the EGP classes, our employment calendars identify the non-work states 'in school', 'in college', 'unemployed' and 'out of the labor force' (see Figure 4).

The family sequences distinguish between living in the parental home, singles living independently, cohabitation, marriage, and separation, each with or without children (see the legend in Figure 5 for an overview). These states represent the most important demographic events and transitions in early adulthood, and are widely used in the literature (Billari 2001; Jalovaara and Fasang 2020; van Winkle 2016).

To account for cohort change in ascribed characteristics, all models control for the respondent's gender, race, and parental education. Race was coded according as “Hispanic”, “Black”, “Asian” or “White”. The latter category includes a small number of individuals of Native American descent. Racial wealth gaps in the United States are large (Conley 1999; Shapiro 2017). It is beyond the scope of this paper to analyze the relationship between race, life course trajectories and wealth outcomes in the level of detail it deserves, so we will leave this as an important topic for further research. Parental education, an important proxy for social origin, is constructed as a continuous variable indicating the highest grade completed by the respondent's mother or father, whichever was higher. Table 2 shows that Millennials were more racially diverse and had significantly higher levels of parental education than Baby Boomers. Because the NLSY was designed to be nationally representative, there were no notable differences in the (weighted) number of female and male respondents.

Analytical Strategy

Our analytical strategy consists of four parts, corresponding to our four research questions. First, we compare the distribution of household wealth at age 35 for each cohort (research question 1). Because the distribution of wealth is extremely skewed, and because of the topcodes applied by the NLSY to protect the identity of very wealthy respondents, comparisons based on the mean

(such as t-tests and Ordinary Least Squares regression) do not provide meaningful information. Instead, we estimate cohort differences at different points (quantiles) in the distribution of wealth.

In a second step, we identify a set a 'typical' work and family trajectories (research question 2), using methods derived from sequence and cluster analysis (Abbott and Hrycak 1990; Studer 2013). This allows us to assess how the prevalence of specific life course trajectories (e.g. single parenthood or manual work) has shifted across cohorts. Specifically, we use optimal matching with indel costs of 1 and substitutions costs of 2 to compare all sequences in a pairwise comparison. This cost specification balances similarity in terms of the timing and order of life course states (Studer and Ritchard 2016). The resulting distance matrix summarizes how similar or dissimilar each pair of sequences is and was entered into a partitioning around medoids (PAM) cluster analysis to identify a typology of similar life course trajectories (Gabadinho et al. 2011). The most appropriate number of clusters was determined based on established cluster cut-off criteria and interpretative substance. The Average Silhouette Width (Studer 2013) was 0.21 for employment and 0.30 for family life courses. For more detailed information on the clustering procedures and outcomes, please refer to Appendix C. In Appendix D, we show that alternative cost specifications lead to qualitatively similar work and family typologies.

Third, we analyze the association between the observed work and family trajectories and wealth accumulation in each cohort (research question 3) using multivalued quantile treatment effects (QTEs), computed using inverse probability weighting (Firpo 2007; Rios-Avila 2020). QTEs have a straightforward individual-level interpretation as the distributional impact of a categorical treatment on the outcome of interest, holding the distribution of other characteristics constant (Borgen, Haupt, and Wiborg 2022; Rios-Avila and Maroto 2022). In our case, for example, this

allows us to assess the difference in median wealth between the ‘unskilled worker’ and ‘skilled worker’ trajectories, controlling for race, gender, and parental education. Quantile regressions have the advantage that wealth does not need to be transformed to reduce the skewness of the distribution, because these models are robust to the influence of outliers (Rios-Avila and Maroto 2022).

Finally, we are interested in the extent to which cohort wealth gaps at different points in the distribution are reduced or attenuated by differences in work-family trajectories (research question 4). Firpo, Fortin, & Lemieux (2018) outline how the classic Kitagawa-Oaxaca-Blinder (KOB) decomposition of differences in the means between two groups (Kitagawa 1955; Oaxaca 1973) can be extended to group differences in the unconditional quantiles of an outcome variable, using the recentered influence function (RIF). Like the conventional KOB decomposition, the procedure they propose decomposes group differences in an outcome into 1) an 'explained' part due to differences in group characteristics (in our case, this would be the compositional effect resulting from shifts in employment and family trajectories across cohorts) and 2) an 'unexplained' part due to differences in the coefficients attached to those characteristics (cohort changes in the returns to specific work and family trajectories). We apply these unconditional quantile decompositions to explain wealth gaps between Baby Boomers and Millennials at three different quantiles: the 10th, 50th and 90th percentile. In addition to looking at cohort differences in the level of wealth, we also decompose changes in wealth inequality. Following the example presented in Firpo et al. (2018), we use a measure of inequality that is not affected by topcoding or negative wealth: the 90-10 differential.

We conducted a number of supplementary analyses and robustness checks. First, we replicated our analyses using multichannel work-family clusters that create a joint typology of similar work and

similar family lives (Gauthier et al. 2010; Pollock 2007) (see Appendix E). Results show that work and family lives are clearly interrelated. The higher-status Professional trajectories are likely to be combined with either late marriage and parenthood or singlehood, while working class trajectories tend to coincide with either early marriage and parenthood or single parenthood. The multichannel clusters are highly heterogeneous, which makes them unsuitable to include as categorical variables in the decomposition analysis, and their substantive added value is too low to favor them over the separate clusters for work and family lives in our analyses. We also checked whether including an expanded set of controls for family background (family structure at age 14 and parental wealth) affected wealth gaps between life course trajectories. Adding these covariates only slightly diminished the returns to advantaged employment and family trajectories. Because these indicators are not consistently available for both cohorts, they could not be included in the final specification. Finally, we replicated our analyses using a wealth measure that was equivalized for household size. The results (available upon request) show that our substantive conclusions remain unchanged when adjusting wealth for household size. In the following sections, we therefore decided to report findings based on non-equivalized household wealth, in line with previous literature.

Results

Cohort Differences in Wealth and Wealth Inequality

Our first research question relates to cohort differences in wealth at age 35. Figure 2 shows a much more unequal distribution of wealth among Millennials than among Baby Boomers. At the lower end and in the middle of the wealth distribution, Millennials are significantly worse off than the previous generation. Around 14% of Millennials had negative net worth at age 35—meaning their debts exceeded their assets—compared to only 8.7% of Baby Boomers. The median Millennial had

over 30% lower inflation-adjusted wealth than the median Baby Boomer at the same age (48.0k vs. 63.1k, $p < 0.000$). Millennials at the 90th percentile of the wealth distribution had about 20% *higher* wealth than their Baby Boomer counterparts, however (457k vs. 373k). In other words, the gap between rich and poor is larger among Millennials than it was for Baby Boomers at age 35, which corresponds with the aggregate trend of increasing wealth inequality that has been observed over the past decades (Piketty 2014; Saez and Zucman 2016).

To further explore differences in wealth between the two generations, we analyzed the individual assets and debts that together constitute net worth. For a typical American household, the most important asset is their own home. About 62% of Baby Boomers were homeowners by age 35, compared to only 49% of Millennials (see Table 2). The steep decline in homeownership at the start of mid-life is likely to have major implications for family formation as well as wealth accumulation. Figure 3 plots the distribution of the four main components of household net worth: home equity, financial assets, non-financial assets (cars, business assets etc.) and non-mortgage debt. While Millennials and Baby Boomers hold roughly similar levels of non-financial assets, Baby Boomers held higher levels of housing equity, particularly in the middle of the distribution. Millennials, on the other hand, held more financial assets, especially at the top of the distribution. Millennials were also far more likely to hold debts: 68% of Millennials held any kind of debt at age 35, compared to 43% of Baby Boomers. Moreover, the amounts of debt held by Millennials were much higher, likely reflecting the increasing cost of college and the corresponding expansion of student loans.

Cohort Differences in Life Course Trajectories

Our second research question asks how early work and family life courses differ between Baby Boomers and Millennials. We empirically identify ten distinct employment clusters and seven distinct family clusters, which represent ‘typical’ life course trajectories between the age of 18 and 35. The employment life courses cluster into 1) “College and Higher Professionals”, 2) College and Lower Professionals”, 3) “Some college and higher service”, 4) “Lower service”, 5) “Technicians and Supervisors”, 6) “Skilled Manual”, 7) “Unskilled Manual”, 8) “Military”, 9) “Mixed low-skilled work”, and 10) “Out of the Labor Force (OLF)”.

Most of the employment clusters were thus dominated by one of the EGP classes (see Table 1); although EGP class IV (self-employed) has been largely absorbed into the Skilled and Unskilled manual as well as the Mixed low-skilled clusters. The ‘Mixed low skill’ cluster is characterized by moving back and forth between low-skilled manual and service work (EGP IIIb and EGP VII), interspersed with periods of unemployment. This trajectory is likely to be the most precarious among the ones we observed and highlights the substitutability of low-wage jobs at the bottom of the labor market. It is striking that there was relatively limited mobility from less to more prestigious occupational classes during the early life course. Frech and Damaske (2019) similarly highlighted notably low mobility in income trajectories. This underlines the importance of early life decisions and opportunities for subsequent trajectories, especially with respect to college attendance and the transition from school to work.

Figure 4 shows a graphical representation of the employment clusters as Relative Frequency Sequence Plots (Fasang and Liao 2014) that select a subset of representative individual sequences for each group. This representation shows, for example, that the ‘Higher Professional’ cluster

largely consists of individuals who completed several years of college and then entered stable employment in an occupation classified as EGP class I (Higher-grade professionals, administrators, and officials). Interruptions due to unemployment or military service were uncommon in this cluster. This can be contrasted with the ‘Skilled manual’ cluster, where college attendance was unusual, and brief stints in unemployment or unskilled manual work were common.

Figure 6 (top panel) shows how the prevalence of each employment trajectory differs between Baby Boomers and Millennials. The figure demonstrates a striking decline in the ‘College and Higher Professional’ trajectory, which incorporates the highest-status occupations, such as lawyers, surgeons and engineers. Around 17% of Baby Boomers belonged to this cluster, compared to just 7.3% of Millennials. The decline in the highest-status early careers may have particularly strong implications for capital accumulation, because this is the trajectory with the highest wages and employment benefits. The drop in Higher professional early careers is partially offset by a 6.9 percentage-point increase in the ‘Lower professional’ cluster among Millennials, which includes occupations such as primary school teachers and computer programmers (see Table 1). We also observe a substantial increase in the ‘Lower service’ and ‘Technicians and Supervisors’ trajectories among Millennials, and a decline in the ‘Skilled manual’ career. This corresponds to the rise of the service economy and the decline of ‘mid-skill’ manufacturing jobs (Acemoglu and Autor 2011; Kalleberg 2011). There was a slight decline in the ‘Out of the labor force’ trajectory among Millennials, which may correspond to increasing female labor force participation.

Family life courses cluster into 1) “Early marriage and parenthood”, 2) “Late marriage and parenthood”, 3) “Childless marriage” 4) “Unmarried parenthood” 5) “Early divorce and parenthood”, 6) “Singlehood” and 7) “Parental home” (Figure 5). Family trajectories were thus

characterized by the presence or absence of particular states (especially marriage and parenthood) as well as by the timing of major life transitions. The ‘Unmarried parenthood’ cluster includes single parents as well as cohabiting parents, with frequent transitions between these states (see Figure 5). Unmarried parenthood and early divorce are associated with socio-economic disadvantage in the United States, whereas delayed marriage and childbearing is more common among high-status couples (McLanahan and Percheski 2008).

Compared to the work trajectories, the family life courses show even more pronounced cohort change (see Figure 6, bottom panel), with strong declines in the 'married' types (early marriage, late marriage and childless marriage) and increases in trajectories dominated by singlehood, unmarried parenthood and staying in the parental home. The decline in the “Early marriage and parenthood” trajectory—in which respondents marry and have children shortly after leaving the parental home—was particularly pronounced: 27% of Baby Boomers belonged to this cluster, compared to only 13.3% of Millennials. These findings are in line with sociological theories on the decline of marriage and the delayed transition to adulthood in American society (Cherlin 2020; Smith et al. 2016).

Table 3 presents a set of key indicators for each family and employment trajectory, such as social origin (indicated by parents' years of education) and the share of women and racial minorities. Women were overrepresented in the 'Higher service' and 'Out of the labor force' clusters, particularly among Baby Boomers. Women and ethnic minorities were underrepresented in the 'Higher professional' and 'Skilled labor' clusters.

Cohort Differences in the Returns to Life Course Trajectories

Our third research question asks whether economic returns to the identified work and family trajectories differ between Baby Boomers and Millennials. To answer this question, we calculated multivalued quantile treatment effects of work and family trajectories at different points in the distribution of wealth for each cohort (see Figure 7 for a graphical representation, and Appendix F for the full results). As discussed in our conceptual framework, the associations between work-family trajectories and wealth outcomes are due to a combination of causal and non-causal pathways (treatment, facilitation, selection, and discrimination), and therefore have a descriptive interpretation only, even after adjusting for ascribed characteristics.

Our findings show that there are large gaps in household wealth at 35 based on work and family trajectories, and these gaps increased across cohorts, especially at the upper end of the distribution. Figure 7 (top panel) plots the predicted wealth holdings by work trajectory at the 10th, 50th, and the 90th percentile for each cohort, adjusted for race, gender, and parental education. At the median, we observe a similar pattern of wealth returns in each cohort, suggesting relatively stable patterns of within-cohort inequality. In both cohorts, the ‘Higher professional’ cluster had the highest median wealth at age 35, followed by the Technicians and Lower professionals. The ‘Out of the labor force’ and ‘Mixed low-skilled’ trajectories were least conducive to wealth accumulation at the median. The similarity at median is quite striking, considering that wealth outcomes in each cohort were observed around 25 years apart: from 1990 onwards for the Baby Boomers, and from 2015 onwards for the Millennials (see Figure 1). The pattern is different, however, when looking at the lower end of the distribution. At the 10th percentile, wealth holdings of Baby Boomers were approximately zero, regardless of work trajectory. Millennials, on the other hand, often held considerable debts, especially those in the ‘Professional’ clusters. This is likely a result of unpaid

student loans, as well as negative housing equity. At the upper end of the distribution, however, we observe the opposite: Millennials in the most high-status employment clusters (Professionals, Higher service, and Technicians) acquired more wealth than Baby Boomers with equivalent trajectories, while the wealth of less advantaged clusters (Lower service, Unskilled manual, Out of the labor force) remained stagnant or even declined relative to the same trajectories in the earlier cohort. These differences are also evident when looking at rates of home ownership: although homeownership declined across cohorts for all work trajectories, the decline was even more pronounced for the 'Unskilled Manual' trajectory (from 56% among Baby Boomers to 41% among Millennials) than for the 'Higher Professional' trajectory (from 74% to 68%) (see Table 3).

