Local Labor Market Polarization and Inequality in Career Earnings Mobility

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Abstract:
Economic polarization is a defining feature of change in the US labor market over the last half century. Polarization is usually thought of along two related dimensions: rising employment in low- and high-paying occupations and shrinking employment in the middle, and rising inequality in occupation-average wages. Much work has demonstrated that polarization is an important driver of rising inequality measured in the cross section. However, it is less well understood how polarization shapes inequalities in earnings mobility over workers' careers. I argue that polarization in local labor markets is an important source of variation in the structure of economic opportunity that workers face as they progress through their careers. Using data from the PSID and US Census and ACS, I demonstrate that polarization amplifies inequalities between local labor markets primarily through its effect on workers' earnings when they enter the labor market. Within highly polarized local labor markets, earnings trajectories for low- and high-earning workers to diverge more than in less polarized labor markets. I find some evidence that polarization disproportionately benefits highly educated workers. Altogether, these dynamics explain a substantial amount of inequality at the beginning of workers' careers and less inequality as workers age.

Introduction

Income inequality in the United States increased substantially over the last half-century, with much of that growth in inequality driven by the top of the earnings distribution (Piketty and Saez 2006; Autor, Katz, and Kearney 2008; Lemieux 2008; Kopczuk, Saez, and Song 2010; Piketty, Saez, and Zucman 2018). Much of the change in overall inequality can be attributed to two types of polarization in the occupational structure. First, employment in low-wage (e.g., food preparation and service) and high-wage (e.g., data scientists) occupations grew while employment in middle-wage occupations (e.g., manufacturing production) shrank. Second, inequality in occupation-average wages rose substantially (Katz and Autor 1999; Autor, Levy, and Murnane 2003; Autor, Katz, and Kearney 2006; Autor et al. 2008; Goos and Manning 2007; Mouw and Kalleberg 2010b; Kalleberg 2011; Goos, Manning, and Salomons 2014).

While much work has investigated how employment and earnings polarization have affected changes in moment-in-time measures of inequality, little research has examined how occupational polarization shapes inequality in workers' opportunity for earnings mobility over their career. Classic models of status attainment and mobility (e.g. Blau and Duncan 1967; Sewell and Hauser 1975; Sørensen 1977) and more recent research on earnings mobility over the life course (e.g. Cheng 2014, 2021) recognize that inequality observed in the cross section is the result of intragenerational labor market processes that unfold over the career. Analyses of intragenerational earnings mobility describe how individuals differ in their earnings trajectories as they progress through the labor market, how individual traits promote or constrain earnings growth, and how such differences create variation in inequality over the life course. I build upon this perspective to examine how occupational polarization affects patterns of intragenerational earnings mobility.

I suggest that the opportunity structure for mobility within a labor market can be characterized by its set of jobs and their associated economic rewards. I argue that occupational polarization has reshaped the opportunity structure for mobility by reducing the number of positions in the labor market available for upward mobility from low-paying jobs and by creating greater earnings inequality between positions. Drawing on Cheng's (2014, 2021) life course trajectory framework, I argue that such polarization will affect inequality at the beginning of workers' careers, inequality in earnings growth over the career, and inequality resulting from advantages that accrue to workers with different levels of education.

I leverage variation in the occupational polarization of local labor markets across the US to examine how polarization shapes patterns of intragenerational earnings mobility. Both labor demand and labor supply vary considerably between local labor markets. Differences in localities' jobs, firms, and industries, as well as in the types of workers competing for those positions, give rise to different opportunity structures for mobility in different parts of the country. Previous research has documented how local labor market contexts contribute to variation in earnings inequality (Moller, Alderson, and Nielsen 2009; Moretti 2012; Manduca 2019; Card, Rothstein, and Yi 2023). I suggest that regional inequalities and earnings inequality may be linked, in part, by how the occupational structure of local labor markets shapes inequalities in earnings mobility over the career.

Using career history data from the Panel Study of Income Dynamics (PSID) and contextual variables derived from the US Census and American Community Survey (ACS), I demonstrate that occupational polarization shapes inequality in earnings mobility over the career both within and between commuting zones (CZs). Polarization affects inequality in earnings mobility within CZs through two mechanisms. Earnings inequality at the beginning of workers'

careers is greater in CZs with higher levels of earnings and employment polarization. Polarization also benefits earnings growth for high-earners more than low-earners, leading earnings trajectories to diverge more as workers age in more polarized CZs. Polarization also contributes to inequalities between CZs through its positive effect on earnings at the beginning of workers' careers. These benefits of polarization are disproportionately enjoyed by workers who hold college degrees. Overall earnings inequality increases over workers' careers, and the initial sorting of workers into CZs of heterogeneous polarization explains a considerable proportion of inequality that is maintained over the life course.

Background

Earnings inequality over the life course

Social scientists have long been interested in the processes by which individuals reach positions within the social structure. Much research on attainment and mobility uses a single static measure to represent an individual's lifetime attainment (e.g., permanent income, highest occupational status, etc.), and examines how such summary measures of socioeconomic status are influenced by demographic, family, and contextual factors. There is, however, substantial evidence that individuals' socioeconomic status varies considerably over their lifetime. Previous research on *intra*generational mobility has shown that individuals change jobs and occupations numerous times throughout their careers, their earnings grow substantially and systematically as they age, and heterogeneity in job mobility and earnings trajectories underlies changes in inequality within cohorts as they age (e.g. Mincer 1988; Rosenfeld 1992; Topel and Ward 1992; Keith and McWilliams 1995; Fuller 2008; Mouw and Kalleberg 2010a; Cheng 2014, 2021; Jarvis and Song 2017).

Individuals' income trajectories and occupational pathways over their careers reflect the actual attainment processes that connect workers to unequal economic rewards (Sørensen 1975; Rosenfeld 1992; Carroll and Powell 2002; Parrado, Caner, and Wolff 2007; Cheng 2014, 2021; Bidwell and Mollick 2015). By situating inequality as a result of career mobility processes such as job changes, job loss, and earnings growth, inequality can be understood as a life course phenomenon. The life course perspective characterizes inequality in wages and occupational attainment as the result of social processes that unfold over time through the continuous interaction between individuals' traits and the social and institutional settings in which they are embedded (Elder 1985; Mayer 2004, 2009; Cheng 2014, 2021; Kalleberg and Mouw 2018). Life course analyses of inequality over the career emphasize wage trajectories and job-to-job linkages as the main outcomes of interest and stress the cumulative nature of economic rewards over the career (Spilerman 1977; Abbott 1983, 1995; Dannefer 1987; DiPrete and Eirich 2006; Cheng 2014, 2021). These analyses emphasize how population-level inequality results from variation in individuals' career paths.

Even though proponents of the life course perspective argue that life course theory offers a micro-macro link between individuals and the social structures and institutions that shape inequality (Elder 1985; Huber 1990; Mayer 2004), research from the life course perspective has largely focused on inequalities that stem from the labor supply side. This work highlights how macro-social patterns of earnings inequality can be explained by variation in the accumulation of human capital over the career (Mincer 1958; Sanders and Taber 2012), heterogenous returns to human capital (Mincer 1996; Heckman, Lochner, and Taber 1998; Katz and Autor 1999; Autor et al. 2008), marital and childbearing transitions (Budig and England 2001; Fuller 2008; Gangl and Ziefle 2009), and race and gender inequalities (Tomaskovic-Devey 1993; Thomas, Herring,

and Horton 1994; Maume 2004a, 2004b; Tomaskovic-Devey, Thomas, and Johnson 2005; Fernandez-Mateo 2009; Cheng 2014). To the extent that intragenerational earnings mobility research has incorporated labor demand, it has largely focused on how earnings mobility is shaped by the jobs, firms, and occupations in which individuals are currently employed (Sørensen 1975; Spilerman 1977; Rosenbaum 1979; Baron 1984; Rosenfeld 1992; Bronars and Famulari 1997; Grodsky and Pager 2001; Fuller 2008; Kalleberg 2009; Bidwell and Briscoe 2010; Mouw and Kalleberg 2010b, 2010a).

Much less work has considered how the linkage between individuals' earnings trajectories and macro-level inequality is influenced by the structure of labor demand, or the full set of jobs that provide workers with alternatives to their current employment. I argue that this shortcoming of current work on intragenerational mobility echoes what Sørensen (1975) observed decades ago: that analyses of attainment over the career have failed to incorporate a direct analysis of the relationship between individuals and the structural features of the labor market that provide an opportunity structure for attainment. Despite sociology's history of interest in relating the economic structure to inequality (e.g. Stolzenberg 1975; Baron and Bielby 1980; Tolbert, Horan, and Beck 1980; Berg 1981; Berg and Kalleberg 2012), little research on mobility processes over the career has managed to link individual career earnings trajectories to concrete structural features of the economy that shape attainment processes. Instead, structural analyses of career mobility have primarily focused on inequality-generating processes within individual firms (Sørensen 2007), failing to connect emergent patterns of inequality and mobility to changes to the broader structure of jobs, firms, occupations, and industries (DiPrete 2007).

Some mobility research has successfully leveraged an ecological perspective to examine how the structure of labor demand affects mobility. Much of this research focuses on how the

ecology of organizations within an industry shapes short-run mobility, demonstrating that outcomes like turnover or job shifts are influenced by organizational founding, dissolution, mergers, size diversity, and other organizational ecological processes (Spilerman 1977; Hannan 1988; Carroll, Haveman, and Swaminathan 1993; Greve 1994; Haveman and Cohen 1994; Fujiwara-Greve and Greve 2000). These studies emphasize that the opportunity structures that individuals face change over time as jobs are created or destroyed. Crucially, synthesizing the ecological perspective with career mobility research offered convincing evidence that micro-level patterns of individual mobility over the career are shaped by macro-level structural dynamics in the labor market.

I advance this perspective in two ways. First, I argue that labor markets' occupational composition is an important structuring feature of the environment where workers compete throughout their careers for mobility into jobs with heterogeneous earnings and potential for earnings growth. Second, I examine the effect of labor markets' occupational structure on individuals' earnings trajectories throughout their prime earning years, rather than just on the probability of individual job transitions. In what follows, I develop a model of matching between workers and jobs, and I argue that matching and mobility over the career is shaped by the relative demand for different types of labor in local labor markets. I contend that occupational polarization – inequality in pay between occupations and relatively high demand for labor in low- and high-paying occupations – is an important feature of the demand for labor that structures workers' opportunity for mobility over the career.

The occupational structure, matching, and earnings mobility

Career earnings mobility, or how workers' earnings change over their career, can be understood as the result of repeated matching processes between workers and jobs as workers age. Most sociological and economic theories of labor market matching start from similar basic premises. Matching within the labor market refers to the social process whereby heterogenous populations of firms and workers simultaneously choose between one another (Jovanovic 1979; Kalleberg and Sorensen 1979; Mincer and Jovanovic 1979; Sørensen and Kalleberg 1981). Each firm holds a set of jobs that it seeks to fill from the labor pool, and workers in the labor pool compete for their most desired jobs. Jobs require specific sets of skills and compensate workers with wages and other desirable job characteristics. Workers leverage their individual resources such as education, experience, social connections, race, gender, and the like to compete for jobs. Firms seek to fill job openings with candidates who maximize profits or perhaps other organizational goals. It is this joint optimization process that determines how individuals are allocated into stratified positions within the economic structure. Over the life course, earnings change as a result of job changes and within-job earnings changes.