We found similar patterns of diverging returns when looking at the distribution of wealth by family trajectory. Median wealth at 35 in the 'Late marriage with children' and 'Childless marriage' clusters was much higher than in any of the other clusters, for both cohorts (Figure 7, bottom panel). Moreover, the wealthiest individuals in these clusters increased their advantage across cohorts relative to other family trajectories. In contrast, life courses characterized by single parenthood, divorce, and staying in the parental home had the lowest wealth outcomes, with little difference between cohorts. When looking at the 10th percentile, the high levels of debt among Millennials who stayed in the parental home stands out. It is plausible that this is due to (inverse) facilitation, where young adults were forced to stay with their parents because they could not afford independent housing. Homeownership rates declined for all family trajectories except 'Late marriage' and 'Unmarried parenthood'. Declines in homeownership across cohorts were particularly pronounced for married couples who had children early (from 67% to 55%) and divorced individuals with children (from 38% to 30%).

In summary, these findings confirm our expectations regarding the polarization of wealth returns to typical working-class trajectories (such as low-skilled manual or service work, early and/or single parenthood) and trajectories associated with the middle class (stable high-status employment, late marriage and parenthood). As a result, similar work and family trajectories led to very different wealth outcomes among Baby Boomers and Millennials, especially at the lower and the upper end of the distribution. The diverging effects at the bottom and at the top of the wealth distribution highlight the importance of looking at differences across quantiles.

Changing Work-Family Trajectories and the Cohort Wealth Gap

Thus far we have observed substantial compositional shifts in life course trajectories across cohorts, as well as a bifurcation in the returns to these trajectories, especially at the upper end of the distribution. It remains unclear, however, to what extent changes in the composition of and returns to work-family life courses can account for observed cohort differences in household wealth (research question 4). We address this question using unconditional quantile decompositions, which are based on a counterfactual scenario in which Millennials are assigned the same life course trajectories as the Baby Boomers, as well as the same returns to these trajectories. Table 4 shows the results of unconditional quantile (RIF) decomposition of wealth gaps between Baby Boomers and Millennials at the 10th, 50th, and 90th percentile. Following Fortin et al. (2018), we also decompose a measure of wealth inequality, the 90-10 differential.

The aggregate decompositions suggest that increases in wealth inequality across cohorts are mainly driven by the diverging returns to 'advantaged' and 'disadvantaged' work and family trajectories, rather than by the compositional shifts in these life course trajectories. As we showed earlier (see Figure 2), the cohort wealth gap turns from negative at the lower end of the distribution to positive

at the top: the poorest Millennials are poorer than their Baby Boomer counterparts, and the richest Millennials are richer. The gap between the 90th and 10th percentile increased by almost 100k across cohorts, from 371k to 468k. In combination, compositional shifts do not explain any of the -13k gap at 10th percentile, nor do they explain much of the 83.7k gap at the 90th percentile or the corresponding increase in the 90-10 range.

The detailed decompositions show how changes in specific work and family trajectories contributed to overall cohort differences in wealth. When looking at the detailed decomposition for the 90th percentile—where the cohort wealth gap is largest—the negative signs on the explained components for work and family trajectories imply that combined compositional shifts in early life courses were detrimental to wealth accumulation in the younger generation. In particular, we see that the steep decline in Higher professional careers worked to the disadvantage of the younger cohort, and therefore decreased wealth inequality—as measured by the 90-10 differential. Our model thus suggests that the richest Millennials accumulated more wealth than the richest Baby Boomers *in spite of* disadvantageous compositional shifts in life course trajectories, rather than as a result of these shifts. This was offset, however, by the effect of increasing parental education, which contributed to higher wealth inequality among Millennials. At the median, if Millennials had the same family trajectories as Baby Boomers—such as lower levels of unmarried parenthood—their median wealth would be 12.6k higher than what was observed. This is consistent with our previous finding that Millennials are less likely to experience the most economically advantageous work and family trajectories (see Figure 6).

Table 4 also shows how changes in the economic *returns* to work and family trajectories are associated with cohort differences in wealth. The detailed decomposition of the returns component

should be interpreted with some caution because it is sensitive to the choice of the reference group (Fortin, Lemieux, and Firpo 2011). However, Kim (2013) states that “any detailed decomposition method is acceptable as long as there are theoretical or practical reasons to believe that the researcher’s choice of reference group (or weighting factors) produces a meaningful decomposition result” (p. 358). We follow Firpo et al. (2018) in choosing a typical working class group (white men, unskilled manual career, early marriage and parenthood, average parental education) as the reference category. The constant term was close to zero at each percentile, suggesting that the distribution of wealth among this relatively disadvantaged group was similar for Baby Boomers and Millennials (in line with Figure 7). Relative to this baseline, changes in the returns to work trajectories, family trajectories and parental education all contributed to increasing wealth inequality, mainly by increasing Millennial wealth at the upper end of the distribution. Returns to work trajectories play a particularly important role here, explaining 43% of the (negative) cohort gap at the 10th percentile, and 74% of the (positive) cohort gap at the 90th percentile. The detailed decomposition results show that increasing returns to high-status work trajectories—especially the ‘Professional’, ‘Higher Service’ and ‘Technicians’ clusters—widened the cohort wealth gap, and therewith contributed to increasing wealth inequality. Similarly, increasing returns to ‘middle-class’ family trajectories—especially delayed marriage and childbearing—explain a substantial share of Millennials' wealth advantage at the top of the distribution.

In sum, the findings from the decomposition analysis suggest that shifts in work-family trajectories (documented in Figure 6) cannot explain the observed trend towards increasing wealth inequality. Instead, the distribution of wealth has become more unequal because of the pattern illustrated in Figure 7: the economic returns to typical middle-class trajectories have increased, especially at the

top of the distribution, while the returns to typical working-class trajectories have stagnated or declined.

Discussion

The purpose of this study was to understand the relationship between life course trajectories and wealth accumulation, using a cohort perspective. It is well known that wealth inequality is increasing in the United States (Piketty 2014; Saez and Zucman 2016), and we assessed the extent to which changes in work and family life courses across two generations contributed to this phenomenon. The comparison between Baby Boomers and Millennials is particularly salient because these labels have become emblematic in the increasingly heated debate over generational injustice. Millennials constituted more than a third of the US labor force in 2018 (Fry 2018), and their economic predicament is a source of major public concern (Leatherby 2017; Thompson 2018).

We showed that wealth is much more unequally distributed among early Millennials than among late Baby Boomers. The poorest Millennials have less wealth than the poorest Baby Boomers at the same age, but the richest have substantially more. The median Millennial had almost 25% lower wealth at age 35 than the median Baby Boomer, and home ownership decreased from 62% to 49%. This is in line with aggregate trends in wealth inequality, which show increasing indebtedness at the bottom of the distribution, and large gains at the top (Saez and Zucman 2016; Wolff 2017).

Using detailed monthly panel data, we reconstructed work and family life courses from age 18 to 35 and clustered them into a set of 'typical' trajectories. The results reveal a steep decline in the most high-status employment careers among Millennials, as well as an increase in low-skill service

work (EGP IIIb) and advanced technical occupations (EGP V). The latter include many jobs associated with the post-industrial knowledge economy, such as designers, sound engineers, and artists. The change in family trajectories is even more pronounced, with a strong decline in the traditional pattern of early marriage and parenthood, and an increase in trajectories characterized by singlehood, single parenthood and staying in the parental home. Findings from multichannel sequence analysis show that Professional work trajectories are often combined with advantaged family trajectories (especially late marriage and parenthood), while working class employment tends to coincide with lower-wealth family trajectories such as early marriage and parenthood or unmarried parenthood.

A decomposition analysis shows that compositional shifts in work and family life courses generally work to the disadvantage of the younger generation, although this only explains a small part of the increase in wealth inequality. Instead, the distribution of wealth has become more unequal because of diverging economic returns to the disadvantaged trajectories associated with the working class (unskilled manual or service work, single parenthood) and the more advantageous trajectories typical of the middle class (professionals, technicians and late or childless marriage). While Millennials in advantageous work-family trajectories accumulated more wealth than their Baby Boomers counterparts, Millennials with typical working class life courses did no better, and sometimes worse, than those with equivalent lives in their parents' generation. We also observed steep declines in homeownership—an important life outcome in its own right—especially among those with the most disadvantaged life course trajectories.

Our findings thus reveal a vicious cycle of polarization in work and family life and increasing economic inequality. This is in line with the diverging destinies literature (McLanahan 2004;

McLanahan and Percheski 2008), which focuses on the polarization of family life, and the literature on job polarization and growing wage inequality (Acemoglu and Autor 2011; Cheng 2021; Dwyer 2013). We show that the rise in low-skill service work is particularly pronounced among Millennials. Unlike the job polarization literature, which focuses on the occupational structure across the entire work force, we also observe a dramatic decline in trajectories defined by the highest-status occupations, such as lawyers, corporate executives, and senior civil servants. At this point it is unclear whether this represents a structural shift or a pattern of delayed entry, and it will be important to follow Millennials' occupational trajectories in the coming years, as the large Baby Boomer cohorts retire from work.

The erosion of wealth in the lower end and the middle of the distribution, in combination with the decline in high-status work trajectories and the increasing class divide in family structure, suggests that concerns about the Millennials' economic wellbeing are generally well-founded. Due to well-known processes of cumulative (dis)advantage—wealth begets wealth—early adulthood is a crucially important stage for wealth accumulation. Inequalities in wealth in early life are likely to persist and amplify over the life course, laying the foundation for future stratification in wealth and related benefits, such as health and longevity. The decline of wealth and homeownership for those in the most disadvantaged work and family trajectories is therefore particularly worrisome.

Our study demonstrates how a longitudinal analysis of changing life course trajectories across cohorts can help us to understand important macro-structural trends in American society, such as the rise in wealth inequality and the increase in social and economic polarization. In doing so, it contributes to a growing body of scholarship analyzing the micro-level foundations of wealth inequality (e.g. Bernardi, Boertien, and Geven 2019; Conley 1999; Keister 2005; Killewald and

Bryan 2018; Lersch et al. 2017; Pfeffer et al. 2013). We extend and complement this literature by 1) using a cohort perspective to understand change over time, 2) using longitudinal life course trajectories as predictors of wealth accumulation, 3) developing a conceptual framework that distinguishes between compositional change in life course trajectories and changes in the returns to these trajectories, and 4) making comparisons across the unconditional distribution of wealth. In doing so, we challenge dominant accounts that emphasize structural shifts work-family lives as the main driver of cohort change in wealth, and highlight the importance of looking at the economic returns to otherwise similar life course trajectories. Popular narratives about the “first generation that is worse off than their parents” overlook increasing within-cohort differentiation in wealth, which has benefited middle-class Millennials, while hurting those in typical working-class trajectories.

Our analysis should be interpreted in view of certain limitations. First, as indicated in our conceptual framework, we do not assess the direction of causality in the association between work and family life courses and wealth accumulation and we cannot isolate the relative contribution of mechanisms of selection, facilitation, reinforcement, and discrimination for generating cohort differences. Instead, we believe that work-family trajectories and wealth accumulation should be interpreted as mutually reinforcing processes, which have become more closely linked over time. It should also be noted that life course typologies we identified have fuzzy boundaries and are subject to methodological judgements about the state space and the clustering algorithm (see Appendix C and D).

Moreover, we have limited information on mechanisms that link life course trajectories and wealth accumulation. Labor earnings from respondents and partners, government and private transfers,

capital appreciation and differences in consumption rates all affect wealth holdings, and may differ between cohorts and trajectories. Cohort differences in wealth can also be caused by macro-level shocks that affect all wealth holdings simultaneously. For example, the global financial crisis of 2008 wiped out a large share of US wealth (Wolff 2017). Data from the Survey of Consumer Finances show that wealth holdings had recovered somewhat, although not fully, by the time our Millennial cohort reached age 35 (2015-2019). Increases in inequality may also result from changes in the returns to different types of assets (Piketty 2014) or changes in the role of bequests and in-vivo transfers from parents and other relatives. Although it is difficult to estimate the exact share of transfers in wealth accumulation, recent evidence suggests that—contrary to popular belief—only a small proportion of young adults receive substantial wealth transfers from parents, and the importance of transfers has declined across cohorts (McKernan et al. 2014; Wolff 2015). However, for those fortunate enough to receive transfers, their average value has increased (Keister et al. 2019; Wolff 2015), which may also have contributed to the increase in wealth inequality at age 35. Finally, as a result of the top-codes imposed on the publicly released NLSY data we were not able to assess cohort changes in wealth at the very top of the distribution, where a large share of household wealth is concentrated (Vermeulen 2016). Future research should seek to disentangle the role of parental transfers, own earnings and partnering in wealth accumulation, and how these have changed over time. The approach presented here could also be used to understand the role of life course trajectories in explaining wealth gaps based on race, class origin and other ascribed characteristics.

These limitations, however, do not diminish our core finding: the polarization in economic returns to work-family life courses is driving increasing wealth inequality across cohorts. The vast and increasing gap between the rich and the poor is a fundamental moral and political challenge.

Economic polarization also contributes to a range of other social problems, including the rise of populist authoritarianism (Norris and Inglehart 2019). Our findings further suggest that changes in the composition of work-family life courses did not have a major impact on cohort changes in wealth, contrary to popular narratives that see increasingly precarious work careers and unstable family lives as the primary cause of Millennials' economic troubles.

These findings have several implications for economic and social policy. Reversing economic polarization requires tax reforms as well as redesigning the institutions that create, perpetuate and magnify wealth inequality (Desmond 2016; Keister 2000; Saez and Zucman 2019; Savage 2021). Policies that enable young families to build assets and attain economic security—such as increasing the minimum wage, providing access to stable housing, and universal health insurance—have large multiplier effects, because they can kickstart an intra- and intergenerational process of cumulative advantage. Spilerman (2000) suggests that "even modest levels of financial assets, which normally provide only a small addition to total income, can cushion a family from the economic shock of illness or job loss, enabling a home mortgage, car loan, and other bills to be paid for a number of months and thereby preventing a temporary loss of employment from snowballing into a wider crisis for the family" (p. 500). We agree with Thomas Shapiro, however, that "a tentative, piecemeal, or fragmentary response will not suffice to create equity and family prosperity" (2017:132).