In structural models of mobility, the shape of inequality in a labor market is determined by the sets of jobs in the market and their associated economic rewards. Individuals move between fixed positions in the labor market when a vacancy opens up, and their access to vacant positions is determined by their individual attributes (White 1970; Sørensen 1977). Career trajectories are characterized by repeated mobility between vacant positions. Earnings mobility is determined by the returns to experience within jobs and occupations and by earnings changes that result from mobility between jobs. Returns to experience vary between jobs, and some positions in the labor market provide access to clear occupational ladders that facilitate earnings growth while others do not, leading to diverging earnings trajectories over the life course

(DiPrete and McManus 1996; Kambourov and Manovskii 2009; Sullivan 2010; Sacchi, Kriesi, and Buchmann 2016). It follows, then, that earnings mobility should vary depending on the set of jobs in a labor market.

Occupational polarization and mobility opportunity across the US

Over the last half century, the opportunity structure for mobility has changed significantly as the occupational structure became more polarized along two dimensions. The first is *earnings polarization*, which describes rising inequality in occupations' average earnings. In addition to describing differences in the economic rewards associated with a given occupation, occupational earnings inequalities are thought to capture, at least to some extent, differences in occupations' skill requirements (Autor et al. 2006; Autor and Dorn 2013). All told, rising inequality between occupations is estimated to explain two-thirds of the change in inequality between the early 1990s and the mid-2000s (Mouw and Kalleberg 2010b). The second dimension of polarization is *employment polarization*, which describes declining employment in "good" middle-class jobs with relatively high wages and employment security, and rising employment in both low-wage, low-job quality jobs and jobs with high wages and benefits (Autor et al. 2006, 2008; Mouw and Kalleberg 2010b; Kalleberg 2011). Measures of employment polarization are commonly used in labor economics to describe the extent to which employment at the top and bottom of the occupational wage distribution compares to employment in the middle of the occupational wage distribution (Autor et al. 2006, 2008; Goos, Manning, and Salomons 2009; Goos et al. 2014; Autor and Dorn 2013; Dauth 2014; Heyman 2016).

Much of this change in earnings and employment patterns can be explained by the uneven effects of technological change across the occupational distribution. Models of routine-

biased technological change suggest that decreasing costs of computing led firms to deploy capital such that it substitutes for easily-programmable routine tasks and complements nonroutine work (Autor et al. 2003, 2006; Acemoglu and Autor 2011; Goos et al. 2014; Acemoglu and Restrepo 2022). Returns to education rose substantially in the last few decades (Lemieux 2006a) and earnings grew disproportionately for highly-skilled occupations (Autor et al. 2006; Acemoglu and Autor 2011; Acemoglu and Restrepo 2022). Acemoglu and Restrepo (2022) estimate that automation of routine tasks accounts for 50 to 70 percent of the change in the US wage structure since 1980. In addition, the decline of labor unions and rising bargaining power of organized corporate interests (Hacker and Pierson 2010; Western and Rosenfeld 2011), the erosion of internal labor markets (Sørensen 2000; Cappelli 2001; DiPrete, Goux, and Maurin 2002; Dencker and Fang 2016), and the rise of nonstandard employment relations (Kalleberg 2000; Kalleberg, Reynolds, and Marsden 2003; Peck and Theodore 2007; Dey, Houseman, and Polivka 2012), all contributed to hollowing out the middle of the occupational distribution and rising inequality between occupations.

The effects of occupational polarization were felt unevenly across the country. As occupational polarization increased, the US experienced a "Great Divergence" in incomes between regions (Moretti 2012). Rising inequality between regions can be explained by a combination of national trends in rising inequality that exacerbate preexisting income differences between regions and by increased sorting of high-education or high-income individuals into cities with the right mix of firms, industries, and highly skilled workers (Storper and Scott 2009; Moretti 2012; Diamond 2016; Manduca 2019). Communities with high employment in jobs characterized by routine tasks saw a substantial reallocation of labor into low-skill service occupations (employment polarization) and experienced wage declines in the middle of the

occupational earnings distribution and gains at the bottom and top (earnings polarization) (Autor and Dorn 2013; Acemoglu and Restrepo 2022).

While previous work has focused on how polarization contributes to income inequalities within and between local labor markets, I consider the consequences of local labor market polarization for inequalities in workers' earnings trajectories over their careers. Workers' career trajectories are primarily structured by their local labor market context – about 84 percent of job-to-job moves occur within states, most people do not leave their regional labor market, and geographic mobility is declining (Beggs and Villmez 2001; Johnson and Schulhofer-Wohl 2019; Azzopardi et al. 2020). Local labor markets differ substantially from one another both in terms of labor supply (see Moller, Alderson, and Nielsen 2009) and labor demand (e.g. Glaeser and Gottlieb 2009; Autor and Dorn 2013). Heterogeneity in the structure of labor market opportunities and processes by which workers are allocated to jobs produces varying structures of income and mobility inequality in local labor markets (Stolzenberg and Waite 1984; Maume 1987; Topel 1994; Beggs and Villmez 2001; Fernandez and Su 2004; Sørensen and Sorenson 2007; Dorn 2009; Moller et al. 2009; Moretti 2010; Connor and Storper 2020; Thiede et al. 2020). Thus, we might expect that variation in polarization at the local labor market level should affect individuals' earnings trajectories.

Implications for earnings mobility

Drawing on Cheng's (2014, 2021) life course framework of intragenerational mobility, I investigate how the occupational polarization of local labor markets may shape earnings mobility over the career. First, I expect that employment and earnings polarization both increase inequality in earnings at the beginning of workers' careers (baseline inequality). Employment

polarization increases the probability that a worker will enter the labor market in a relatively high- or low-paying occupation, while earnings polarization increases the average difference in earnings between occupations where workers enter the labor market.

H1: Polarization increases inequality in earnings at the beginning of workers' careers.

I also expect that within similarly polarized local labor markets, there will be heterogeneity in earnings growth rates. That individuals differ in their career earnings trajectories is well established.

H2: Earnings growth rates vary among individuals in similarly polarized local labor markets.

Next, I consider how occupational polarization may affect inequalities in earnings mobility within local labor markets. I expect that polarization disproportionately improves upward earnings mobility for workers at the top of the labor market. Mechanically, employment polarization reduces the number of "middle-paying" vacancies available to promote upward mobility out of low-paying occupations. Occupational mobility already tends to produce more substantial earnings growth for high earners. Mobility for lower-earning workers occurs largely within their class boundaries (Kim 2013), leading to circulation between low-paying jobs and less upward mobility out of low-wage work. As the labor market has become more polarized, mobility also became increasingly determined by occupational skill requirements, and pathways connecting low-paying to high-paying occupations have become much less common (Cheng and Park 2020; Lin and Hung 2022). I expect that employment polarization reduces low-earners' chances of upward earnings mobility by decreasing low-earners' opportunity for upward occupational mobility.

Earnings polarization is also likely to disproportionately benefit earnings growth for high earners. Higher inequality between occupation-average earnings means that upward occupational mobility will produce greater earnings gains on average. Because earnings polarization is disproportionately driven by rising wages in high-paying occupations (Autor and Dorn 2013), we might expect that upward occupational mobility in high-earning occupations will produce larger earnings gains than upward mobility in low-earning occupations. High earners who remain in the same occupation may also benefit from earnings polarization because the returns to occupation-specific experience are higher in high-paying occupations than in low-paying occupations (Sullivan 2010; Cortes 2016). Altogether, these dynamics suggest that the relationship between early-career earnings and upward earnings mobility should be greater in more polarized local labor markets.

H3: The association between individuals' baseline earnings and earnings growth rates is greater in more polarized labor markets.

Occupational polarization may also contribute to between-labor-market inequalities in intragenerational earnings mobility. Because both employment and earnings polarization are primarily driven by growth at the top of the occupational distribution, I expect that average earnings at the beginning of workers' careers and average rates of earnings growth are higher in more polarized local labor markets. This would also be consistent with recent work showing that rising inequalities between US regions are largely driven by the sorting of highly productive workers into higher paying firms and industries (Moretti 2012; Manduca 2019; Card et al. 2023).

H4a: Average baseline earnings are higher in more polarized labor markets.

H4b: Average earnings growth rates are higher in more polarized labor markets.

If it is the case that polarization creates disproportionate opportunities for earnings growth among highly skilled workers as described above, we would expect that college educated workers experience higher returns to polarization than non-college-educated workers. These returns may manifest as higher baseline earnings, faster rates of earnings growth, or both. If polarization is associated with higher baseline earnings and faster earnings growth for college educated workers, we can say that polarization produces cumulative advantages to education that amplify inequality as workers' progress in their careers (DiPrete and Eirich 2006).

H5a: Baseline earnings for workers with college degrees increase more with polarization than for those without college degrees.

H5b: Earnings growth rates for workers with college degrees increase more with polarization than for those without college degrees.

Cohort differences

Earnings and employment polarization have risen considerably, resulting in changes to the structure of economic opportunity over time. The effect of polarization on earnings attainment may be driven by a combination of age, period, and cohort (APC) effects. I choose to study changes in the effect of polarization on intragenerational mobility by examining differences between cohorts. This approach is preferable when change is thought to occur through its influence on individuals in their early years rather than through a uniform effect on all individuals at a given point in time (Bell and Jones 2015). I expect that variation in career paths is more attributable to cohort trends rather than period trends largely because economic attainment is highly path dependent. Individuals' jobs and incomes over their careers are strongly predicted by the positions where they enter the labor market. Inequality upon entry to the labor

market can lead to greater divergences in outcomes over the career due to access to different occupational pathways, differences in returns to human capital or other individual resources, or differences in investment in human capital (Mincer 1958; Blau and Duncan 1967; Merton 1968; Featherman and Hauser 1978; Rosenbaum 1979; Dannefer 1987; DiPrete and Eirich 2006). Moreover, examining differentiation within cohorts as they age focuses the analysis on differences between individuals' career paths, which are characterized by successive and interconnected changes in their own economic status over time, rather than differences in age-earnings profiles over time, which describe how earnings vary between different-aged individuals at a given point in time (Riley 1987; Cheng 2014).

I expect that occupational polarization will have different effects on intragenerational mobility across cohorts. For more recent cohorts, these earnings gains at the top of the earnings distribution can be attributed to rising demand for skilled labor but little change in educational attainment on the labor supply side. The increased returns to education were largely realized at the beginning of workers' careers, resulting in higher levels of inequality when workers entered the labor market and less change in inequality as workers aged (Card and Lemieux 2001; Heckman, Lochner, and Todd 2003; Lemieux 2006b). Because polarization since the 1980s has been driven largely by increased earnings at the top of the occupational earnings distribution and polarized labor markets provide a venue for highly skilled workers to capitalize on the demand for skilled labor, I expect that in more recent cohorts, polarization will benefit earnings growth for high earners more than low earners:

H6: In more recent cohorts, polarization disproportionately benefits earnings growth for high-earners.

Data and Methods

Career earnings mobility is modeled using data from the Panel Study of Income Dynamics[1] (PSID), a longitudinal panel survey of US households. PSID respondents are linked using restricted-use state- and county-level identifiers to local labor market characteristics derived from the US Census (5 percent samples for 1980, 1990, and 2000) and American Community Survey (ACS; 5 percent 5-year samples for 2010 and 2020) obtained from IPUMS[2].

The PSID sample

PSID respondents were surveyed yearly from 1968 to 1997 and every other year after. The PSID collects earnings and employment data from each household's reference person and their spouses/partners. The reference person is the adult male with the most financial responsibility within a household. If there is no adult male present, the reference person is the adult female with the most financial responsibility.

This study uses data from the 1980-2020 PSID waves for all PSID Sample Members[3] born between 1960 and 1980 to capture respondents who entered the labor market after 1980. These restrictions are implemented for two reasons. First, the Census Bureau's occupational coding schemes and collection of county-level data both changed significantly starting in 1980. As a result, measures of occupational polarization from before 1980 are not comparable to measures from 1980 onwards. Second, respondents born after 1980 are dropped because we cannot observe enough of their career to model their earnings trajectories. Only reference

[1] Panel Study of Income Dynamics, restricted use dataset. Produced and distributed by the Survey Research Center, Institute for Social Research, University of Michigan, Ann Arbor, MI.
[2] Steven Ruggles, Sarah Flood, Matthew Sobek, Danika Brockman, Grace Cooper, Stephanie Richards, and Megan Schouweiler. IPUMS USA: Version 13.0 [dataset]. Minneapolis, MN: IPUMS, 2023. https://doi.org/10.18128/D010.V13.0
[3] PSID Sample Members include all individuals who were living in the original family unit and all their descendants born after 1968. The PSID constructs attrition-adjusted longitudinal weights only for these individuals.

persons and their spouses/partners are included in the sample. Observations where respondents report working for less than 1000 hours in a year are dropped. Earnings growth is modeled for the first 20 years of workers' careers. Observations with missing data on earnings, geographic identifiers, and other variables used in these analyses are dropped from the sample. To ensure reliable model estimation and statistical power, individuals who meet these criteria in fewer than 3 occasions are dropped (Curran, Obeidat, and Losardo 2010). The final sample includes 33,926 observations of 4,148 individuals.

PSID variables

Earnings include all income from labor, including tips and overtime, and are standardized to year-2000 dollars. The logarithm of earnings is the outcome in each analysis. Potential experience is measured as $\text{age} - \text{years of education} - 6$. If the respondent has less than 12 years of education, potential experience is recorded as $\text{age} - 18$. *Birth cohorts* are coded in 5-year intervals starting in 1960, 1965, 1970, and 1975. *Race* is coded as White, Black, or Other. Education is measured using an indicator for if a respondent holds a *college degree*.

The American Community Survey sample

Measures of occupational polarization within local labor markets are constructed using data from the IPUMS 5% sample of the US Census in 1980, 1990, and 2000, and the 5-year ACS samples from 2010 and 2020. *Earnings* is measured using labor income standardized to year-2000 dollars. The sample is limited to individuals between 18 and 65 years old who are employed, are not missing non-imputed[4] income data, are employed in civilian occupations, and who live in

[4] See Mouw and Kalleberg (2010) for a discussion of the consequences of using imputed income data to estimate between-occupation income inequality.

one of the fifty US states. Individuals in occupations with 20 or fewer respondents in the same occupation and labor market are dropped from the sample because within-occupation inequality cannot be reliably estimated with such small cell sizes.

Commuting zones

In order to capture variation in economic outcomes that result from spatially constrained interactions between firms and workers, the following analyses operationalize local labor markets at the commuting zone (CZ) level. Commuting zones are defined as "clusters of counties that are characterized by strong commuting ties within CZs, and weak commuting ties across CZs" (Dorn 2009, p. 135; see Tolbert and Killian 1987; Tolbert and Sizer 1996). Operationalizing labor markets at the CZ level is preferred to doing so at the state level because economic activity within a state is often divided across multiple localities and because some labor markets cross state boundaries. CZs are also preferred over metropolitan statistical areas (MSAs) because CZs cover the entire country while MSAs only cover major metropolitan areas. CZs are defined empirically by their ability to capture distinct regions of local economic activity, making them the optimal unit of analysis for studies of local labor markets.

Measures of occupational polarization

I use two measures of occupational polarization that capture distinct dimensions of inequality between occupations. The first measure describes *employment polarization*. Previous analyses of historical changes in employment polarization rank occupations according to their earnings in some baseline year and predict changes in occupational employment levels using a regression of employment on occupational earnings rank and its square (e.g. Autor et al. 2006, 2008; Dauth

2014). The steepness of the quadratic fit reflects the extent of polarization – that is, if employment in low- and high-paying occupations grows much more than employment in the middle, polarization is high and the relationship between occupational earnings rank and change in employment is steeply U-shaped.

I take a similar approach to measure employment polarization in the cross-section. For each Census/ACS year, I rank occupations according to their average earnings nationally. Then for each occupation within each CZ, I calculate the ratio of total employment within that occupation to the average level of employment within occupations in that CZ:

$$Standardized\ occupational\ employment_{oct} = \frac{total\ employment_{oct}}{total\ employment_{ct} / number\ of\ occupations_{ct}} \quad (1)$$

I call this "standardized occupational employment". Subscripts *o*, *c*, and *t* represent occupation, CZ, and year, respectively. Using the ratio of employment within an occupation to average employment within an occupation in the same CZ, instead of raw employment levels or the proportion of employment within an occupation, accounts for between-CZ differences in total employment and in total occupations.

I then regress standardized occupational employment on occupational earnings rank and its square:

$$Standardized\ occupational\ employment_{oct} = \beta_0 + \beta_1 Y_{ot} + \beta_2 Y_{ot}^2 \quad (2)$$

Y represents the national average income rank for occupation *o* in year *t*. The coefficient β_2 describes the steepness of the U-shaped relationship between occupational average earnings rank and occupations' adjusted employment share in a local labor market. This coefficient is used as the measure of local employment polarization.

The second measure of occupational polarization is *earnings polarization*. This measure describes earnings inequality between occupations within a local labor market. For each Census/ACS year, I measure between-occupation earnings inequality within CZs using a decomposition of the Theil's L index (Theil 1972). The Theil index measures the logarithm of the ratio of each occupation's average earnings to overall average earnings, weights the ratio according to each occupation's size, and sums across occupations. This measure is decomposable across nested levels, allowing me to decompose inequality into three levels: between local labor markets, within local labor markets between occupations, and within occupations within local labor markets. The Theil statistic is defined as:

$$L_{ioc} = \sum_c \sum_o \sum_i \frac{1}{N} ln\left(\frac{Y_{ioc}}{\bar{Y}_{oc}}\right)$$
$$= \sum_c \frac{N_c}{N} ln\left(\frac{\bar{Y}_c}{\bar{Y}}\right) + \sum_c \frac{N_c}{N} \sum_o \frac{N_{oc}}{N_c} ln\left(\frac{\bar{Y}_{oc}}{\bar{Y}_c}\right) + \sum_c \frac{N_c}{N} \sum_o \frac{N_{oc}}{N_c} \sum_i \frac{1}{N_{oc}} ln\left(\frac{Y_{ioc}}{\bar{Y}_{oc}}\right) \quad (3)$$

where *i* represents individuals, *o* represents occupations, and *c* represents CZs. The second component of the decomposition can be used to obtain between occupation earnings inequality within CZs by summing each occupation's contribution to inequality within the local labor market as follows:

$$\sum_o \frac{N_{oc}}{N_c} ln\left(\frac{\bar{Y}_{oc}}{\bar{Y}_c}\right) \quad (4)$$

Both measures of polarization are linearly interpolated within CZs between Census/ACS years.

Labor market contextual variables

In some analyses, I also control for other local labor market characteristics. Using Census and ACS data, I construct CZ-level measures of the proportion of workers in each industry group

using the Census Bureau's 1990 industry coding scheme and the proportion of workers who are female, white and college educated.

Earnings growth curves

I use a two-level hierarchical linear model of occasions nested within individuals to estimate earnings growth curves for PSID respondents. Analyses are run separately by cohort. The models are specified as:

Level 1:

$$y_{ti} = \beta_{0i} + \beta_{1i}\mathrm{EXP}_{ti} + \beta_2\mathrm{EXP}_{ti}^2 + e_{ti}$$

Level 2:

$$\begin{aligned}\beta_{0i} = {} & \gamma_{01}\mathrm{POL(Q1)}_i + \gamma_{02}\mathrm{POL(Q2)}_i + \gamma_{04}\mathrm{POL(Q4)}_i + \gamma_{05}\mathrm{POL(Q5)}_i + u(\mathrm{Q1})_{0i} * \mathrm{POL(Q1)}_i \\ & + u(\mathrm{Q2})_{0i} * \mathrm{POL(Q2)}_i + u(\mathrm{Q3})_{0i} * \mathrm{POL(Q3)}_i + u(\mathrm{Q4})_{0i} * \mathrm{POL(Q4)}_i \\ & + u(\mathrm{Q5})_{0i} * \mathrm{POL(Q5)}_i \\ \beta_{1i} = {} & \gamma_{11}\mathrm{POL(Q1)}_i + \gamma_{12}\mathrm{POL(Q2)}_i + \gamma_{14}\mathrm{POL(Q4)}_i + \gamma_{15}\mathrm{POL(Q5)}_i + u(\mathrm{Q1})_{1i} * \mathrm{POL(Q1)}_i \\ & + u(\mathrm{Q2})_{1i} * \mathrm{POL(Q2)}_i + u(\mathrm{Q3})_{1i} * \mathrm{POL(Q3)}_i + u(\mathrm{Q4})_{1i} * \mathrm{POL(Q4)}_i \\ & + u(\mathrm{Q5})_{1i} * \mathrm{POL(Q5)}_i \\ \beta_2 = {} & \gamma_{20}\end{aligned} \qquad (5)$$

In this model, y_{ti} represents and individual's log earnings at time t. EXP refers to years of potential experience. POL refers to an individual's average exposure over their career to one of the two measures of occupational polarization within a CZ. POL is cohort-mean centered and standardized to a standard deviation of approximately 1. POL(QN) is an indicator variable for belonging to the Nth quintile of exposure to polarization (e.g., POL(Q5) equals 1 for respondents

with 80th to 99th percentile levels of average exposure to polarization over their career). The bottom quintile of POL is the base category. All analyses are weighted using PSID attrition-adjusted longitudinal weights. While the PSID does not post-stratify weights to national surveys like the ACS or Current Population Survey (CPS), estimated population distributions from the weighted PSID sample closely mirror estimates from these surveys (Chang et al. 2019).

Separate random intercepts and slopes are estimated for each quintile of polarization. β_{0i} is the random intercept. It is comprised of coefficients γ_{01} through γ_{05} and random errors $u(\mathrm{Q1})_{0i} * \mathrm{POL(Q1)}_i$ through $u(\mathrm{Q5})_{0i} * \mathrm{POL(Q5)}_i$. Because there are no constants in the level-2 model, the coefficients represent average log earnings when individuals begin their careers in a given level of polarization, and the errors describe the difference between an individual's baseline earnings and their quintile of polarization's average baseline earnings. The variance of these errors describes inequality in earnings when workers start their careers.