Tables

Table 1: The EGP class schema adopted in this study

Class	Class label	Illustrative examples
I	Higher-grade professionals, administrators, managers, and officials	Lawyers, Surgeons, Engineers
II	Lower-grade professionals, administrators, managers, and officials	Social workers, Primary school teachers, Computer programmers
IIIa	Routine non-manual and service employees, higher-grade	Secretaries, Sales representatives, Office clerks
IIIb	Routine non-manual and service employees, lower-grade	Hairdressers, Security guards, Waiters
IV	Farm owners and non-professional self-employed workers, with or without employees	Farmers, Garage owners
V	Higher-grade technicians and repairers, public safety workers, performers, and supervisors of manual workers	Police officers, Designers, Chefs
VI	Skilled manual workers, lower-grade technicians, installers, and repairers	Car mechanics, Carpenters, Electricians
VII	Semiskilled and unskilled manual and agricultural workers	Dishwashers, Truck drivers, Farm workers
Military	All members of the armed forces	Sergeants, Soldiers

Note: adapted from Morgan (2017:12–15)

Table 2: Comparing Baby-Boomers and Millennials at age 35 (weighted)

	Baby Boomers (N=6,681)	Millennials (N=6,062)	Difference	p-value
Median household wealth (in 1,000 2018 USD)	63.1	48.0	-15.1	0.000
Homeowner	61.6 %	48.8 %	-12.8	0.000
Work trajectory typology:				
Higher professionals	17.3 %	7.3 %	-10.0	0.000
Lower professionals	11.4 %	18.3 %	6.9	0.000
Higher service	11.6 %	12.3 %	0.7	0.303
Lower service	6.6 %	13.4 %	6.9	0.000
Technicians	1.3 %	6.1 %	4.9	0.000
Skilled manual	8.2 %	5.3 %	-2.9	0.000
Unskilled manual	19.0 %	15.2 %	-3.7	0.000
Military	3.2 %	2.8 %	-0.4	0.272
Mixed low-skill	10.6 %	10.7 %	0.2	0.793
Out of the labor force	10.9 %	8.5 %	-2.5	0.000
Family trajectory typology:				
Early marriage w/ child(ren)	27.3 %	13.3 %	-14.0	0.000
Late marriage w/ child(ren)	28.3 %	20.9 %	-7.4	0.000
Marriage w/o child(ren)	15.2 %	13.6 %	-1.6	0.027
Unmarried parenthood	5.0 %	16.7 %	11.7	0.000
Divorce w/ child(ren)	7.0 %	7.0 %	0.0	0.972
Singlehood	10.8 %	18.2 %	7.5	0.000
Parental Home	6.4 %	10.3 %	3.9	0.000
Race:			-10.8	0.000
White	79.5 %	68.7 %	6.3	0.000
Hispanic	6.5 %	12.8 %	3.2	0.000
Black	13.2 %	16.4 %	1.3	0.000
Asian	0.9 %	2.2 %		
Female	48.0 %	48.1 %	-0.1	0.915
Parents: Highest grade (mean)	12.4	13.6	1.2	0.000

Table 3: Descriptives of the family and work clusters, by cohort

	Female (%)		Minority ethnic (%)		Parents average education (years)		Homeowner at 35 (%)	
	BB	MIL	BB	MIL	BB	MIL	BB	MIL
Work trajectories								
Higher professionals	36.8	43.7	13.5	20.9	14.0	15.5	74.3	68.2
Lower professionals	59.8	57.8	14.7	25.3	13.7	14.9	74.2	63.9
Higher service	79.9	65.0	19.2	29.6	12.6	14.0	70.8	59.3
Lower service	48.7	64.5	18.0	36.1	12.9	13.4	62.9	42.3
Technicians	12.8	30.0	15.8	30.0	12.2	14.1	81.2	62.4
Skilled manual	5.9	1.9	13.4	19.2	11.8	12.8	66.4	59.7
Unskilled manual	19.7	13.7	25.2	34.2	11.2	12.5	56.0	41.1
Military	8.5	16.2	34.7	31.1	12.1	13.7	39.1	47.0
Mixed low-skill	84.2	76.5	20.1	38.2	12.0	12.8	50.8	30.0
Out of the labor force	80.3	59.1	34.9	43.0	10.9	12.5	38.2	16.1
Family trajectories								
Early marriage w/ child(ren)	59.4	59.3	20.7	27.3	11.6	12.7	67.1	55.3
Late marriage w/ child(ren)	42.1	45.2	13.8	19.6	13.0	14.3	76.5	76.4
Marriage w/o child(ren)	48.6	51.9	11.9	20.8	13.2	14.4	68.0	60.1
Unmarried parenthood	51.2	56.1	69.3	55.0	10.9	12.5	20.1	28.4
Divorce w/ child(ren)	58.8	62.3	24.4	30.8	11.5	12.9	38.0	29.7
Singlehood	34.2	37.3	19.2	28.3	13.4	14.5	50.1	40.3
Parental Home	33.0	31.1	30.6	41.7	11.9	13.4	34.0	30.4
All	48.0	48.1	20.5	31.3	12.4	13.6	61.6	48.8

Note: Weighted. BB=Baby Boomers, MIL=Millennial

Table 4: RIF-Oaxaca decomposition of cohort differences in wealth at different quantiles

	Q10	Q50	Q90	Q90-Q10
Overall				
Millennials	-10.8***	48.1***	457.2***	468.0***
Baby Boomers	2.2**	63.1***	373.5***	371.3***
Difference	-13.0***	-15.1***	83.7***	96.6***
Composition	0.0	-10.3***	2.4	2.4
	(-0,2%)	(68,7%)	(2,9%)	(2,4%)
Returns	-13.1***	-4.7	81.3***	94.3***
	(100,2%)	(31,3%)	(97,1%)	(97,6%)
Composition				
Unskilled manual	<i>ref.</i>	<i>ref.</i>	<i>ref.</i>	<i>ref.</i>
Higher professionals	-0.2	-7.5***	-32.4***	-31.8***
Lower professionals	0.1	4.4***	12.2***	12.0***
Higher service	0.0	0.3	0.7	0.7
Lower service	0.1	1.1 ⁺	5.9*	5.7*
Technicians	0.5***	2.6**	7.7	7.1
Skilled manual	-0.1 ⁺	-0.8**	-0.7	-0.5
Military	0.0	-0.0	0.0	0.0
Mixed low-skill	-0.0	-0.0	0.1	0.1
Out of the labor force	0.2*	0.7**	-2.1*	-2.3**
Total work trajectories	0.6*	0.7	-8.4	-8.9
	(-4,6%)	(-4,5%)	(-10,1%)	(-9,2%)
Early marriage w/ child(ren)	<i>ref.</i>	<i>ref.</i>	<i>ref.</i>	<i>ref.</i>
Late marriage w/ child(ren)	-0.0	-1.6***	-7.8***	-7.7***
Marriage w/o child(ren)	0.0	-0.0	-1.9 ⁺	-1.9 ⁺
Unmarried parenthood	-0.9*	-6.2***	-2.5	-1.6
Divorce w/ child(ren)	-0.0	-0.0	-0.0	-0.0
Singlehood	-0.5*	-2.8***	-2.2	-1.7
Parental Home	-0.1	-1.9***	-2.1 ⁺	-2.0
Total family trajectories	-1.5**	-12.6***	-16.5***	-14.9***
	(11,5%)	(83,9%)	(-19,7%)	(-15,4%)
Female	-0.0	-0.0	-0.0	-0.0
White	<i>ref.</i>	<i>ref.</i>	<i>ref.</i>	<i>ref.</i>
Hispanic	-0.1	-1.8***	-0.7	-0.6
Black	-0.1*	-2.1***	-4.0***	-3.8***
Asian	0.1	0.2	2.7	2.6
Parental education	1.1***	5.4***	29.4***	28.1***

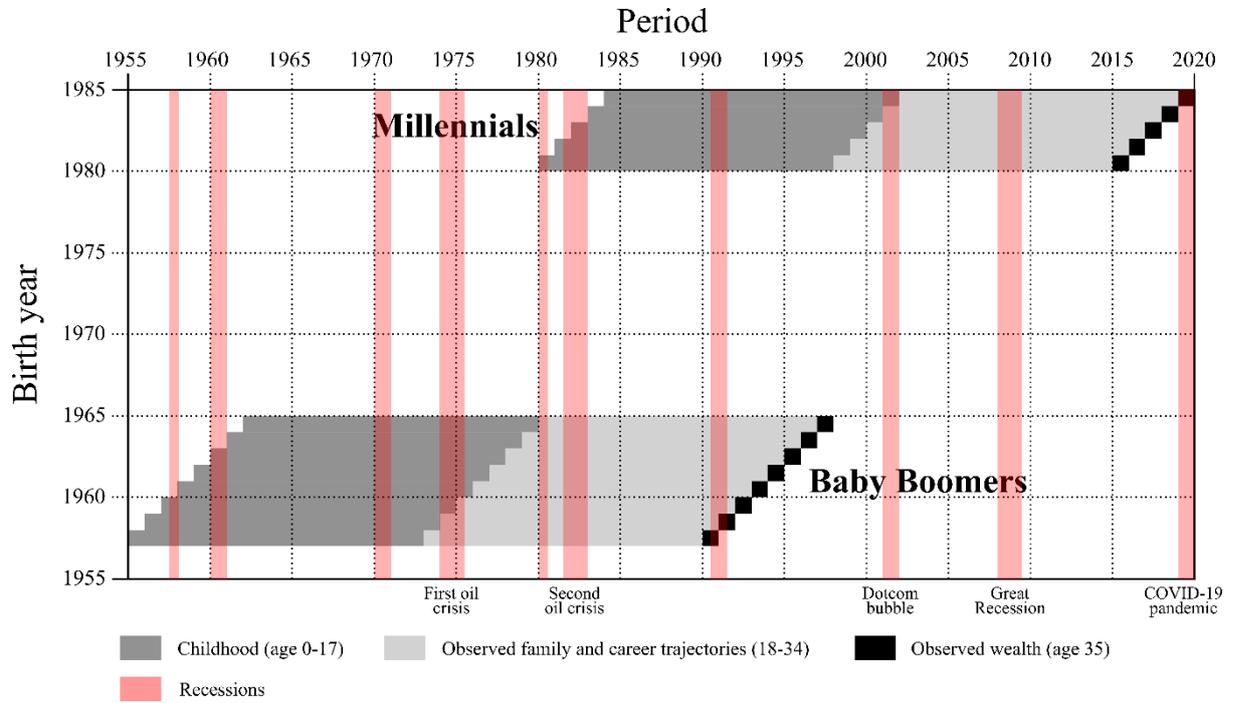
...cont.

Returns				
Unskilled manual	<i>ref.</i>	<i>ref.</i>	<i>ref.</i>	<i>ref.</i>
Higher professionals	-0.8*	-0.2	17.6*	18.7**
Lower professionals	-2.8***	-2.9	21.9 ⁺	25.0*
Higher service	-0.9 ⁺	-0.7	17.2*	18.2*
Lower service	-1.4*	-1.5	-9.7	-8.1
Technicians	-0.6*	0.7	12.3	12.9 ⁺
Skilled manual	0.0	0.1	4.5	4.5
Military	-0.3	1.2**	0.4	0.7
Mixed low-skill	0.4	-0.1	0.7	0.5
Out of the labor force	0.9*	-1.0	-2.8	-3.6
Total work trajectories	-5.5*	-4.4	62.2⁺	68.9*
	(42,5%)	(29,4%)	(74,2%)	(71,3%)
Early marriage w/ child(ren)	<i>ref.</i>	<i>ref.</i>	<i>ref.</i>	<i>ref.</i>
Late marriage w/ child(ren)	1.7*	-0.3	26.8*	25.3 ⁺
Marriage w/o child(ren)	0.8	-0.5	0.9	0.4
Unmarried parenthood	1.8*	1.4	-7.2	-9.0
Divorce w/ child(ren)	1.0*	1.2	-3.8	-4.8
Singlehood	0.7	1.4	7.6	6.9
Parental Home	-0.3	-0.8	-4.9	-4.6
Total family trajectories	5.6*	2.4	19.4	14.2
	(-43,3%)	(-15,9%)	(23,2%)	(14,7%)
Female	-1.3	-3.8	-18.7	-17.5
White	<i>ref.</i>	<i>ref.</i>	<i>ref.</i>	<i>ref.</i>
Hispanic	0.4	1.2	-5.6	-6.0
Black	-0.9 ⁺	3.4***	-6.3	-5.6
Asian	-0.0	-0.1	2.9	2.9
Parental education	-1.5**	-3.6**	20.4*	22.2*
Constant	-9.9**	0.3	7.0	15.2
Observations	12,743	12,743	12,743	12,743

Note: Estimated using the rif_oaxaca command in Stata 17 (Rios-Avila 2020) with weights and robust standard errors. All percentages in this table are calculated relative to the total difference, e.g. for the total composition component of the 50th percentile $-10.3/-15.1 = 68.0\%$.

Figures

Figure 1: Location of the observed birth cohorts in historical time



Note: the graph should be read from the left to the right: birth cohorts pass through historical periods

Figure 2: Cohort Differences in Wealth at Each Decile (weighted)

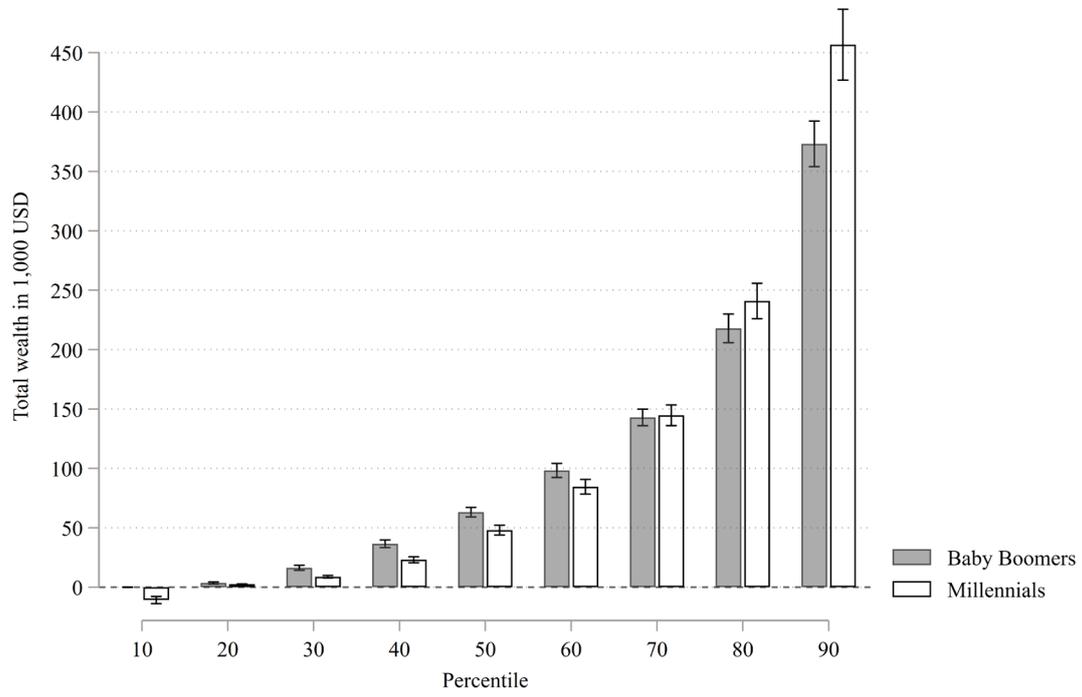


Figure 3: Cohort Differences in Wealth Components at Each Decile (weighted)