Random slope β_{1i} and fixed slope β_2[5] describe the earnings growth rate for individuals in CZs at a given level of polarization. Again, the level-2 model is estimated without a constant. The coefficients γ_{11} through γ_{15} represent the average earnings growth rate among individuals in CZs at a given level of polarization, and $u(\mathrm{QN})_{1i} * \mathrm{POL(QN)}_i$ describes the difference between an individual's rate of earnings growth and the average rate of earnings growth within their polarization quintile. Its variance describes heterogeneity in earnings growth. Wald tests are used to test if level-2 intercepts and slopes vary across quintiles of polarization. The correlation between the intercept and slope errors ($corr(u(\mathrm{QN})_{0i} * \mathrm{POL(QN)}_i, u(\mathrm{QN})_{1i} * \mathrm{POL(QN)}_i)$) describes the association between baseline earnings and earnings growth within the Nth quintile

[5] Experience-earnings profiles are typically fit with quadratic terms to account for declining rates of earnings growth over the career (Mincer 1974; Lemieux 2006b). It is common in multilevel modeling applications to assume for the sake of parsimony that the slope on linear experience varies randomly while the slope on higher order terms is fixed (Kim and Sakamoto 2008; Cheng 2014)

of polarization. All analyses assume an unstructured variance-covariance matrix, which estimates unique covariances between occasions within individuals.

H1 is tested by comparing the variance of $u(\mathrm{QN})_{0i}$ across levels of polarization. If the variances increase with polarization, baseline earnings are more unequal in CZs with higher levels of polarization. H2 is tested by checking for positive variances of $u(\mathrm{QN})_{0i}$ at each quintile of polarization. H3 predicts that polarization disproportionately benefits earnings mobility for high earners. It is tested by examining $corr(u(\mathrm{QN})_{0i} * \mathrm{POL}(\mathrm{QN})_i, u(\mathrm{QN})_{1i} * \mathrm{POL}(\mathrm{QN})_i)$. A positive correlation indicates that within a quintile of polarization, earnings grow faster for individuals with higher baseline earnings. H3 is supported if this correlation increases with polarization.

H4a predicts that polarization is associated with higher average baseline earnings, and therefore that γ_{02}, γ_{03}, γ_{04}, and γ_{05} will be greater than γ_{01}. H4b predicts that polarization increases the steepness of average earnings trajectories and is supported if γ_{12}, γ_{13}, γ_{04}, and γ_{15} are greater than γ_{11}.

To examine how education interacts with polarization to shape individuals' earnings trajectories, I run separate models by cohort for individuals with and without college degrees. H5a and H5b are supported if there is a stronger relationship between polarization and baseline earnings (5a) and earnings growth (5b) for individuals with college degrees.

H6 predicts that in more recent cohorts, polarization disproportionately improves earnings growth rates for high earners. I test this hypothesis by examining how the correlation between baseline earnings and earnings growth ($corr(u(\mathrm{QN})_{0i} * \mathrm{POL}(\mathrm{QN})_i, u(\mathrm{QN})_{1i} * \mathrm{POL}(\mathrm{QN})_i)$) changes with polarization across cohorts. Table 1 restates the hypotheses developed earlier and lists how each hypothesis will be tested using the models described above.

[[Insert Table 1 here]]

Addressing potential confounders

Observed associations between polarization and workers' earnings trajectories may be biased by individual- or CZ-level traits that are correlated with both polarization and earnings. At the CZ level, more polarized CZs may also have industry agglomerations that amplify earnings inequalities. They may also have labor pools that systematically differ on traits such as education, race, and gender, which would affect competition for jobs and productivity in jobs. To account for confounding on CZ-level traits, I run the main analyses from equation (5) with additional controls for CZs' industrial composition and the proportions of workers who are college educated, white, and female.

Individuals may also nonrandomly select into labor markets with different levels of polarization. For example, highly educated workers may select into highly polarized labor markets if they expect doing so will increase their lifetime earnings. Workers may also select into labor markets near where they grew up. If this is the case, we may see nonrandom selection into polarization on demographic traits like race due to regional differences in racial composition. Men and women may also select into different local labor markets based on differences in their occupations or industries or due to differences in family and fertility decisions. Because earnings trajectories may vary by education, race, and gender, it is important to account for this form of selection when estimating the effect of polarization on earnings trajectories.

I account for selection on observable individual traits by using inverse probability weighting (IPW). IPW weights are constructed to achieve balance on a set of covariates across

levels of a treatment. For these analyses, I construct weights for each cohort such that within each level of polarization, the distribution of race, gender, and education matches the distribution of those variables in the middle quintile of polarization. This weighting scheme allows me to estimate the effect of changing workers' exposure to polarization for the set of workers who are in labor markets with average polarization. More details on the construction of these weights can be found in Appendix 1.

Results

Occupational polarization across the US

Occupational polarization in CZs grew significantly between 1980 and 2020. The top panel of Figure 1 presents smoothed plots of standardized occupational employment by occupational earnings rank. In 1980, employment was highest in low-earning occupations and declined almost linearly with average occupational earnings. In 2000, employment in higher-earning occupations grew significantly. Polarization increased even more by 2020. Low- and high-paying occupations accounted for much higher shares of employment compared to middle-paying occupations.

[[Insert Figure 1 here]]

Polarization in occupation average earnings follows similar trends (Figure 1 bottom panel). Between 1980 and 2020, the national Theil index increased by about 26 percent. About half of this rise in inequality was driven by growing inequality in occupation average earnings, while the other half is explained by rising earnings inequality in within occupations. The proportion of total earnings inequality explained by differences between occupations grew from 23 percent to 28 percent, while the within-occupation component shrank from 74 to 68 percent of

total inequality. The proportion of inequality explained by differences in CZ-average earnings remained relatively stable around 4 percent. Figure 2 presents distributions of CZ-level employment and earnings polarization in 1980, 2000, and 2020. Both measures of polarization increased considerably between 1980 and 2020. Altogether, these data suggest that occupational polarization in employment and earnings increased significantly between 1980 and 2020, and there is substantial variation in polarization between CZs.

[[Insert Figure 2 here]]

Polarization and earnings growth over the career

I use career history data from the PSID to model heterogeneity in how individuals' earnings change over their careers and how such earnings mobility is influenced by occupational polarization within CZs. Across cohorts in the analytic sample, about 60 percent of respondents are white and 30 percent are Black (Table 2). The sample is about evenly split by gender. While only 21 percent of respondents in the 1960 cohort hold a college degree, nearly 40 percent of the 1975 cohort is college educated. In more recent cohorts, a greater proportion of respondents work in managerial and professional and service occupations while fewer work in production or manual labor occupations. Similarly, employment in manufacturing declined while employment in business services, professional services, and FIRE grew. Average yearly earnings increased from around $24,000 in the 1960 cohort to $43,000 in the 1975 cohort (year-2000 dollars).

[[Insert Table 2 here]]

Table 3 presents coefficients and variance components from growth curve models where log earnings is regressed on measures of earnings and employment polarization, their interaction with potential experience, and potential experience squared. Average best linear unbiased

predictions (BLUPs) of log earnings trajectories for individuals in each quintile of polarization are presented in Figure 3. These BLUPs incorporate estimates of both fixed and random effects.

[[Insert Table 3 here]]

[[Insert Figure 3 here]]

The first three hypotheses consider how inequalities in workers' career earnings trajectories differ in labor markets with low and high levels of occupational polarization. The variance components in Table 3 suggest that polarization has a strong effect on inequalities within CZs. Figure 4 illustrates these inequalities by showing average earnings trajectories for individuals with low, medium, and high baseline earnings in CZs with different levels of polarization. Hypothesis 1 predicts that polarization is positively associated with inequality in baseline earnings. In Table 3, the variance component labeled Var(intercept) corresponds to $Var(u(\mathrm{QN})_{0i})$ and describes inequality in baseline earnings. For all cohorts except the 1975 cohort, inequality in baseline earnings increases with earnings and employment polarization, indicating that inequality at the beginning of workers' careers is higher in more polarized labor markets. In Figure 4, we see that for the 1960, 1965, and 1975 cohorts, earnings inequality at 0 years of potential experience is greatest in the most polarized CZs. Consistent with Hypothesis 2, earnings growth rates vary within similarly polarized CZs.

[[Insert Figure 4 here]]

Hypothesis 3 predicts that polarization disproportionately benefits earnings growth for high earners. The correlation between the intercept and slope describes the relationship between baseline earnings and earnings growth within similarly polarized CZs. A positive correlation would suggest that individuals with relatively high earnings at the beginning of their career also experience faster earnings growth than low-earning individuals. In all birth cohorts, earnings

growth rates decline with baseline earnings. However, in support of Hypothesis 3, in all birth cohorts except the 1965 cohort, the correlation between baseline earnings and earnings growth increases with polarization. This suggests that polarization amplifies inequality in earnings mobility in a manner consistent with the idea that polarization expands economic opportunity at the top of the labor market.

Hypotheses 4a and 4b predict that employment and earnings polarization also create cumulative advantages associated with sorting between labor markets. In support of Hypothesis 4a, for each birth cohort, both earnings polarization and employment polarization are associated with higher baseline earnings. Compared to individuals in the least polarized CZs, average baseline earnings for individuals in the most polarized CZs are between 30 and 50 percent higher. The positive slopes on potential experience and negative slopes on its square indicate that average earnings grow at a decelerating rate over the career. However, contradicting Hypothesis 4b, there is no evidence that average earnings growth rates vary significantly with polarization. Together, these results suggest that the effect of polarization on between-CZ inequalities in earnings mobility operates through early-career earnings.

Next, I consider how polarization may amplify inequalities between college-educated and non-college-educated workers. Hypothesis 5 predicts that polarization should provide higher returns to college educated workers. Table 4 presents coefficients from growth curve models run separately by cohort and educational attainment. In general, we see that college educated workers have higher baseline earnings and higher rates of earnings growth than non-college-educated workers. However, it is not clear that polarization has a systematically different effect on the earnings trajectories of workers with and without college degrees. In the 1965 and 1970 cohorts, earnings polarization is associated with higher baseline earnings for workers with

college degrees but not for workers without college degrees. Employment polarization has a similar effect in the 1970 cohort. In the 1975 cohort, there is a weak positive association between earnings polarization and average earnings growth rates for college educated workers but not for those without college degrees. For the 1970 and 1975 cohorts, employment polarization is associated with faster earnings growth for college educated workers. Altogether, these results weakly suggest that polarization disproportionately benefits the earnings trajectories of college educated workers.

[[Insert Table 4 here]]

[[Insert Figure 5 here]]

The cumulative advantages in earnings that college educated workers experience from polarization can be observed in Figure 5. Figure 5 presents BLUPs of earnings trajectories by cohort and educational attainment for workers in the least and most polarized CZs. For the 1965 and 1970 cohorts, we can see that average baseline earnings increase with polarization. In the 1975 cohort, we see that earnings trajectories diverge between college-educated workers in the least and most polarized CZs.

Hypothesis 6 predicts that polarization has a stronger effect on inequality in earnings trajectories in more recent cohorts. I do not find evidence in support of this hypothesis. The relationship between polarization and workers' earnings trajectories is consistent between the 1960, 1970, and 1975 birth cohorts.

Consequences for inequality over the life course

Local labor market polarization is associated with inequalities in average lifetime earnings trajectories between workers employed in different CZs and affects inequality in earnings

trajectories within CZs. How is the lifecycle patterning of earnings inequality shaped by the sorting of workers into CZs with different levels of polarization? Figure 6 presents results from a simulation that compares observed levels of earnings inequality as workers progress in their careers against counterfactual estimates of earnings inequality assuming all workers live in CZs in the bottom quintile of earnings and employment polarization. More information about how this counterfactual is constructed can be found in Appendix 2.

[[Insert Figure 6 here]]

In each cohort, variation in local labor market polarization explains a significant proportion of total earnings inequality over workers' careers. Across all cohorts, observed earnings inequality at the beginning of workers' careers is 1.5 to 2 times greater than inequality in the counterfactual scenario where all workers are employed in labor markets with low polarization. In the 1965, 1970, and 1975 cohorts, polarization has little effect on how earnings inequality changes as workers age until later in their careers when its effect attenuates. In the 1960 cohort, polarization amplifies earnings inequality as workers age. Overall, these results are consistent with the notion that polarization affects workers' earnings trajectories and earnings inequality primarily through sorting at the beginning of workers' careers.

Robustness

Next, I consider how the observed associations between polarization and earnings may be biased by nonrandom differences between CZs in their local labor market characteristics and by nonrandom selection by workers into CZs. To account for between-CZ differences in local labor market characteristics that may also affect workers' earnings trajectories, I rerun the main set of models with added controls for local industrial composition and for the proportions of workers in

each CZ who are female, white, and college educated. Estimated coefficients and variance components from these models are presented in Appendix 1 Table 1. There is no meaningful difference between the results from these models and the original models presented in Table 3.

It is also possible that the observed relationship between occupational polarization and inequality in workers' earnings trajectories is driven by nonrandom selection into local labor markets on individual characteristics that affect workers' earning potential. Appendix 1 Table 2 presents results from growth curve models where IPW weights are implemented to account for selection into local labor markets of different levels of polarization by education, race, and gender. The fixed effects estimates do not change meaningfully from those obtained without weighting (Table 3). Polarization is still associated with higher baseline earnings and has no effect on earnings growth rates. The variance components also do not change much. Inequality in baseline earnings still increases somewhat with polarization, and the correlation between baseline earnings and earnings growth still increases with polarization in all cohorts except for the 1965 cohort.

Conclusions

A defining feature of economic transformation in the US labor market over the last half century has been its polarization into "good" and "bad" jobs (Kalleberg 2011). These analyses focus on two important dimensions of polarization between jobs. Employment growth at the bottom and top of the occupational earnings distribution dramatically outpaced growth in the middle. At the same time, earnings inequality between occupations at the bottom and top of the earnings distribution grew substantially. Occupational polarization has played a central role in prominent explanations of rising income inequality in recent decades, with recent research finding that most

of the change in inequality can be explained by a combination of workers moving out of middle-paying jobs into low- and high-paying jobs and by rising inequality in average earnings for low- and high-end jobs (Autor et al. 2006; Mouw and Kalleberg 2010b; Autor and Dorn 2013; Acemoglu and Restrepo 2022). However, it is not well understood how occupational polarization shapes individuals' economic mobility over their career. Those concerned with inequality in economic opportunity may worry that occupational polarization creates barriers to career advancement for low-earners and creates new and more rewarding opportunities for high-earners, resulting in a cumulative advantage process that amplifies earnings inequality and reproduces economic stratification over workers' careers.

I find that occupational polarization affects inequalities in earnings trajectories within local labor markets and between local labor markets through mechanisms that combine to explain a substantial proportion of earnings inequality over the career. I show that at the beginning of the career, earnings inequality is greater in CZs with higher levels of polarization. On average, workers who begin their careers with relatively low earnings experience faster earnings growth than those with higher baseline earnings, resulting in some convergence in earnings as workers age. This negative dependence between baseline earnings and earnings growth is strongest in the least polarized CZs and weakest in the most polarized CZs. As a result, earnings inequality in highly polarized CZs is more persistent over workers' careers. Across CZs, polarization is associated with higher baseline earnings and no differences in average earnings growth, suggesting that most inequality between places can be explained by the initial sorting of different workers into different local labor markets.

These patterns contribute to inequalities between workers with different educational attainment. The benefits of occupational polarization are primarily enjoyed by workers with

college degrees, who experience disproportionate gains both in baseline earnings and in earnings growth. Moreover, there is some evidence that polarization provides more unequal returns to lifecycle earnings growth among college educated workers in more recent cohorts. These patterns also explain a substantial proportion of total earnings inequality at the beginning of workers' careers. In most cases, earnings inequality due to polarization persists as workers age.

These results speak more broadly to the important role local labor markets play in explaining inequality across the US. Income inequality is rising between US regions, largely due to rising overall levels of inequality and the increased sorting of skilled workers into highly productive local labor markets (Moretti 2012; Manduca 2019). It is possible that polarization benefits high earners due to a combination of worker sorting on skill and industry agglomerations in a few high-paying, high-cost-of-living, and highly polarized cities (Glaeser and Gottlieb 2009; Moretti 2012; Card et al. 2023). Consistent with the sorting perspective, I show that the effect of polarization on overall levels of inequality occurs largely through geographic sorting at the beginning of workers' careers.

At the same time, these analyses also shed new light on how variation in labor market structure also affects how inequalities emerge within local labor markets. I show that polarization of local labor markets' occupational structure plays an important role in maintaining inequalities among workers within local labor markets. While low-earners in low-polarization labor markets experience relatively high rates of earnings growth compared to high-earners, that advantage diminishes substantially in high-polarization labor markets. Polarization appears to accelerate earnings growth for high-skill workers and stymie earnings growth for low-earners, maintaining inequality as workers age. Polarization amplifies earnings mobility advantages for high-earning, high-skill workers that accumulate over the career.

These analyses are not without limitations. Perhaps most importantly, these analyses do not account for selection on unobservables into CZs. Individuals may select into more or less polarized CZs based on how they expect their potential earnings to differ between CZs. Bias due to endogenous mobility between CZs throughout the career is also somewhat of a concern, as one third of respondents move at least once during their career. Results from analyses that control for local labor market characteristics and individual characteristics suggest that model estimates are not strongly affected by selection on observables. Future research should search for sources of exogenous variation in labor market structure to examine the causal effects of polarization on career earnings mobility.

Future research may also be interested in examining the consequences of labor market polarization for the intergenerational transmission of economic status. These results have shown that polarization increases the importance of early-career status in shaping inequality over the career. Status attainment research has long shown that socioeconomic and demographic background play an outsized role in influencing first jobs. Future work may investigate if polarization strengthens the relationship between family background and attainment. Future work may also be interested in investigating the occupational pathways that facilitate earnings growth in differently polarized labor markets. What types of job transitions facilitate earnings growth among different classes of workers in polarized and less polarized labor markets?

Overall, these results highlight the importance of connecting analyses of attainment to the labor market structures that shape workers' opportunity for mobility over the career. I have shown that variation between local labor markets' job structures gives rise to inequality in the career patterns of attainment across places and creates different regimes of inequality within local labor markets.

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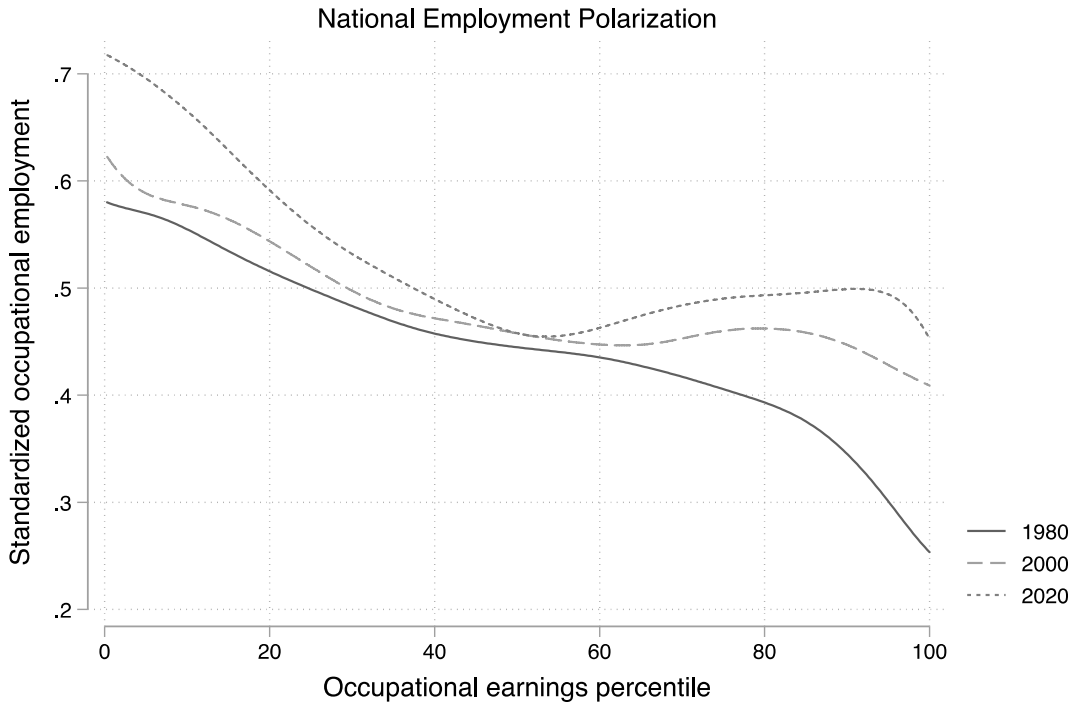
TABLES AND FIGURES

Table 1. Hypotheses and tests

Hypothesis	Test	Supported?
H1: Polarization increases inequality in earnings at the beginning of workers' careers.	$var(u(\mathrm{QN})_{0i})$ increases with N	1965, 1970: yes 1960, 1975: no
H2: Earnings growth rates vary among individuals in similarly polarized local labor markets.	$var(u(\mathrm{QN}))_{1i} > 0$	Yes
H3: The association between individuals' baseline earnings and earnings growth rates is greater in more polarized labor markets.	$corr(u(\mathrm{QN})_{0i} * \mathrm{POL}(\mathrm{QN})_i, u(\mathrm{QN})_{1i} * \mathrm{POL}(\mathrm{QN})_i)$ increases with N	1960, 1970, 1975: yes 1965: no
H4a: Average baseline earnings are higher in more polarized labor markets.	$\gamma_{01} < \gamma_{02}, \gamma_{03}, \gamma_{04}, \gamma_{05}$	Yes for polarization quintile >2
H4b: Average earnings growth rates are higher in more polarized labor markets	$\gamma_{11} < \gamma_{12}, \gamma_{13}, \gamma_{14}, \gamma_{15}$	No
H5a: Baseline earnings for workers with college degrees increase more with polarization than for those without college degrees.	College: $\gamma_{01} < \gamma_{02}, \gamma_{03}, \gamma_{04}, \gamma_{05}$ Non-college: $\gamma_{01} = \gamma_{02}, \gamma_{03}, \gamma_{04}, \gamma_{05}$	1965, 1970: yes 1960, 1975: no
H5b: Earnings growth rates for workers with college degrees increase more with polarization than for those without college degrees.	College: $\gamma_{11} < \gamma_{12}, \gamma_{13}, \gamma_{14}, \gamma_{15}$ Non-college: $\gamma_{11} = \gamma_{12}, \gamma_{13}, \gamma_{14}, \gamma_{15}$	1975: yes 1960, 1965, 1970: no
H6: In more recent cohorts, polarization disproportionately benefits earnings growth for high-earners.	$corr(u(\mathrm{QN})_{0i} * \mathrm{POL}(\mathrm{QN})_i, u(\mathrm{QN})_{1i} * \mathrm{POL}(\mathrm{QN})_i)$ increases with N more in younger cohorts than older cohorts	No