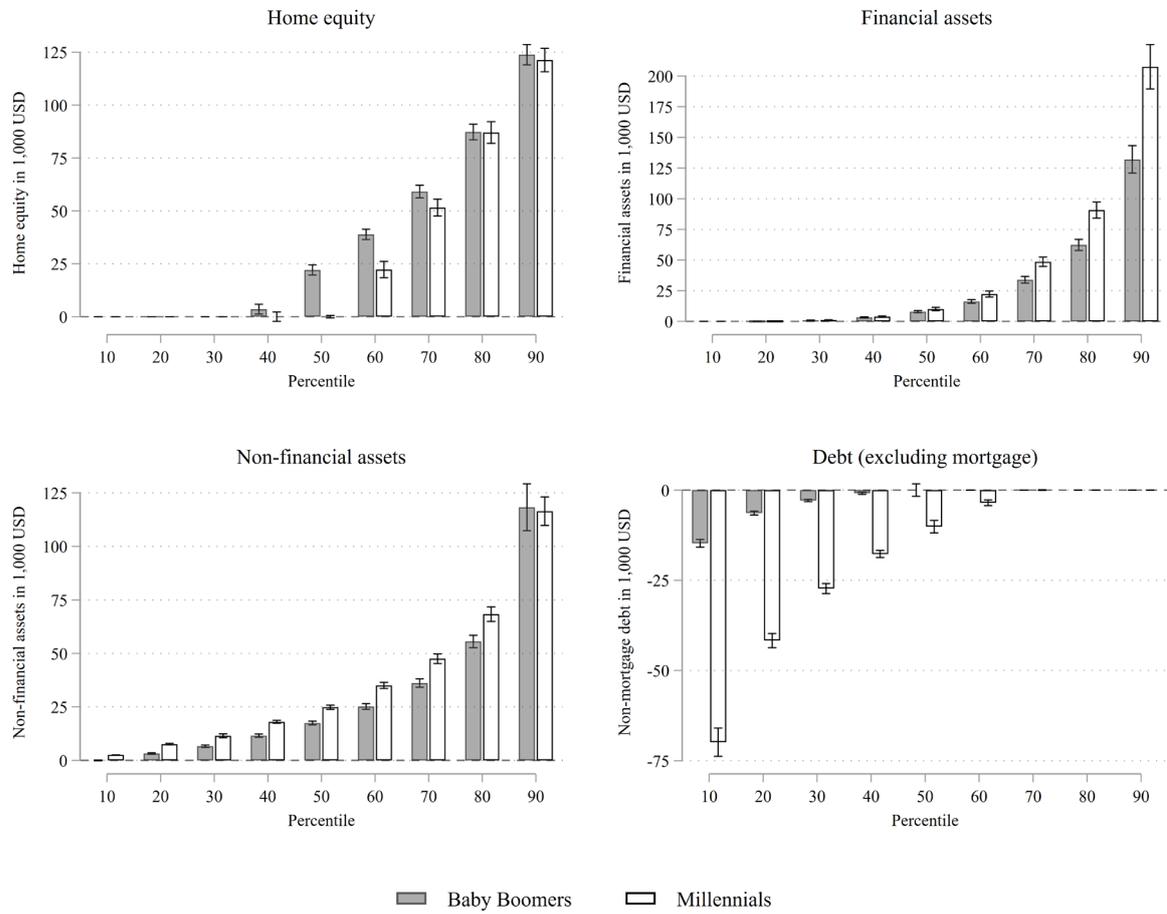
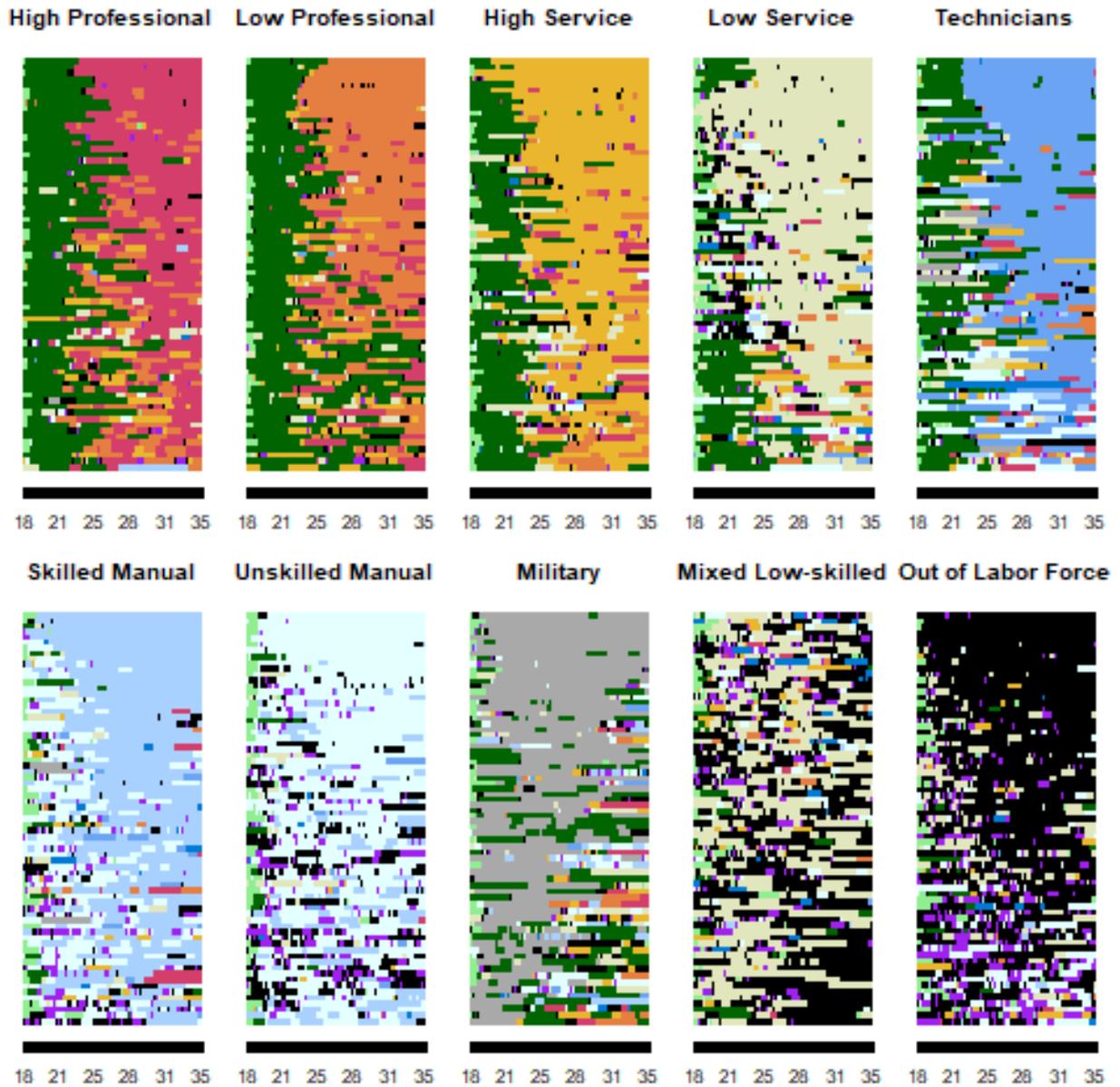
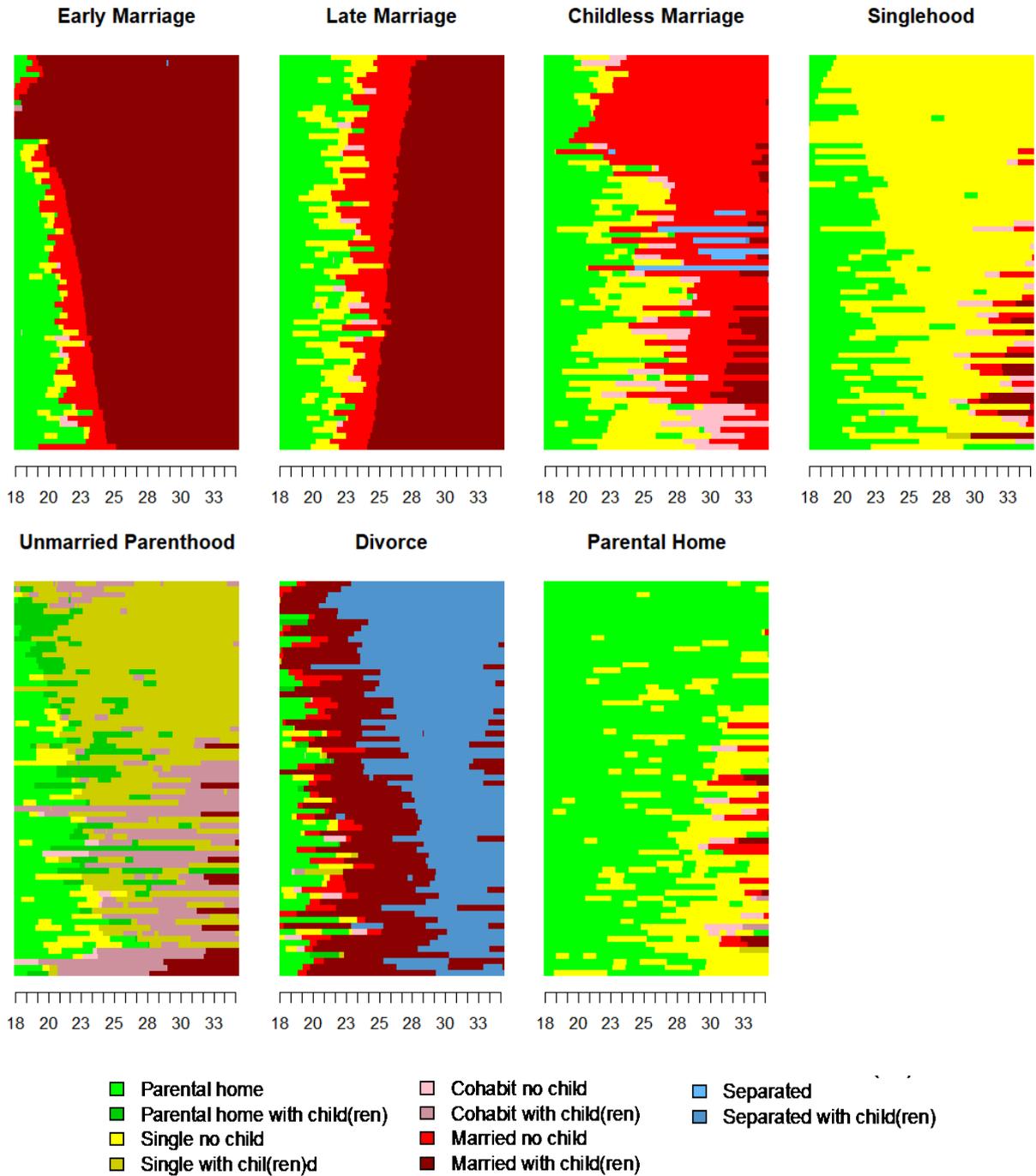


Figure 4: Work trajectories: Relative Frequency Sequence Plots (*view in color*)



Note: Relative Frequency Sequence Plots (Fasang and Liao 2014) of work trajectories, $k=70$ representative sequences per cluster, age on x-axis, sorted descending by silhouette: strongest representatives of the cluster at the top, outliers and poorly classified sequences at the bottom.

Figure 5: Family trajectories: Relative Frequency Sequence Plots (*view in color*)



Note: Relative Frequency Sequence Plots (Fasang and Liao 2014) of family trajectories, $k=70$ representative sequences per cluster, age on x-axis, sorted descending by silhouette: strongest representatives of the cluster at the top, outliers and poorly classified sequences at the bottom.

Figure 6: Composition: Cohort Change in Work and Family Trajectories

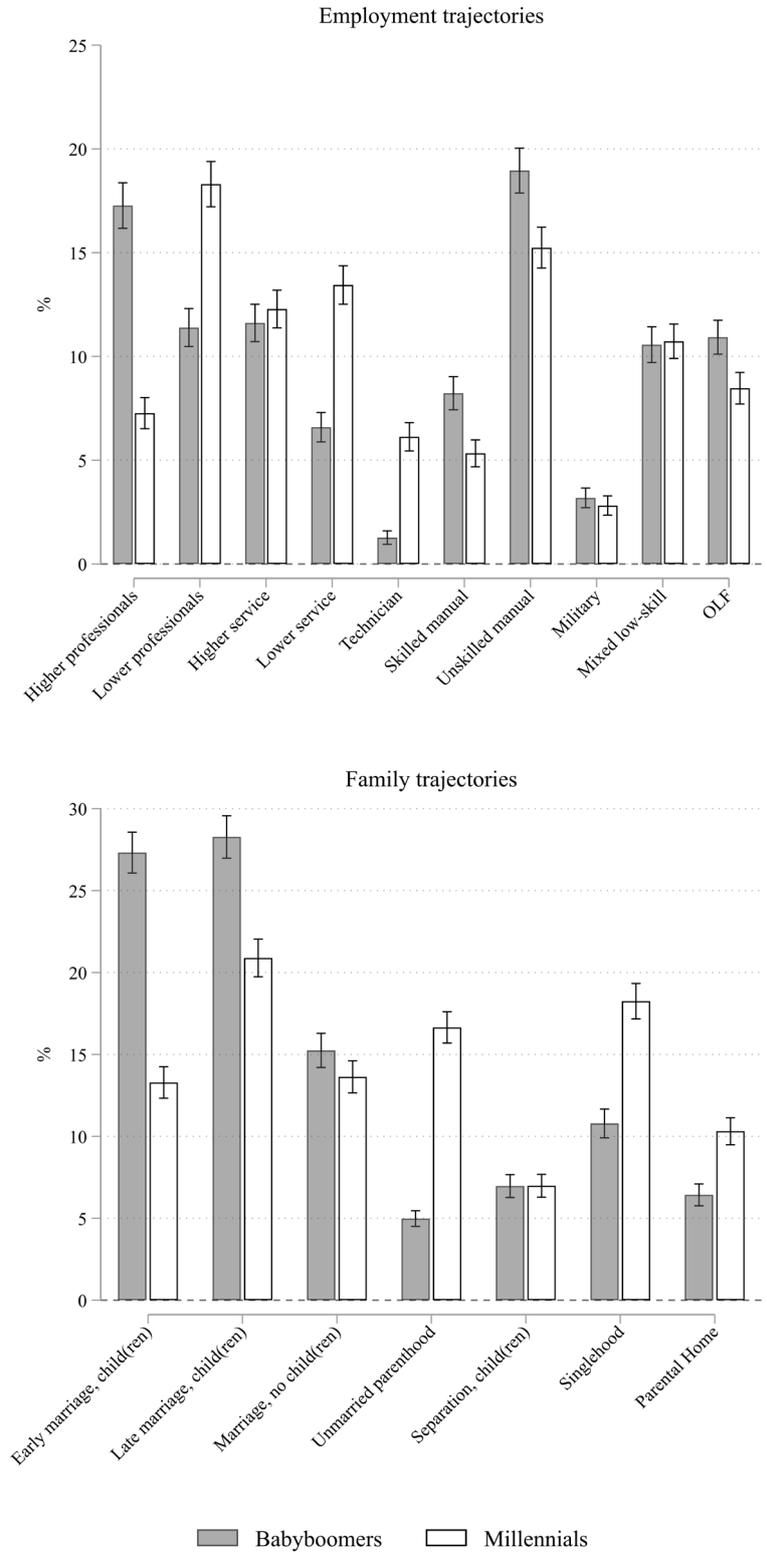
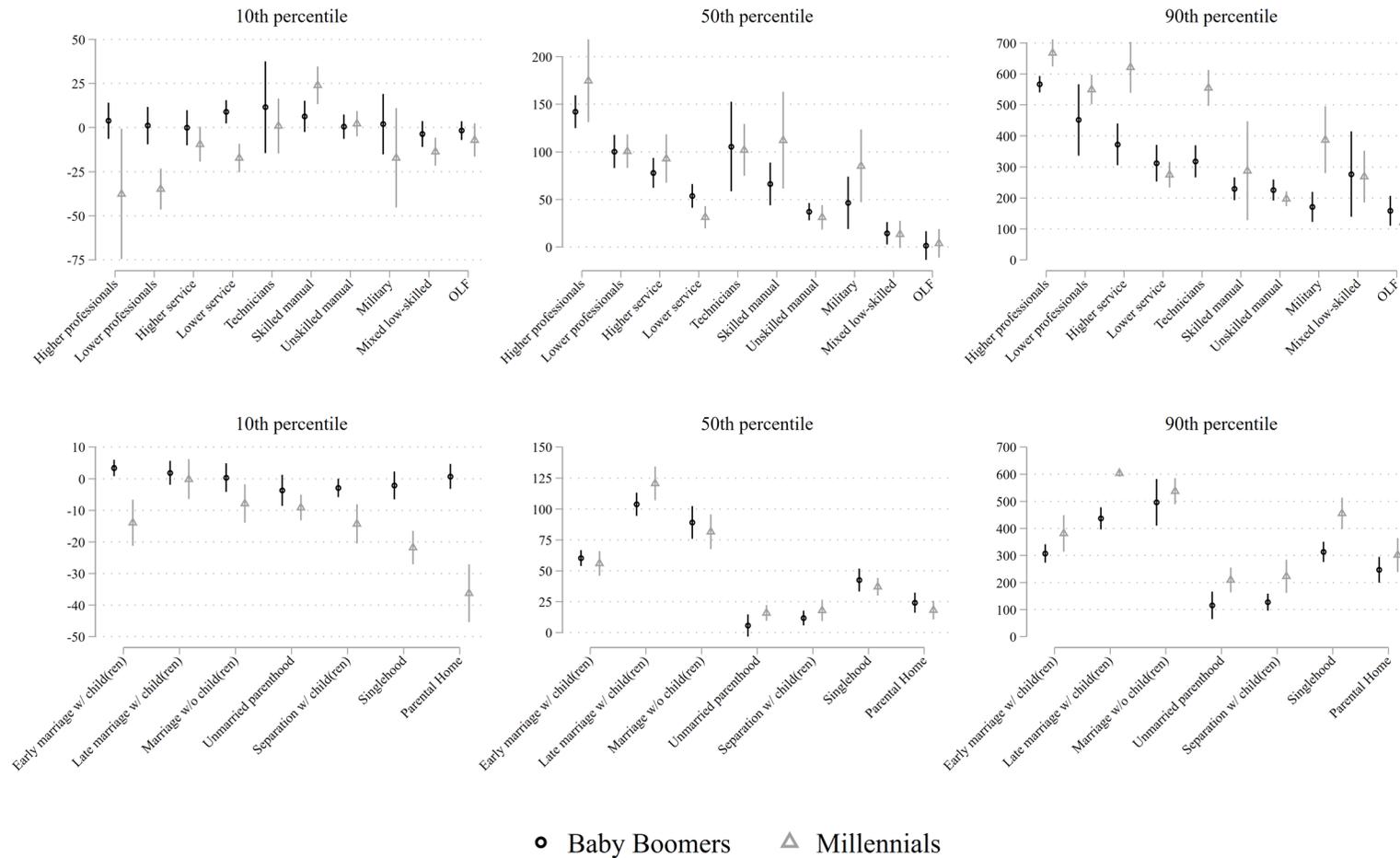


Figure 7: Returns: Cohort Differences in Predicted Wealth across the Distribution, by Work



Note: Predicted wealth adjusted for race, gender, and parental education. Based on multivalued quantile treatment effects with inverse probability weighting, calculated in Stata 17 using the *rifhdreg* command (Rios-Avila, 2020). Full regression results are presented in Appendix E.

Appendix A: Converting NLSY occupational codes to EGP classes

The NLSY categorizes respondents' job descriptions using the three-digit US Census Standard Occupational Classification (SOC). Comparing occupational classifications in the NLSY79 and NLSY97 is complicated because the NLSY79 uses the 1970 SOC, while the NLSY97 uses the 2000 SOC. The differences between these two coding schemes are so fundamental that it is not possible to convert one into the other (Mitnik and Cumberworth 2016). Instead, we use crosswalks to convert both sets of classifications to EGP classes, the dominant class schema used in the international sociological literature (Erikson et al. 1979). To convert the 1970 Census occupational codes to EGP classes, we employed a widely used crosswalk developed by Michael Hout (2005). For the 2000 SOC codes, we use the crosswalk developed by Stephen Morgan for the General Social Survey (Morgan 2017). Morgan sought to create a version of the EGP class schema that follows the spirit of the 1970s original, yet takes into account the subsequent evolution of job titles, responsibilities and skill requirements. This implies that our class schema reflects the occupational structure at the time of data collection. For the sake of simplicity, we combine some of the smaller subcategories into single classes (IVa/b/c into IV and VIIa/b into VII). There is a degree of subjectivity involved in allocating jobs to specific classes, especially when the underlying occupational classification changes. However, Mitnik and Cumberworth show that class measures tend to be fairly robust to using different conversion strategies (2016). The final class schema employed in this study, including some illustrative occupations, is presented in Table 1. In creating the longitudinal work trajectories, we assigned the class labels to monthly employment codes. In case of respondents with multiple jobs, we use the primary occupation based on the number of hours worked. In addition to the occupational classes, the work trajectories include four non-occupational states: secondary education, tertiary education, unemployed and out of the labor force.

Appendix B: Harmonizing wealth variables in the NLSY79 and the NLSY97

We are interested in comparing household net worth (hereafter referred to as wealth) at age 35 between the NLSY79 cohort (the 'Baby Boomers') and the NLSY97 cohort (the 'Millennials'). Wealth is measured in slightly different ways in the NLSY79 and the NLSY97. Below we explain how we obtained our harmonized "Household Wealth at 35" variable.

In the NLSY79, detailed information on assets and debt was calculated in each survey year. We take wealth information from the survey round in which the respondent was aged 35 (round 1992 to 2000). If a respondent was not interviewed at age 35, we take the average of wealth observed at age 34 and age 36. A robustness check (available upon request) shows that our results are substantively similar when only using wealth collected at age 35.

In the NLSY97, detailed information on assets and debts was calculated at three points: after the respondent turned 25, 30 and 35, respectively. We only include respondents for whom wealth information at age 35 is available. This means we exclude 194 NLSY97 respondents who had not yet turned 35 when the most recent survey was conducted (Round 19, fielded in 2019-20, released in December 2021).

To harmonize our wealth indicators, we first adjust for inflation by converting all wealth variables to 2017 USD using the Annual Consumer Price Index provided by the Federal Reserve Bank of St. Louis (<https://fred.stlouisfed.org/categories/9>). Wealth variables in the NLSY are topcoded to protect the anonymity of respondents with high asset values. Different rules for topcoding were applied in the NLSY79 and the NLSY97. To ensure consistency between cohorts we applied the stricter NLSY97 topcode to all respondents. This implies that real wealth holdings above 600k (in 2017 USD) were replaced with the 600k topcode. This topcode was applied to 3.5% of the Baby Boomer sample and 4.9% of the Millennial sample.

We do not know the actual wealth holdings of the topcoded households, and we can therefore not provide meaningful estimates for means, GINI coefficients, wealth shares and other parameters that rely on full information across the distribution. In this study we therefore only report results based on wealth quantiles, which are not affected by the topcoding of high net-worth households.

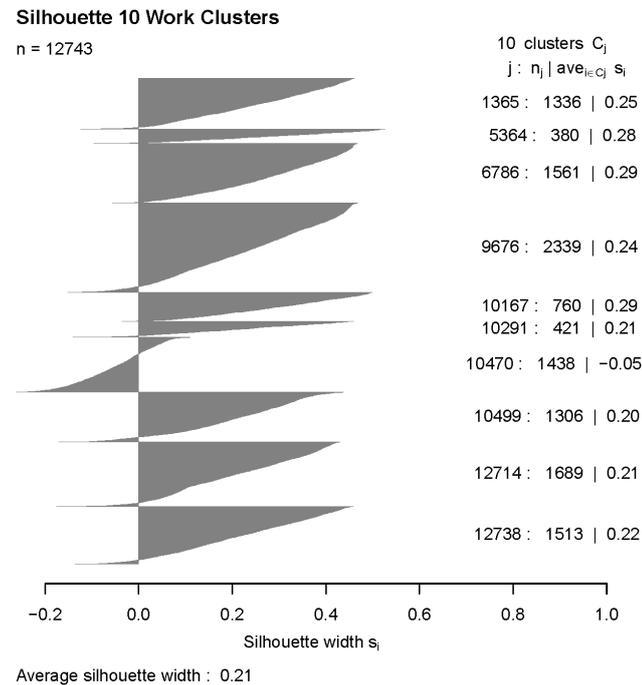
In analyses of household income, it is standard practice to adjust for household size and composition using an internationally recognized equivalence scale, such as the modified OECD equivalence scale. Equivalized income measures assume that larger households need more income to achieve the same standard of living, but also acknowledges that there are economies of scale in living together, particularly through the shared residence. The use of equivalence scales is much less common in studies on household wealth, and the OECD 'Guidelines for Micro Statistics on Household Wealth' state that "no internationally agreed equivalence scales exist, and there is no consensus on whether the scales used for income are appropriate for wealth" (2013:169). Cowell and van Kerm (2015) argue that if one "interprets wealth as an indication of status or power, there is little reason to adjust wealth for household size at all" (p. 6). In this study we therefore decided to report findings based on non-equivalized household wealth, in line with previous literature.

Appendix C: Sequence analysis and clustering

We constructed work sequences from the weekly employment calendars that were updated at each wave. Employment status was aggregated to the monthly level (using the mode) and linked with EGP class (if the individual was in employment), as described in Appendix A. If respondents were both in employment and in education in a given month, we gave precedence to the education state. Family sequences were reconstructed from key family indicators such as the birthdays of children, changes in partnership status etc. If respondents had 'gaps' of up to two years in their sequences we used backward and forward filling, a standard practice in sequence analysis. Analyses of employment and family sequences were performed using the TraMineR package in R (Gabadinho et al. 2011). As discussed in the 'Analytical Strategy' section, we used optimal matching with indel costs of 1 and substitutions costs of 2 to compare all sequences in a pairwise comparison.

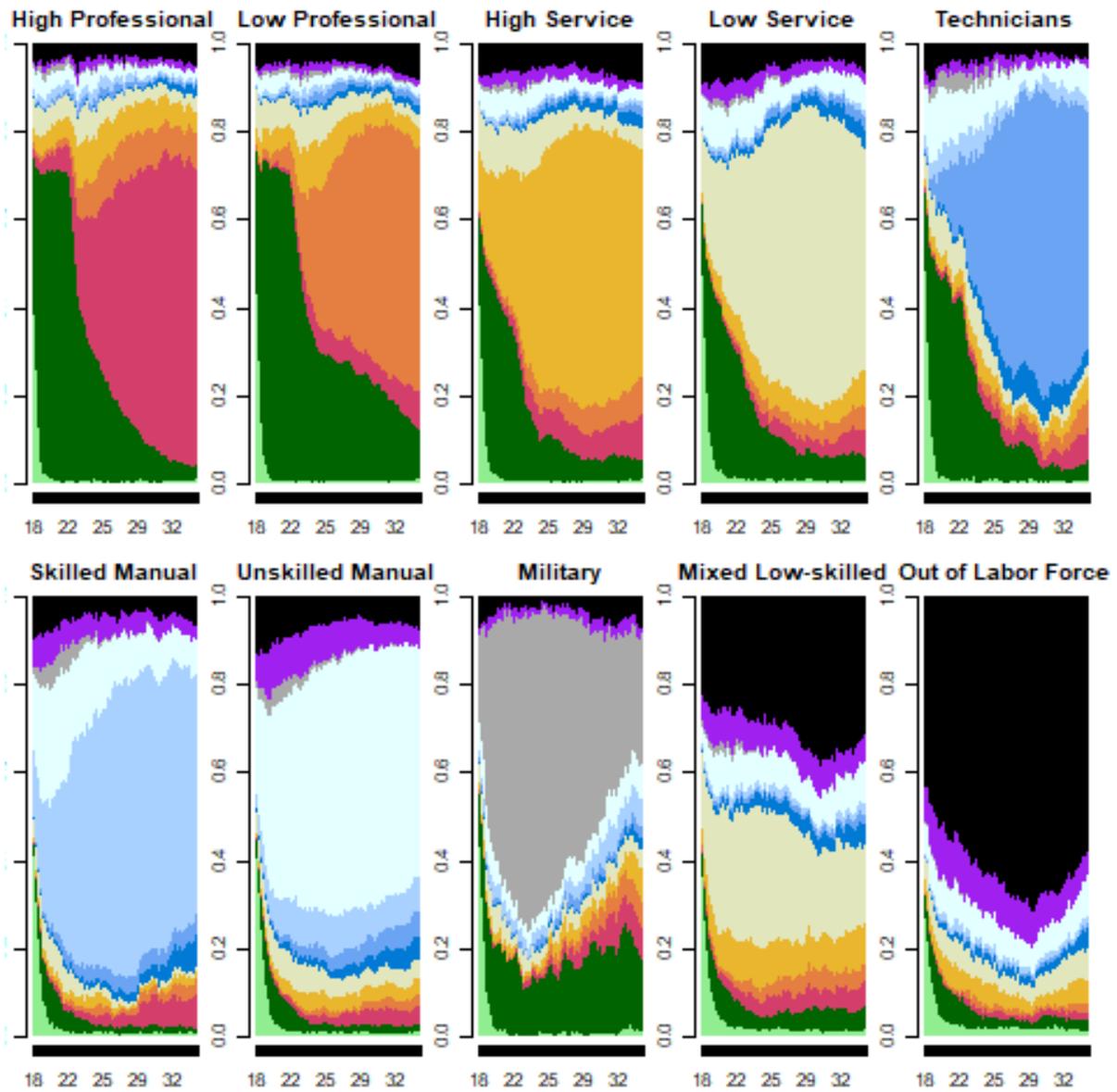
The Average Silhouette Width was used to establish the optimal number of work and family clusters. These trajectories can be interpreted as 'typical' life course trajectories, characterized by the occurrence of similar states and transition at similar stages in the life course. Figure C1 visualizes the individual silhouettes and average silhouettes per work cluster and provides information on the degree of cluster classification error within and across clusters. Silhouette values may range between -1 (low coherence) and +1 (high coherence). Within clusters, negative silhouette values indicate poorly classified individuals may have been grouped into another cluster, while positive values indicate that individuals strongly reflect the main pattern of the cluster.