Figure 1. National employment and earnings polarization



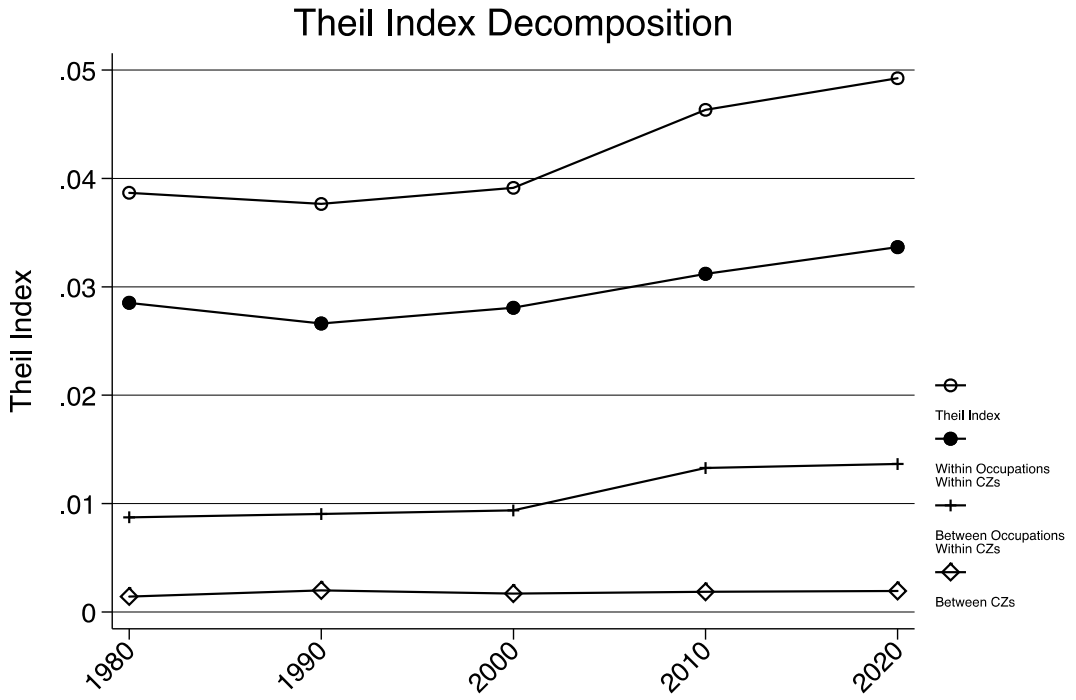


Figure 2. CZ-level variation in polarization

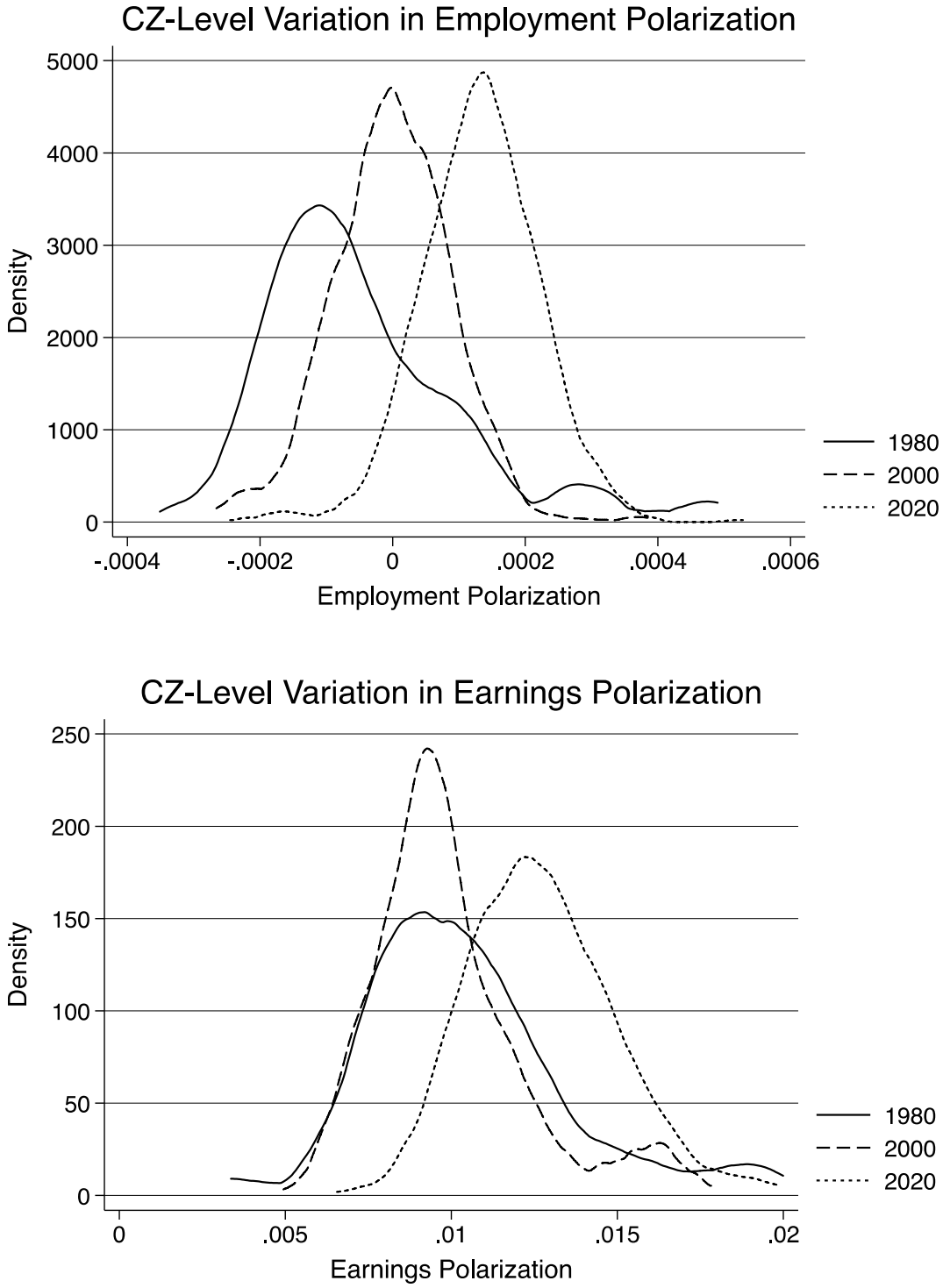


Table 2. Descriptive statistics

Variable	Mean or %			
Birth cohort	1960	1965	1970	1975
Age				
Race				
White	58	57.4	63	59.8
Black	35.2	32.7	29	31.5
Other	6.7	9.9	8.1	8.7
Female	48.3	49.2	49.6	51.6
College degree	21	24.2	30	39.4
Occupation				
Managerial and professional specialty	34.3	34.1	40.6	41.2
Technical, sales, and administrative support	20.7	22.1	20.6	20.5
Service	14.2	13.4	15.1	16.2
Farming, forestry, and fishing	2.8	2.1	1.7	1.5
Precision production, craft, and repair	7.9	7	4.9	3.7
Operators, fabricators, and laborers	20.1	21.2	17.2	17
Industry				
Agriculture, forestry, and fisheries	2	2.2	2.2	1.3
Mining	0.5	0.08	0.05	0.3
Construction	5.7	6.1	5	6.7
Manufacturing	20.9	20.4	15.3	12.9
Transportation, communications, and other public utilities	8.9	6.3	7	6.8
Wholesale trade	2.5	2.5	2.3	3.4
Retail trade	12.8	15.1	15.1	12.7
Finance, insurance, and real estate	6.2	5.2	7	7.4
Business and repair services	5.2	7.6	7.2	7.9
Personal services	3.1	2.6	3.8	3.5
Entertainment and recreation services	0.7	0.8	1	1.4
Professional and related services	24.1	23.5	27.1	29.4
Public administration	7.3	7.6	6.9	6.3
Income (2000 $)	24376	28526	35445	42616
N				
Occassions	12704	7925	6492	6805
Individuals	1310	959	893	986

Note: descriptive statistics are unweighted

Table 3. Estimated coefficients and variance components from growth curve models of log earnings by cohort

	Earnings polarization				Employment polarization			
	1960-1964	1965-1969	1970-1974	1975-1980	1960-1964	1965-1969	1970-1974	1975-1980
Fixed effects								
Polarization quintile								
1 (Lowest)	8.813	8.932	9.101	9.328	8.728	8.851	9.056	9.411
2	8.854	9.035	9.042	9.422	8.740	8.982+	9.113	9.314
3	8.851	9.103*	9.315**	9.613***	8.990***	9.144***	9.208*	9.566*
4	9.091***	9.218***	9.242+	9.551**	9.017***	9.220***	9.210*	9.578*
5 (Highest)	9.198***	9.216**	9.343**	9.805***	9.277***	9.296***	9.460***	9.859***
Polarization quintile X potential experience								
1 (Lowest)	0.103	0.117	0.134	0.116	0.110	0.122	0.136	0.110
2	0.111	0.119	0.142	0.115	0.108	0.117	0.137	0.122*
3	0.112	0.120	0.137	0.115	0.104	0.120	0.135	0.114
4	0.104	0.124	0.145	0.120	0.107	0.126	0.149*	0.118
5 (Highest)	0.098	0.128	0.146+	0.122	0.102	0.125	0.140	0.117
Potential experience^2	-0.002	-0.003	-0.004	-0.003	-0.002	-0.003	-0.004	-0.003
Variance components								
Var(intercept)								
1 (Lowest)	0.275	0.254	0.245	0.375	0.372	0.247	0.205	0.356
2	0.427	0.284	0.385	0.401	0.375	0.285	0.483	0.392
3	0.509	0.276	0.315	0.313	0.300	0.298	0.335	0.345
4	0.297	0.392	0.382	0.316	0.354	0.388	0.404	0.271
5 (Highest)	0.408	0.606	0.487	0.352	0.402	0.453	0.317	0.370
Var(slope)								
1 (Lowest)	0.00151	0.00180	0.00179	0.00155	0.00130	0.00114	0.00077	0.00194
2	0.00215	0.00067	0.00148	0.00154	0.00199	0.00134	0.00172	0.00135
3	0.00205	0.00084	0.00134	0.00140	0.00237	0.00093	0.00200	0.00114
4	0.00166	0.00138	0.00115	0.00134	0.00167	0.00219	0.00118	0.00129
5 (Highest)	0.00120	0.00307	0.00088	0.00112	0.00150	0.00148	0.00108	0.00142
Corr(intercept, slope)								
1 (Lowest)	-0.411	-0.224	-0.485	-0.529	-0.470	-0.324	-0.260	-0.536
2	-0.469	-0.187	-0.462	-0.433	-0.426	-0.208	-0.558	-0.545
3	-0.355	-0.273	-0.426	-0.514	-0.300	-0.388	-0.451	-0.348
4	-0.132	-0.533	-0.240	-0.335	-0.342	-0.600	-0.290	-0.241
5 (Highest)	-0.351	-0.658	-0.272	-0.362	-0.323	-0.477	-0.197	-0.432

***p<0.001 **p<0.01 *p<0.05 +p<0.10 . Stars indicating significant difference from coefficient at polarization quintile=1 as determined by Wald test.