Figure C1: Individual silhouette values for 10 work clusters



An overall cluster silhouette of 0.25 is considered to indicate adequate structure and coherence within the cluster. As can be seen in Figure C1, our Out of the Labor Force (ASW = 0.29), Military (ASW = 0.28), and Higher Professional (ASW = 0.25) clusters display an adequate structure with very few individuals have negative silhouettes, highlighting the orderly nature of these career types. Other clusters, i.e. the Lower Service (ASW = 0.20), Higher Service (ASW = 0.22), and Unskilled Manual (ASW = 0.24), fall slightly below this threshold likely due to higher volatility within the cluster, for example due to labor market entrances and exits as experienced by Millennials, who are overrepresented within these clusters. Only our Mixed Low-Skill cluster (ASW = -0.05) displayed a low overall silhouette demonstrating that this cluster is highly heterogeneous. However, we consider this to be substantively important, because individuals with high employment volatility will only be captured as a group with low cluster coherence.

Figure C2: State distribution plots of work trajectories

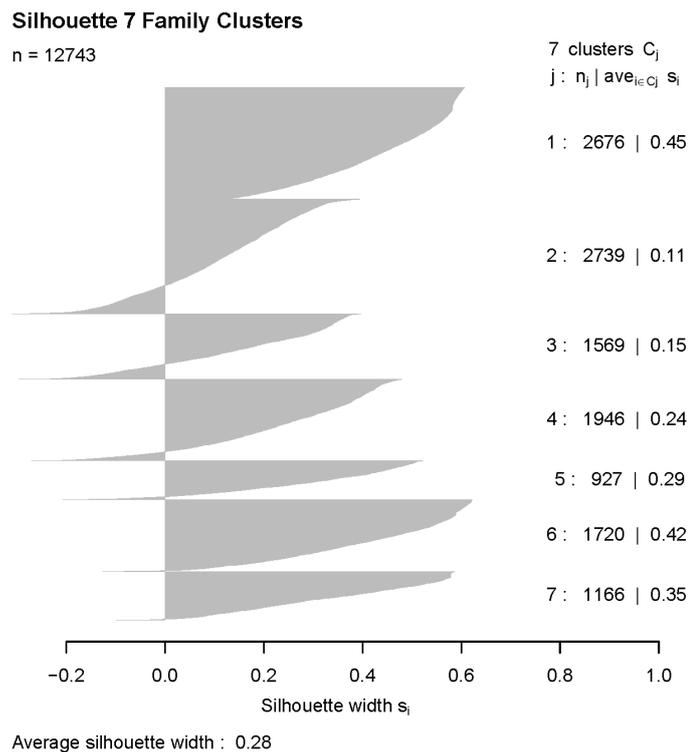


- | | |
|---|--|
| <ul style="list-style-type: none"> ■ School or voc. training ■ College ■ I: Higher Professionals ■ II: Lower Professionals ■ IIIa: Higher non-manual and service ■ IIIb: Lower non-manual and service | <ul style="list-style-type: none"> ■ IV: Self-employed and farmer ■ V: Technicians and supervisor ■ VI: Skilled manual ■ VII: Unskilled manual ■ Military ■ Unemployed ■ OLF |
|---|--|

Figure C2 displays the distribution of sequence states within each work cluster at a given age. In combination with the Relative Frequency Sequence Plots presented in Figure 4 it helps us to understand the work trajectories identified by the clustering algorithm. For example, it becomes evident that individuals in the 'Military' cluster were more likely to attend college in their late twenties and early thirties than those in other trajectories. It is also clear that unemployment spells were more common in the manual than in the non-manual trajectories.

We followed a similar procedure for the family clusters. Figure C3 visualizes the individual silhouettes and average silhouettes per family cluster.

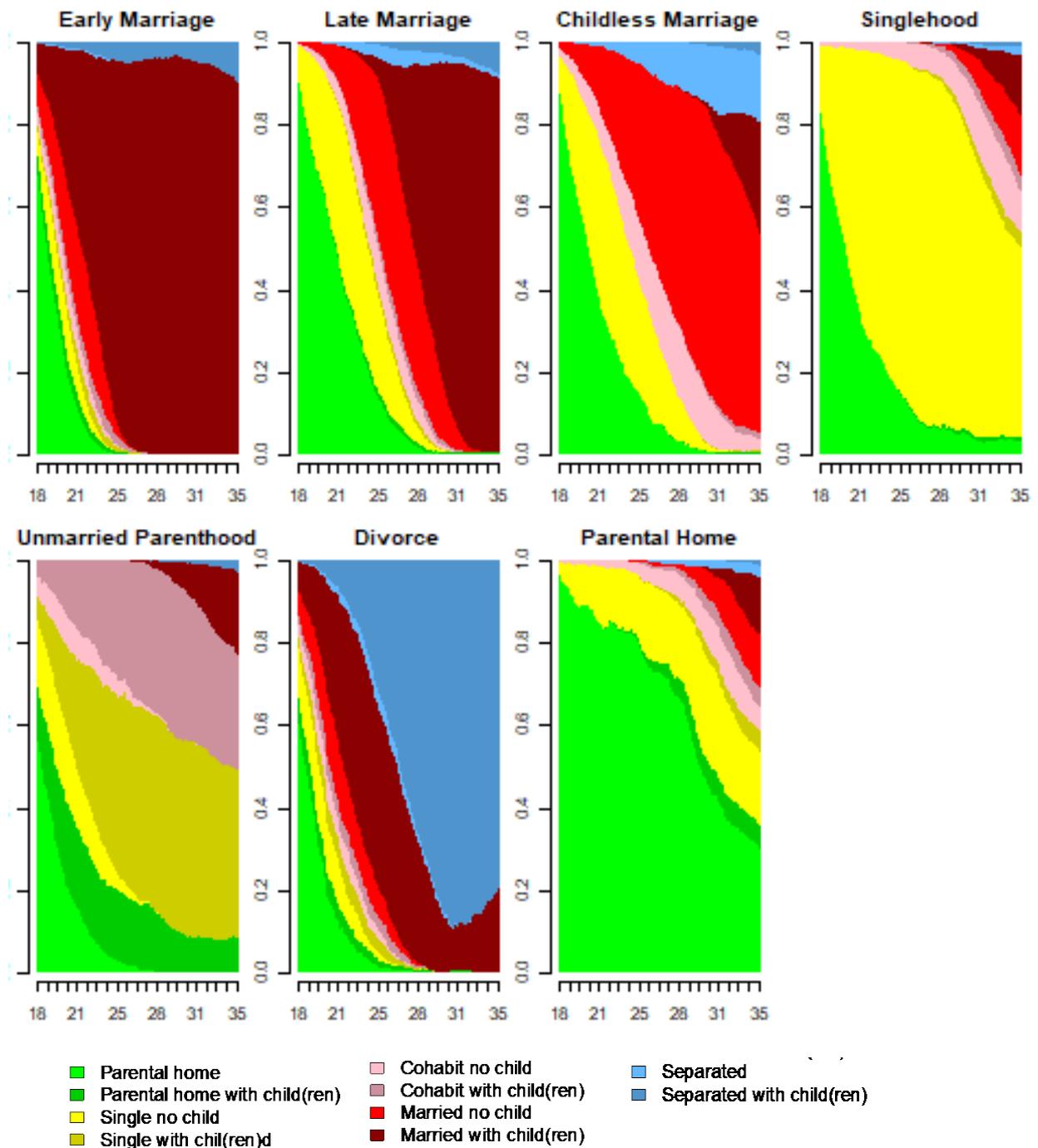
Figure C3: Individual silhouette values for seven family trajectories



Compared to the work clusters, our family clusters are overall well-structured with high internal coherence. Only two clusters, Late Marriage (ASW = 0.11) and Childless Marriage (ASW = 0.15) fall below the threshold of 0.25 indicating an adequate structure. This is likely driven by heterogeneous living arrangements preceding marriage, especially common among

Millennials, such as returning to the parental home, singlehood, and cohabitation. Figure C4 displays the distribution of sequence states within each family cluster at a given time point, supporting the interpretation of the family clusters.

Figure C4: State distribution plot of family sequences



Appendix D: Robustness of sequence typologies to different cost specifications

Social sequence analysts have developed different ways to establish the similarity between pairs of sequences, according to the weight or ‘cost’ attached to the operations—insertion, deletion, and substitution—that would be needed to equalize them. Using different cost specifications may result in different cluster solutions and hence in different typologies of work-family life courses (Warren et al. 2015; Wu 2000). In this appendix we compare our preferred cost specification, Optimal Matching (OM), to two potential alternatives. We find that the work and family typologies resulting from the three different cost specifications are highly similar, and slight deviations between the typologies are in line with expectations based on the sequence features emphasized in the different cost specifications. Importantly, the main clusters for which we find significant difference in wealth returns between Baby Boomers and Millennials in the quantile decomposition remain present and of very similar size in all three cost scenarios. This strengthens our confidence in the original OM specification in the main manuscript and suggests that our key findings do not unduly depend on the chosen cost specification.

Common cost specifications in social sequence analysis

To create the work and family life course typologies presented in the main paper, we used optimal matching with indel costs of 1 and substitutions costs of 2 to determine sequence similarity. This approach is popular approach in the life course sequence literature because it considers both the timing and the sequencing of life events (Aisenbrey and Fasang 2010; Studer and Ritchard 2016). We chose this cost specification because our theoretical background assumes that life courses have changed across cohorts both in the timing—for example, of marriage and first birth—and the order of sequence states—for example, increased transitions between low-paid service work and non-employment.

Recent methodological research using simulated data has shown that different cost specifications can identify and distinguish between different features of sequences (Liao and Fasang 2021; Studer and Ritchard 2016). This is advantageous because it allows researchers to specify which dimensions of similarity should be emphasized in building the typology, in line with their research question. Therefore, when different cost specifications result in different typologies, this does not necessarily indicate that they are not “robust”. Instead, it is likely to reflect the fact that different cost specifications compare the similarity of sequences along different dimensions.

In the context of our application, it is relevant to assess to what extent the identified typologies of work and family trajectories are driven by our preferred cost specification. Following the scenarios presented in the simulation studies of Liao and Fasang (2021), we evaluate two common alternative cost specifications. First, we consider the Dynamic Hamming Distance (DHD) (Lesnard 2010), which emphasizes similarity in the timing of events. DHD only uses substitution operations which preserve the timing of events, no indel operations, and substitution costs at each time point are determined by the transition probability between two states at each time point. This cost specification is most sensitive to sequence similarity in the timing of events and has therefore become the cost specification of choice in time-use applications of sequence analysis, although it has also been used in some life course studies. Second, we use the OMspell distance specification (Studer and Ritchard 2016). OMspell emphasizes the occurrence of states, that is, whether the same states occur in two sequences irrespective of timing. We present the resulting typologies for the DHD and OMspell specifications below, and compare them to our preferred OM specification.

Determining the optimal number of clusters

Figure D1 and Figure D2 present graphs of the cluster cut-off criteria for each of the three cost specifications for work and family sequences. The average silhouette widths are highest when using the OM specification for work trajectories, suggesting that OM is best at discriminating between different types of employment trajectories. The cluster cut-off criteria for work sequences provide strong support for an 8 or a 10-cluster solution using OM, a 10-cluster solution using DHD, and a 9 to 11-cluster solution using OMspell. Because absolute values of the ASWs for the solutions are very similar, and to ensure comparability, we proceed with a 10-cluster solution for each specification.

For the family sequences, the OM and the DHD specification both shows strong support for a 7-cluster solution, with an ASW of .23, whereas OMspell suggests 5 clusters. The absolute silhouette widths are again highest for our preferred OM cost specification. To ensure comparability, we proceed with the 7-cluster solution for each specification.

Figure D1: Cluster cut-off criteria for work clusters using three different cost specifications

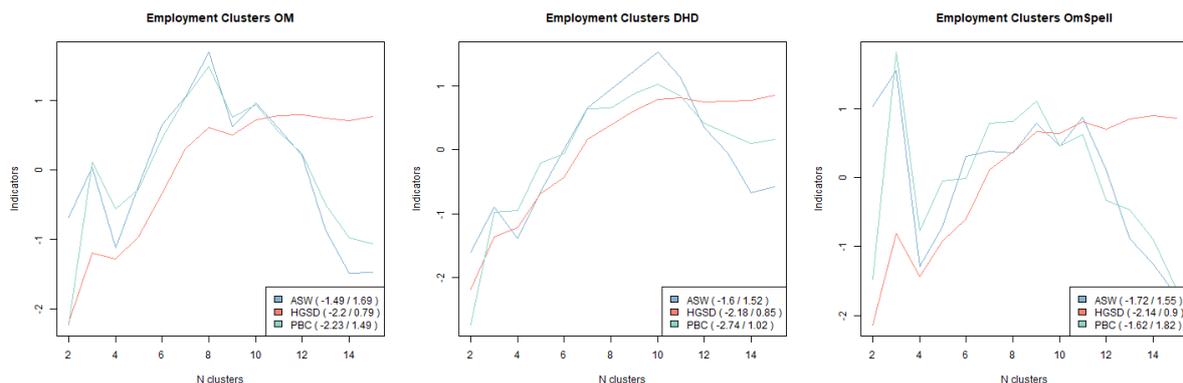
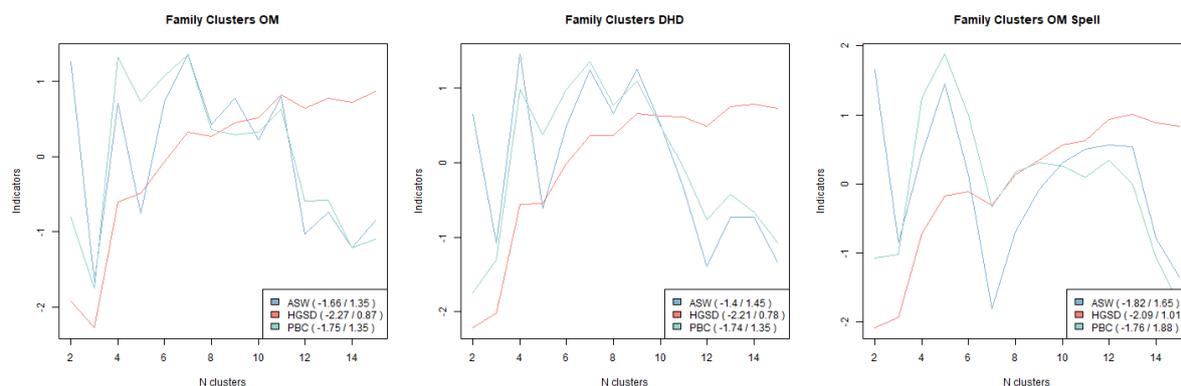


Figure D2: Cluster cut-off criteria for family clusters using three different cost specifications



Comparing life course typologies using different cost specifications

Table D1 compares the work and family clusters that were observed using the different cost specifications. For the employment sequences, the 10-cluster solutions for each of the three cost specifications are qualitatively similar, and the main clusters are of similar size. For example, the most advantaged ‘High Professional’ cluster constitutes 10.4% of the sample in OM, 9.5% in DHD, and 10.2% in OMspell (see Table D1). Similarly, the disadvantaged ‘Unskilled manual’ cluster constitutes 18.4% in OM, 18.3% in DHD, and 15.1% in OMspell. The main difference between the cluster specifications relates to the small ‘Technicians’ employment cluster, which disappears when using OMspell, and in the ‘High Service’ cluster, which is divided into a stable an unstable and version when using OMspell. The DHD typology also contains a ‘Extended Education’ cluster that is not present in the other two specifications. These variations are relatively minor and can be explained by the different emphasis of the three approaches—for example, DHD emphasizing the longer duration of education for some individuals.

Table D1: RF Plots of family cluster solutions for OM, DHD and OMspell

	OM	DHD	OMSpell
Work clusters			
High professionals	10.4	9.5	10.2
Low professionals	13.3	10.2	12.9
High service	11.9	11.6	6.4
Low service	10.3	13.0	11.7
Technicians	3.3	3.1	-
Skilled Manual	6.0	6.2	7.6
Unskilled Manual	18.4	18.3	15.1
Military	3.0	2.6	3.5
Mixed Low skilled	11.3	18.6	9.7
Out of Labor Force	12.3	-	13.8
Unstable high service	-	-	9.2
Extended education	-	7.0	-
Family clusters			
Early Marriage	21.0	24.2	15.9
Late Marriage	21.5	19.5	18.5
Childless Marriage	12.3	10.5	13.9
Unmarried Parenthood	15.3	13.00	15.9
Divorce	7.3	7.1	9.4
Singlehood	13.5	16.5	12.5
Parental home	9.2	9.1	-
Singlehood / Late Marriage	-	-	13.9

The family sequences also showed high levels of overlap in the identified typologies, regardless of the cost specification (see Table D1). For example, each of the specifications finds a socio-economically advantaged “Late Marriage” cluster of similar size (21.5%, 19.5% and 18.5%, respectively) and a disadvantaged “Unmarried Parenthood” cluster (15.3%, 13.0%, and 15.9%). The main deviations occur with the OMspell specification, which does not identify a ‘Parental home’ family cluster, and instead suggests a cluster defined by extended singlehood

followed by late marriage and childbearing. It is important to note, however, that the OMspell specification largely ignores the timing and duration of family states, which is theoretically undesirable.

In sum, we find that the groups driving the cohort differences in wealth accumulation between Baby Boomers and Millennials remain largely similar when using different cost specifications. The differences in the typologies that do emerge do not necessarily reflect a lack of robustness of our preferred OM cost specification, but rather the different dimensions of similarity—timing for DHD, and occurrence for OMspell—that are emphasized in the alternative cost specifications. For theoretical as well as empirical reasons, it is desirable to consider both the order and the timing of states in assessing sequence similarity, which is why we favor the more balanced OM specification.

Appendix E: Multichannel sequence analysis

Numerous studies show that work and family life courses are closely intertwined (e.g. Aisenbrey and Fasang 2017; Fasang and Aisenbrey 2022). It is possible that specific combinations of work and family life courses are particularly beneficial or detrimental to wealth accumulation, which would suggest specifying the life courses multidimensionally focusing on the most prevalent combinations of work and family lives. We therefore used multichannel sequence analysis to identify clusters of combined work family life courses and assessed how they changed across cohorts. The multichannel analysis reveals interesting groups that change prevalence across cohorts in meaningful ways (Figures A2 and A3). Although we acknowledge that work and family life courses are interdependent, we present the single channel analysis in the main paper for two reasons:

First, the effects for the multichannel clusters in the RIF regression and decomposition are substantively in line with the single channel clusters in the paper, but less informative and less predictive of changes in the wealth distributions across cohorts, our central research focus. Specifically, the multichannel clusters had less explanatory power when included in the decomposition analysis (Table E1). This is likely the case because the multichannel clusters always tend to be heterogeneous, simply because they include more sequence variation, namely on two life course dimensions and the way they combine, compared to single channel sequence analysis, which always tends to generate more coherent clusters.

Second, using heterogeneous clusters as independent variables in the RIF regression and decomposition is problematic because differential effects of relatively heterogeneous sequences might cancel each other out in the average, falsely suggesting null effects. In the RIF decomposition, it is therefore preferable to include clearly specified grouping variables, which we obtain to a much greater extent with the single channel cluster analysis. In addition, this

allows us to independently assess the role of cohort change in family and employment and is therefore more suitable for our core research questions.

It is an important task for future research to explore in more detail how the interrelatedness between work and family lives has changed across cohorts, and how such changes differed by gender, race, and class.

Findings from multichannel sequence analysis

We calculated multichannel optimal matching (Aisenbrey and Fasang 2017; Gauthier et al. 2010; Pollock 2007) with subcost = 2 and indel cost = 1 and a combined Ward and PAM cluster analysis (Studer 2013). Findings are robust when using the dynamic Hamming distance (Lesnard 2010). Both the sequence objects for work and family and the cluster analysis apply the survey weights provided in the NLSY. The cluster results and percentages in the groups are qualitatively the same with and without weights. The largest deviations are found for precarious single parents, who are somewhat less frequent when weighted. This is related to the oversampling of Blacks and Hispanics in the NLSY, who disproportionately experience these life courses.

The local maxima in Figure E1 of three cluster cut-off criteria (Average Silhouette Width ASW, Huber's Gamma Sommer's D HGSD, and the Point Biserial Correlation PBC) support an eight-cluster solution, with a low ASW of .08. Figures E2 shows the multichannel clusters as state distribution plot, and Figure E3 shows their prevalence in each cohort. We identified three comparatively high-status trajectories characterized by Professional or Upper Service (EGP IIIa) employment and either late marriage and parenthood or singlehood. Working class occupations tend to coincide either with stable early marriage and parenthood (especially among Baby Boomers) or single parenthood. Strikingly, the clusters that increased most across cohorts is the 'Lower service / singlehood' and 'Mixed low-skill / unmarried parenthood'

trajectories, which are clearly the most disadvantaged among the eight clusters identified. When looking at the returns to different multichannel trajectories (Figure A8) we observe a pattern that is similar to the one observed with the separate work and family trajectories (Figure 7): individuals in the most advantaged trajectories expand their wealth across cohorts, especially at the top of the distribution, while those in lower status trajectories experience little change.

The low average silhouette width compared to a minimum acceptable benchmark of about .25 (Studer 2013) illustrates the large within cluster heterogeneity. Large within-group heterogeneity makes the multichannel cluster variables particularly unsuitable for further analysis with regression and decomposition methods. One possibility would be to exclude poorly classified sequences that have low individual silhouette values (see Jalovaara and Fasang 2020) and only include the share of the population that is coherently classified into sharing a distinct work-family life course type in a group. However, in our case only five percent of the sample have silhouettes above the recommended minimum threshold of .25. Twenty percent of the sample have negative individual silhouettes (below 0) and 58 percent have silhouettes below .10. We would therefore exclude very large parts of our sample with less typical work-family life courses that might be particularly relevant in the context of our research question. This would be the case if less typical work-family life combinations have changed across cohorts, and if they are systematically related to cohort change in wealth accumulation. While the multichannel clusters remain informative descriptively, by highlighting the great heterogeneity as well as some discernible patterns in combined work-family life courses, they are less desirable as categorical predictors in regression-based analyses.

Figure E1: Cluster cut-off criteria for combined Ward and PAM clustering on distance matrix from multichannel optimal matching (subcost=2, indel=1).

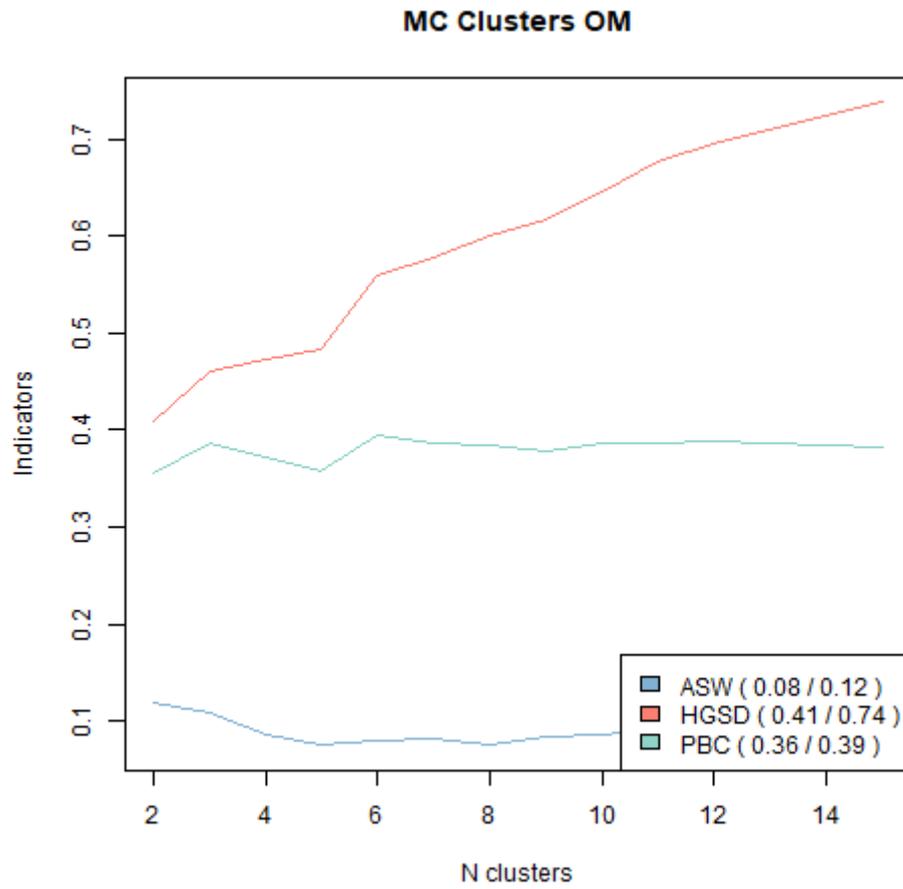


Figure E2: Proportional state distribution blot for the multichannel work (left) and family (right) clusters