Figure 3. Average earnings trajectories by polarization

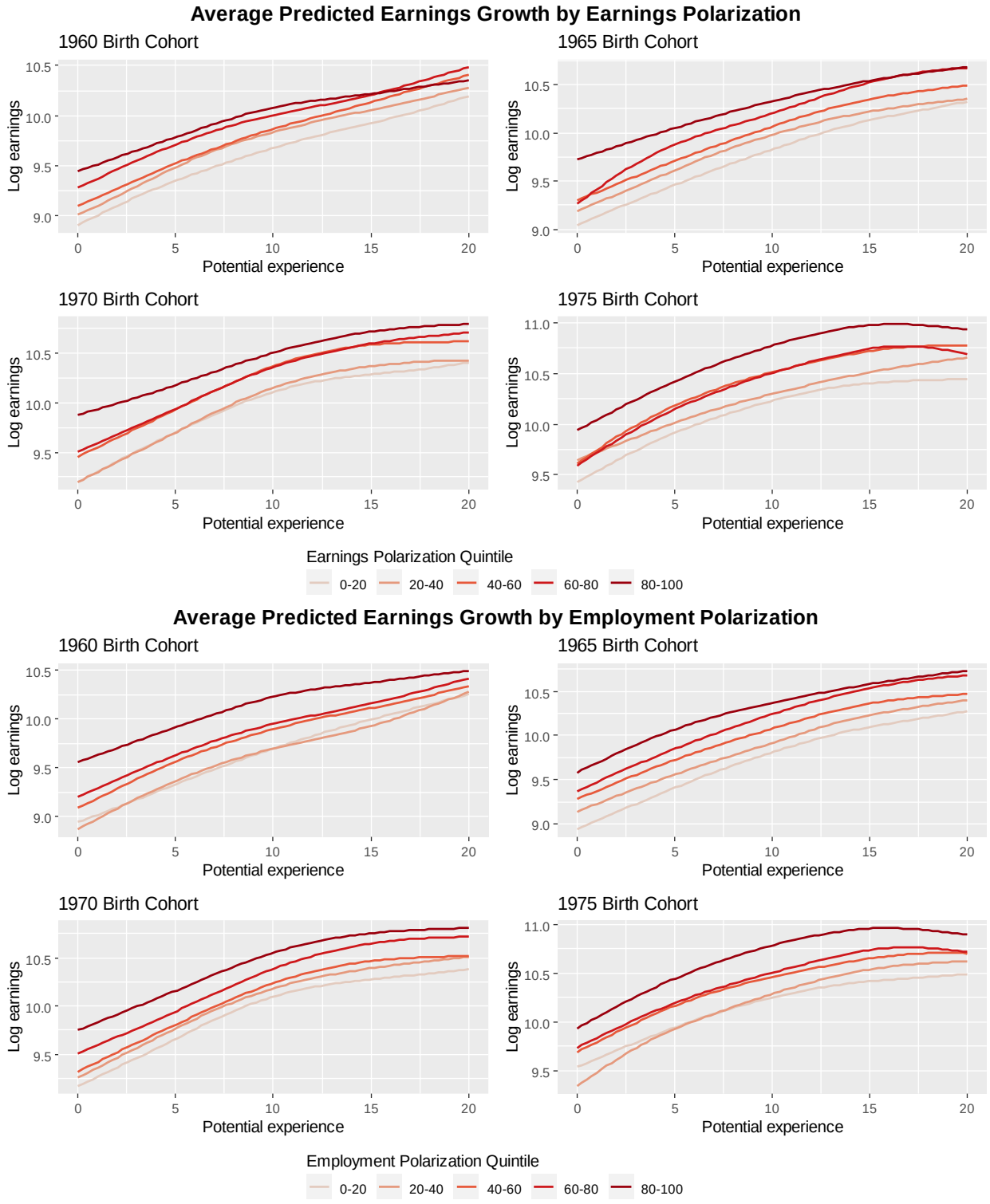


Figure 4. Predicted earnings trajectories by baseline earnings and polarization

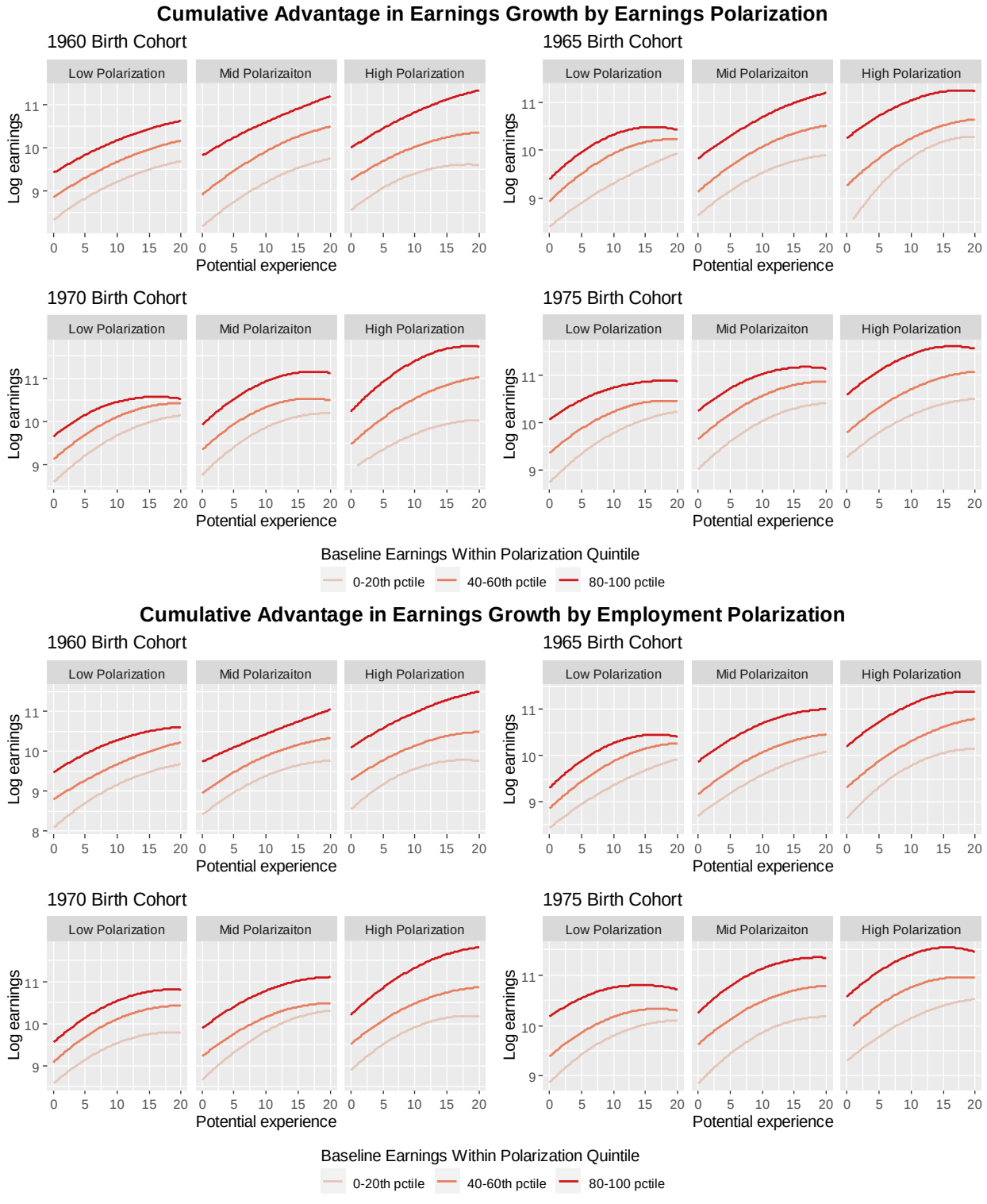


Table 4. Estimated coefficients from growth curve models of log earnings by cohort and education

	Earnings polarization							
	1960-1964		1965-1969		1970-1974		1975-1980	
	No College	College	No College	College	No College	College	No College	College
Fixed effects								
Polarization quintile								
1 (Lowest)	8.802	9.197	8.902	9.214	9.069	9.328	9.217	9.793
2	8.783	9.390	9.012	9.197	8.988	9.255	9.245	9.903
3	8.736	9.251	9.019	9.460+	9.167	9.709*	9.462**	9.919
4	8.998**	9.487*	9.039	9.731***	9.006	9.696*	9.300	9.980
5 (Highest)	9.042**	9.581**	9.038	9.616*	8.953	9.936***	9.410*	10.176*
Polarization quintile X potential experience								
1 (Lowest)	0.091	0.120	0.105	0.152	0.134	0.133	0.119	0.091
2	0.099	0.122	0.103	0.151	0.135	0.152	0.118	0.094
3	0.096	0.136	0.110	0.132+	0.135	0.136	0.113	0.101
4	0.086	0.140	0.117	0.125**	0.141	0.141	0.119	0.106+
5 (Highest)	0.083	0.123	0.117	0.150	0.150+	0.138	0.124	0.105+
Potential experience^2	-0.00143	-0.00297	-0.00216	-0.00327	-0.00365	-0.00365	-0.00305	-0.00231
	Employment polarization							
	1960-1964		1965-1969		1970-1974		1975-1980	
	No College	College	No College	College	No College	College	No College	College
Fixed effects								
Polarization quintile								
1 (Lowest)	8.703	9.119	8.861	8.985	9.021	9.366	9.289	9.920
2	8.737	9.126	8.926	9.269	8.985	9.459	9.178	9.765
3	8.894**	9.395*	9.058**	9.614**	9.086	9.681*	9.308	10.028
4	8.936**	9.466**	9.115**	9.603**	9.101	9.630+	9.400	10.007
5 (Highest)	9.088***	9.707***	9.065*	9.762***	9.148	9.899***	9.466+	10.121
Polarization quintile X potential experience								
1 (Lowest)	0.098	0.125	0.110	0.150	0.132	0.127	0.113	0.085
2	0.090	0.139	0.101	0.142	0.134	0.138	0.125+	0.100
3	0.093	0.118	0.107	0.132+	0.128	0.134	0.118	0.097
4	0.091	0.138	0.113	0.145	0.138	0.154*	0.115	0.105+
5 (Highest)	0.0858*	0.127	0.118	0.132+	0.141	0.137	0.119	0.104*
Potential experience^2	-0.00145	-0.00298	-0.00216	-0.00326	-0.00352	-0.00358	-0.00305	-0.00231

***p<0.001 **p<0.01 *p<0.05 +p<0.10 . Stars indicating significant difference from coefficient at polarization quintile=1 as determined by Wald test.