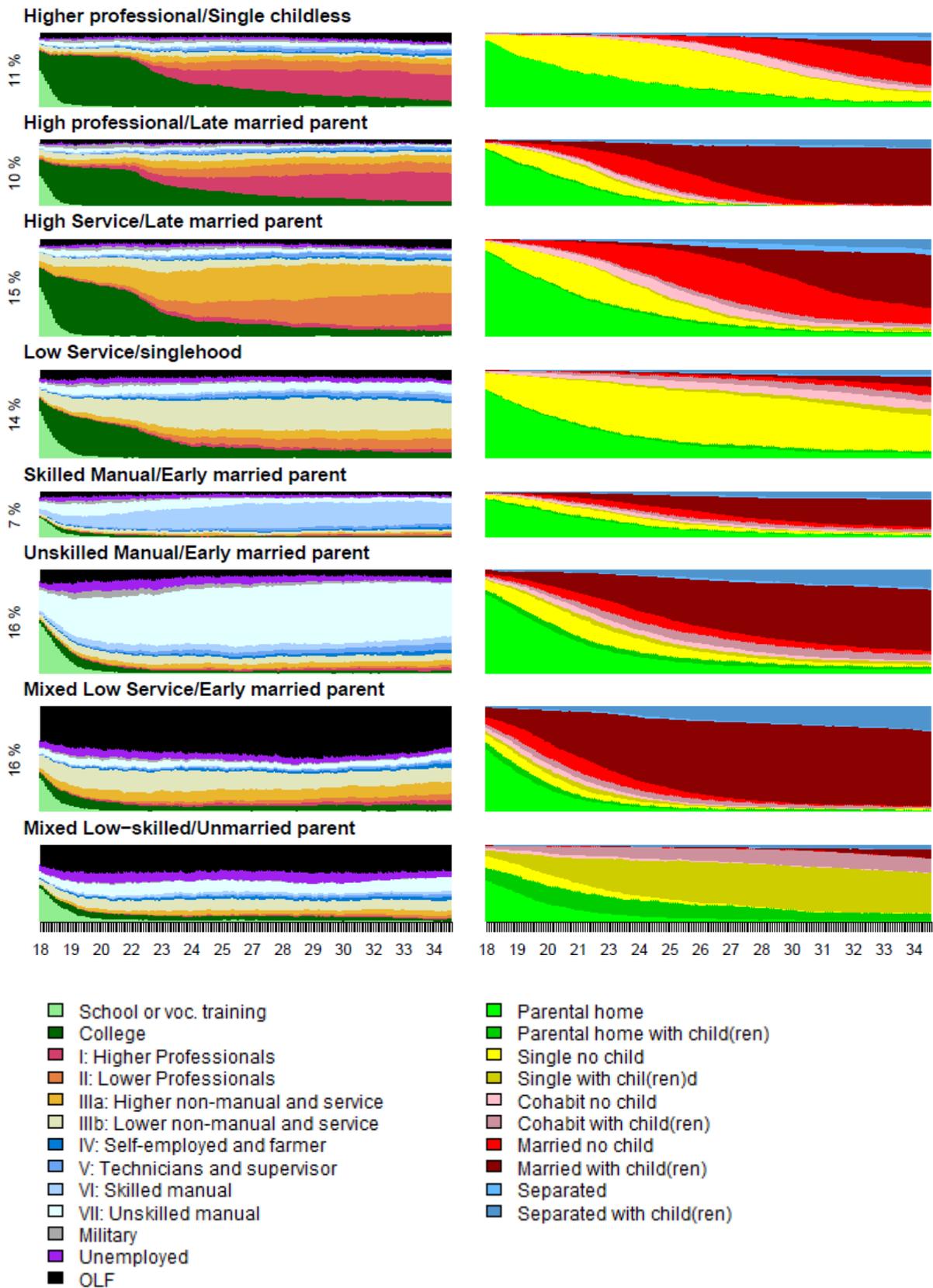


Figure E3: Composition: Cohort Change in Multichannel Work-Family Trajectories

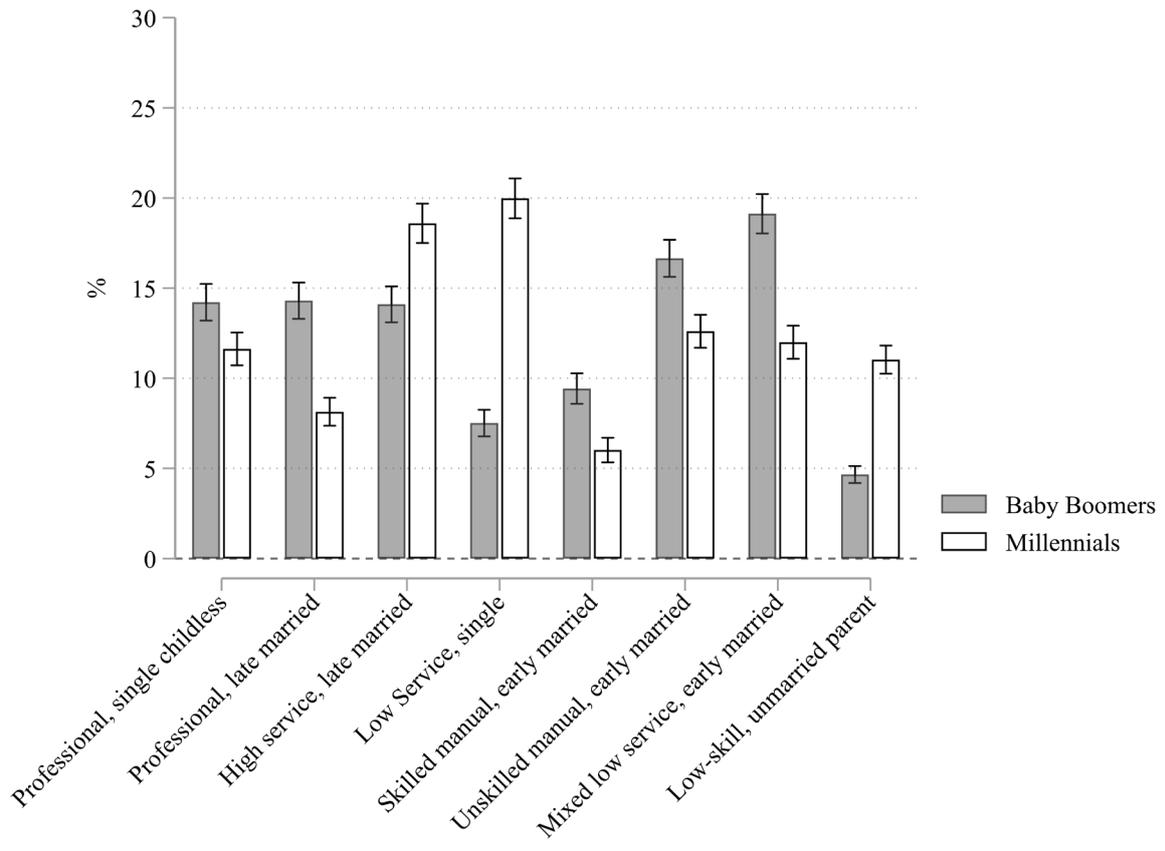
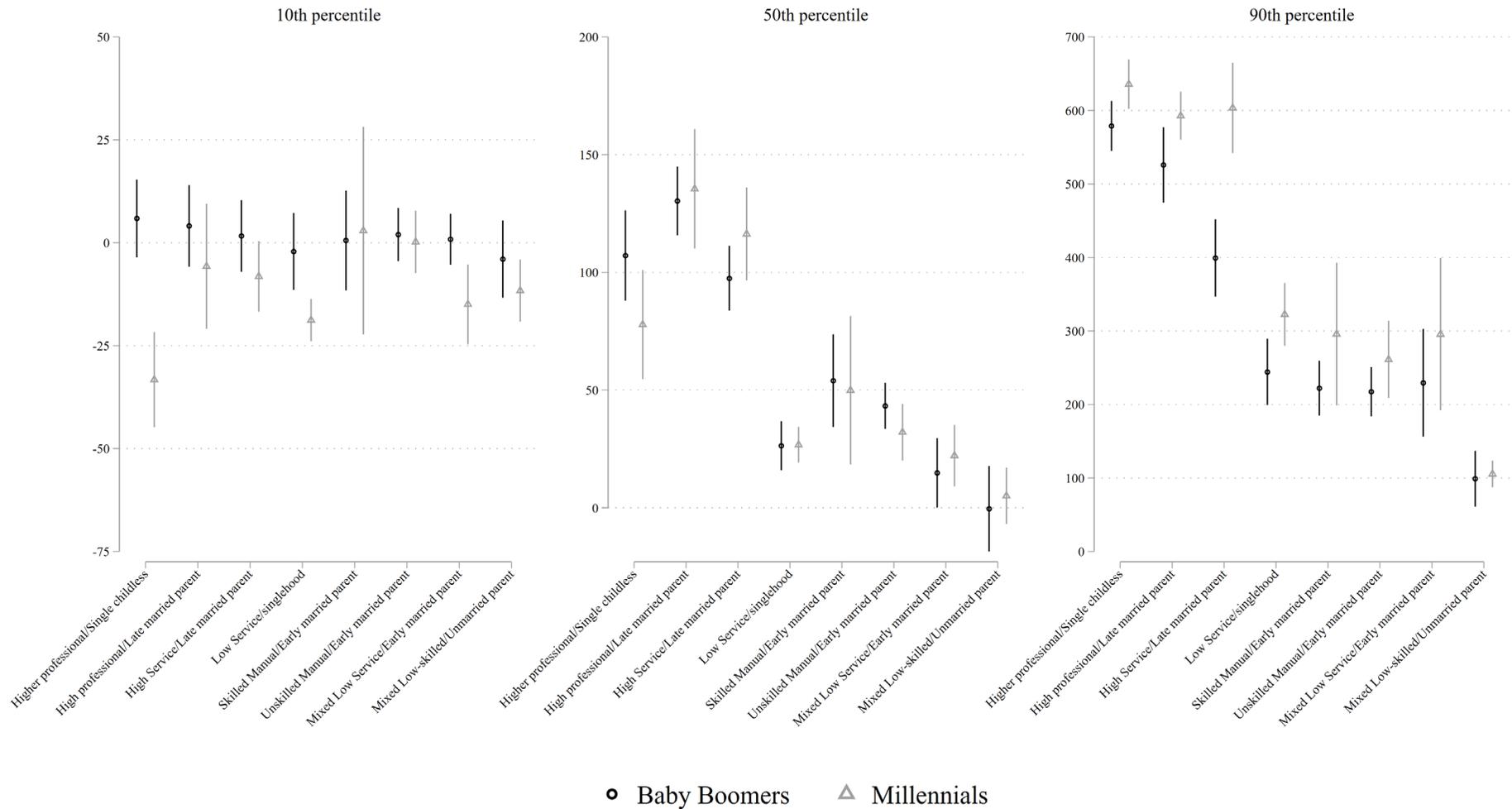


Figure E4: Returns: Median Wealth by Multichannel Work-Family Trajectory



Note: Predicted wealth adjusted for race, gender, and parental education. Based on multivalued quantile treatment effects with inverse probability weighting, calculated in Stata 17 using the *rifhdreg* command (Rios-Avila, 2020).

Table E1: RIF-Oaxaca decomposition of cohort differences in wealth with multichannel clusters

	Q10	Q50	Q90	Q90-Q10
Overall				
Millennials	-10.8***	48.1***	457.2***	468.0***
Baby Boomers	2.2**	63.1***	373.5***	371.3***
Difference	-13.0***	-15.1***	83.7***	96.6***
Composition	0.4 (-2,9%)	-7.2*** (47,8%)	14.7 ⁺ (17,5%)	14.2 ⁺ (14,7%)
Returns	-13.4*** (102,9%)	-7.9** (52,2%)	69.0*** (82,5%)	82.5*** (85,3%)
Composition				
Unskilled Manual/Early married parent	<i>ref.</i>	<i>ref.</i>	<i>ref.</i>	<i>ref.</i>
Higher professional/Single childless	-0.0	-1.5***	-7.9***	-7.8***
High professional/Late married parent	-0.2	-4.4***	-15.7***	-15.3***
High Service/Late married parent	0.2 ⁺	2.5***	8.0***	7.7***
Low Service/singlehood	-0.4	-3.1**	3.2	3.6
Skilled Manual/Early married parent	-0.2 ⁺	-0.5 ⁺	-0.2	-0.1
Mixed Low Service/Early married parent	0.5*	1.1*	-6.4**	-6.7**
Mixed Low-skilled/Unmarried parent	-0.5 ⁺	-3.7***	3.9*	4.3*
Total work-family trajectories	-0.6 (4,2%)	-9.6*** (63,6%)	-15.0** (-17,9%)	-14.3** (-14,8%)
Female	-0.0	-0.0	-0.0	-0.0
White	<i>ref.</i>	<i>ref.</i>	<i>ref.</i>	<i>ref.</i>
Hispanic	-0.1	-1.8***	-1.0	-0.9
Black	-0.2**	-2.5***	-4.8***	-4.6***
Asian	0.1	0.2	3.0	2.9
Parental education	1.1***	6.5***	32.6***	31.2***

Returns				
Unskilled Manual/Early married parent	<i>ref.</i>	<i>ref.</i>	<i>ref.</i>	<i>ref.</i>
Higher professional/Single childless	-1.8***	-2.6*	15.9 ⁺	18.1*
High professional/Late married parent	-0.4	-0.3	11.3	11.9 ⁺
High Service/Late married parent	-0.7	-0.3	24.8*	25.8*
Low Service/singlehood	-1.4	3.4	0.1	1.6
Skilled Manual/Early married parent	-0.2	0.0	4.1	4.3
Mixed Low Service/Early married parent	0.1	-0.7	-7.9	-7.8
Mixed Low-skilled/Unmarried parent	1.1 ⁺	0.6	-8.7 ⁺	-9.6 ⁺
Total work-family trajectories	-3.4 (25,9%)	0.1 (-0,9%)	39.6 (47,4%)	44.3 (45,8%)
Female	-1.7	-3.3	-9.9	-8.3
White	<i>ref.</i>	<i>ref.</i>	<i>ref.</i>	<i>ref.</i>
Hispanic	0.2	0.8	-7.9	-8.1
Black	-0.8	4.0***	-7.8	-7.2
Asian	-0.1	-0.2	2.4	2.4
Parental education	-1.8***	-3.4**	25.3**	27.4**
Constant	-5.8*	-5.9	27.4	32.0
Observations	12,743	12,743	12,743	12,743

Note: Weighted. Decomposition based on the models presented in Table A2. Robust standard errors. All percentages in this table are calculated relative to the total difference. Analyses conducted using the `rif_oaxaca` command in Stata 17 (Rios-Avila 2019).

Appendix F: Quantile Treatment Effects (QTE) Regression Results

Table F1: Results from Quantile Treatment Effects (QTE) regression results for employment trajectories, by cohort

	Baby Boomers			Millennials		
	Q10	Q50	Q90	Q10	Q50	Q90
Unskilled manual	<i>ref.</i>	<i>ref.</i>	<i>ref.</i>	<i>ref.</i>	<i>ref.</i>	<i>ref.</i>
Higher professionals	3.4	105.0***	341.1***	-39.7*	143.4***	470.5***
Lower professionals	0.6	63.2***	225.9***	-36.9***	69.5***	352.0***
Higher service	-0.6	40.8***	147.2***	-11.5	61.7***	424.0***
Lower service	8.4	16.6*	86.8*	-19.3***	0.1	77.8**
Technicians	11.1	68.4**	92.7**	-1.3	70.8***	357.4***
Skilled manual	5.8	29.2*	4.0	21.8**	81.0**	90.3
Military	1.4	9.3	-54.5	-19.3	54.0**	190.3***
Mixed low-skill	-4.2	-22.7**	51.0	-15.7**	-17.9	71.8
Out of the labor force	-2.2	-35.7***	-67.2*	-9.2	-27.4**	-76.6***
Female	-1.0	7.0	-9.4	-1.0	2.6	-54.8*
White	<i>ref.</i>	<i>ref.</i>	<i>ref.</i>	<i>ref.</i>	<i>ref.</i>	<i>ref.</i>
Hispanic	3.4	-35.8***	28.5	-6.3	-50.0***	-103.0**
Black	-16.1**	-86.1***	-155.3***	-22.1**	-102.8***	-133.2***
Parents: highest grade	2.9***	5.2***	17.6***	-0.2	4.6	-4.5
Constant	3.5	50.3***	253.6***	7.5	47.6***	267.8***
<i>N</i>	6681	6681	6681	6062	6062	6062

Note: Estimated using the *rifhdreg* command in Stata 17 with weights and robust standard errors (Rios-Avila 2020). *t* statistics not shown.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.00$

Table F2: Results from Quantile Treatment Effects (QTE) regression results for family trajectories, by cohort

	Baby Boomers			Millennials		
	Q10	Q50	Q90	Q10	Q50	Q90
Early marriage w/ child(ren)	<i>ref.</i>	<i>ref.</i>	<i>ref.</i>	<i>ref.</i>	<i>ref.</i>	<i>ref.</i>
Late marriage w/	-1.5	43.6***	129.7***	13.8**	64.7***	222.7***
Marriage w/o child(ren)	-3.0	28.9***	189.1***	6.1	25.6**	156.0***
Unmarried parenthood	-7.1*	-54.6***	-191.9***	4.8	-40.1***	-172.0***
Divorce w/ child(ren)	-6.3**	-48.5***	-180.0***	-0.4	-38.0***	-158.5***
Singlehood	-5.5*	-17.8**	5.9	-7.9	-18.8**	73.9
Parental Home	-2.7	-36.1***	-60.3*	-22.3***	-37.8***	-79.8
Female	-2.3	-0.7	1.2	-9.5***	-8.5*	-71.5***
White	<i>ref.</i>	<i>ref.</i>	<i>ref.</i>	<i>ref.</i>	<i>ref.</i>	<i>ref.</i>
Hispanic	-1.0	-16.8***	9.8	-0.5	-14.2**	-39.2
Black	-8.8***	-60.8***	-143.5***	-11.6**	-53.3***	-140.6***
Parents: highest grade	1.3***	6.3***	25.5***	-0.8	4.5***	24.1***
Constant	5.8***	70.4***	326.7***	-6.5	65.6***	415.8***
<i>N</i>	6681	6681	6681	6062	6062	6062

Note: Estimated using the *rifhdreg* command in Stata 17 with weights and robust standard errors (Rios-Avila 2020). *t* statistics not shown.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.00$

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