Figure 5. Predicted earnings trajectories by polarization and education

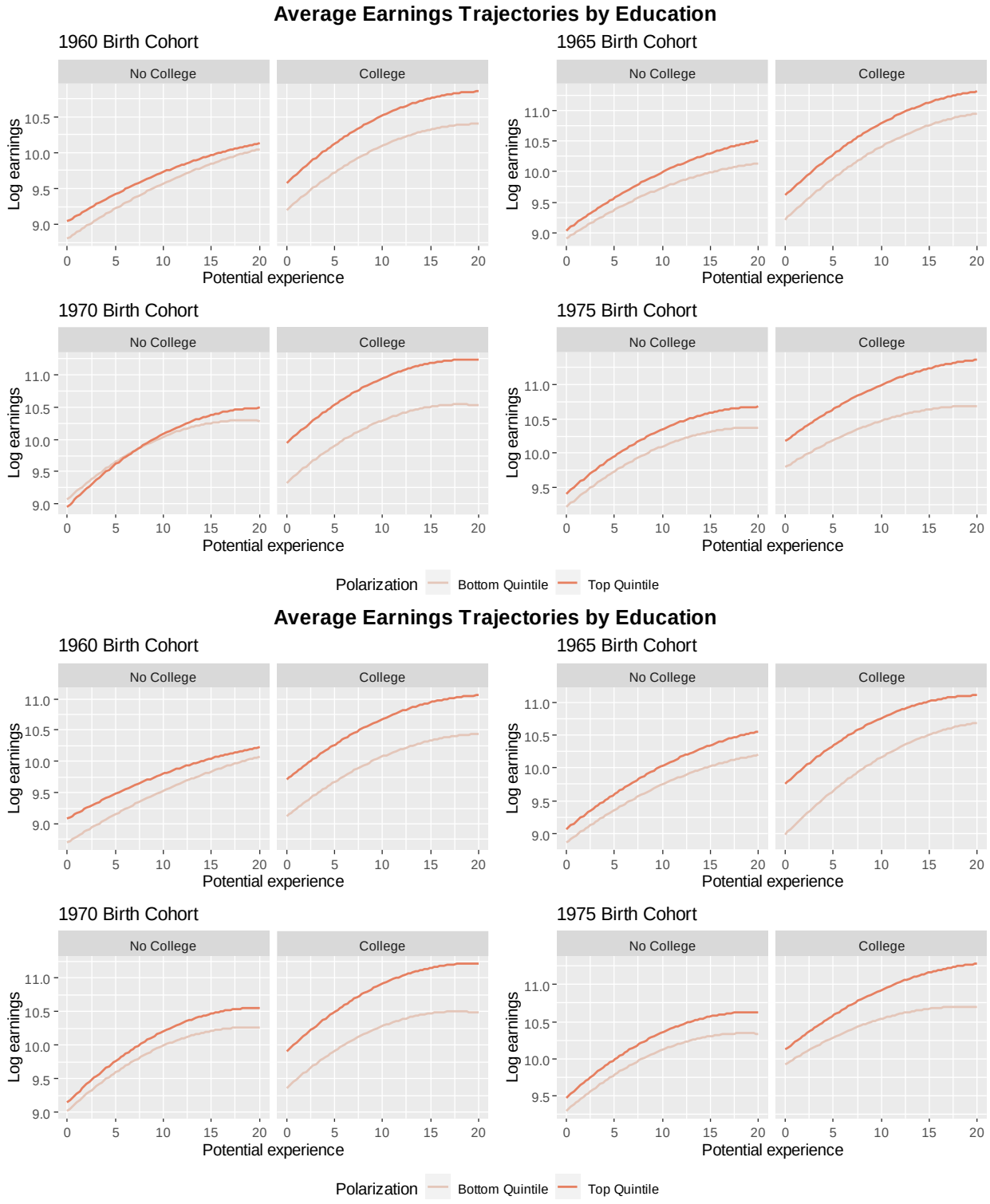
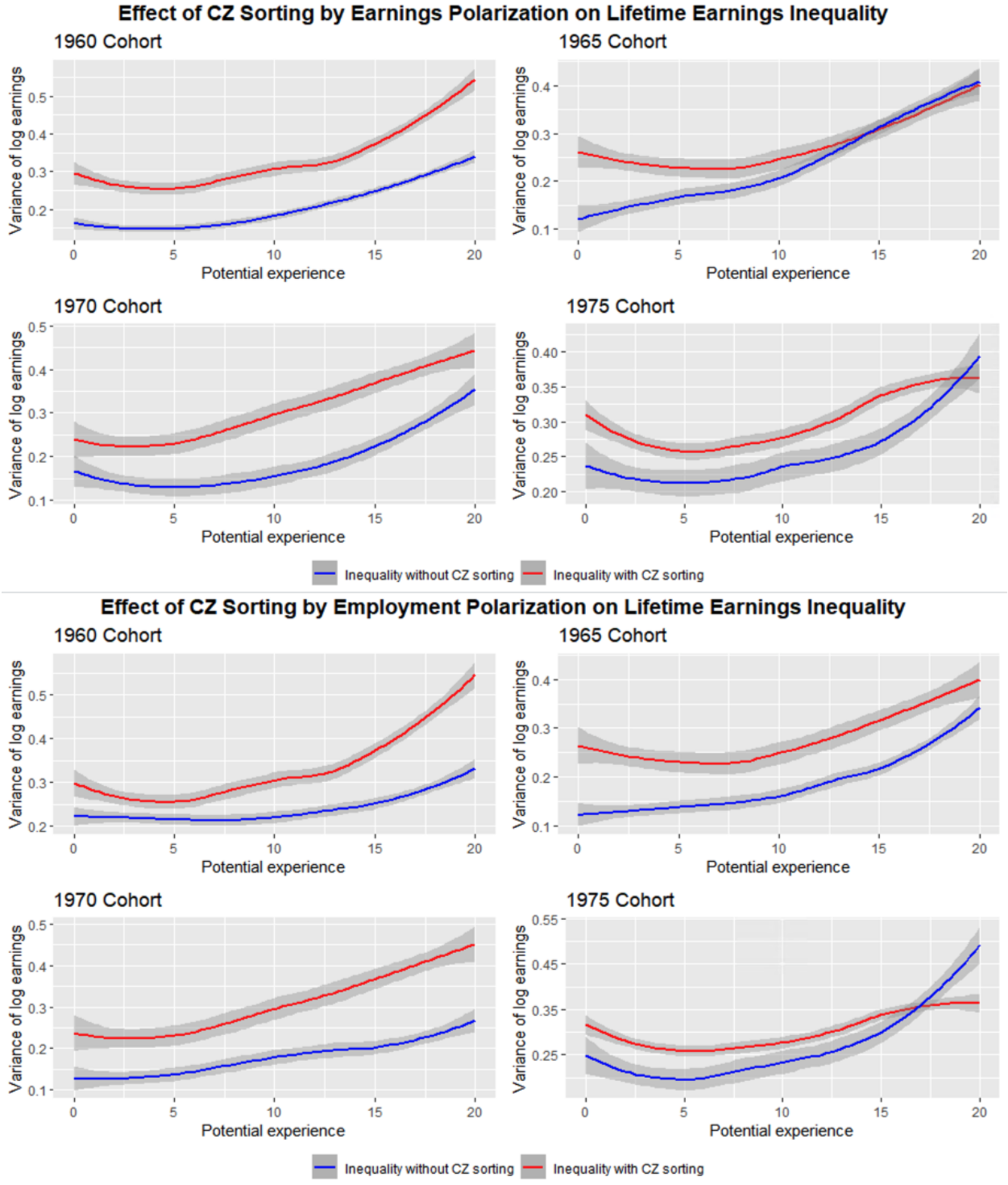


Figure 6. Observed and counterfactual lifecycle earnings inequality



Appendix 1. Robustness

Controlling for Local Labor Market Characteristics

I re-run the models presented in Table 3 with added controls for the proportion of workers in each industry group defined by the 1990 Census industry coding scheme. Details for this coding scheme can be found from IPUMS (Ruggles et al. 2023) under the variable IND1990. I also control for the proportions of workers within a CZ who are female, white, and college educated. The table below presents estimated coefficients and variance components from these models with added controls. There is no appreciable difference between these results and those presented in Table 3.

Table A1.1. Estimated coefficients and variance components from growth curve models of log earnings by cohort (with local labor market controls)

	Earnings polarization				Employment polarization			
	1960-1964	1965-1969	1970-1974	1975-1980	1960-1964	1965-1969	1970-1974	1975-1980
Fixed effects								
Polarization quintile								
1 (Lowest)	9.009	9.181	9.171	9.308	8.928	9.107	9.138	9.422
2	9.040	9.256	9.093	9.389	8.924	9.208	9.164	9.305
3	9.039	9.317+	9.342*	9.597***	9.154***	9.353***	9.240	9.523
4	9.267***	9.402**	9.267	9.510**	9.142**	9.385***	9.248	9.539
5 (Highest)	9.327***	9.374+	9.358+	9.754***	9.380***	9.448***	9.479***	9.806***
Polarization quintile X potential experience								
1 (Lowest)	0.087	0.097	0.125	0.118	0.096	0.101	0.126	0.112
2	0.093	0.095	0.132	0.117	0.094	0.094	0.128	0.123*
3	0.095	0.096	0.128	0.116	0.088	0.097	0.124	0.115
4	0.087	0.100	0.136	0.122	0.092	0.104	0.138*	0.120
5 (Highest)	0.084	0.107	0.138+	0.123	0.088	0.104	0.130	0.118
Potential experience^2	-0.002	-0.002	-0.003	-0.003	-0.002	-0.002	-0.003	-0.003
Variance components								
Var(intercept)								
1 (Lowest)	0.269	0.246	0.240	0.358	0.379	0.246	0.198	0.362
2	0.394	0.251	0.375	0.398	0.366	0.251	0.497	0.366
3	0.481	0.276	0.317	0.286	0.282	0.276	0.319	0.333
4	0.264	0.368	0.362	0.292	0.340	0.368	0.405	0.268
5 (Highest)	0.347	0.390	0.474	0.342	0.345	0.390	0.291	0.359
Var(slope)								
1 (Lowest)	0.00153	0.00115	0.00174	0.00155	0.00134	0.00115	0.00082	0.00193
2	0.00214	0.00146	0.00150	0.00154	0.00205	0.00146	0.00178	0.00128
3	0.00215	0.00100	0.00137	0.00139	0.00239	0.00100	0.00197	0.00111
4	0.00174	0.00222	0.00117	0.00130	0.00163	0.00222	0.00115	0.00130
5 (Highest)	0.00114	0.00149	0.00088	0.00103	0.00146	0.00149	0.00107	0.00138
Corr(intercept, slope)								
1 (Lowest)	-0.425	-0.301	-0.484	-0.500	-0.476	-0.301	-0.262	-0.535
2	-0.474	-0.175	-0.470	-0.433	-0.432	-0.175	-0.562	-0.515
3	-0.375	-0.371	-0.451	-0.479	-0.312	-0.371	-0.443	-0.301
4	-0.152	-0.619	-0.230	-0.322	-0.337	-0.619	-0.312	-0.228
5 (Highest)	-0.324	-0.516	-0.270	-0.331	-0.310	-0.516	-0.161	-0.421

***p<0.001 **p<0.01 *p<0.05 +p<0.10 . Stars indicating significant difference from coefficient at polarization quintile=1 as determined by Wald test. Controls include proportion of workers employed by industry group and proportions of workers who are female, white, and college educated.

Controlling for Worker Characteristics using IPW Weights

Construction of IPW Weights

Inverse probability weights are constructed to estimate the effect of polarization on workers' earnings trajectories, net of selection on observables into labor markets with varying levels of polarization. I construct IPW weights that estimate the average treatment effect on the treated (ATT), where I define the treated group as workers in the middle quintile of earnings polarization. This allows me to estimate how changing levels of polarization would affect the earnings trajectories of workers who work in moderately polarized labor markets. ATT weights are constructed as follows:

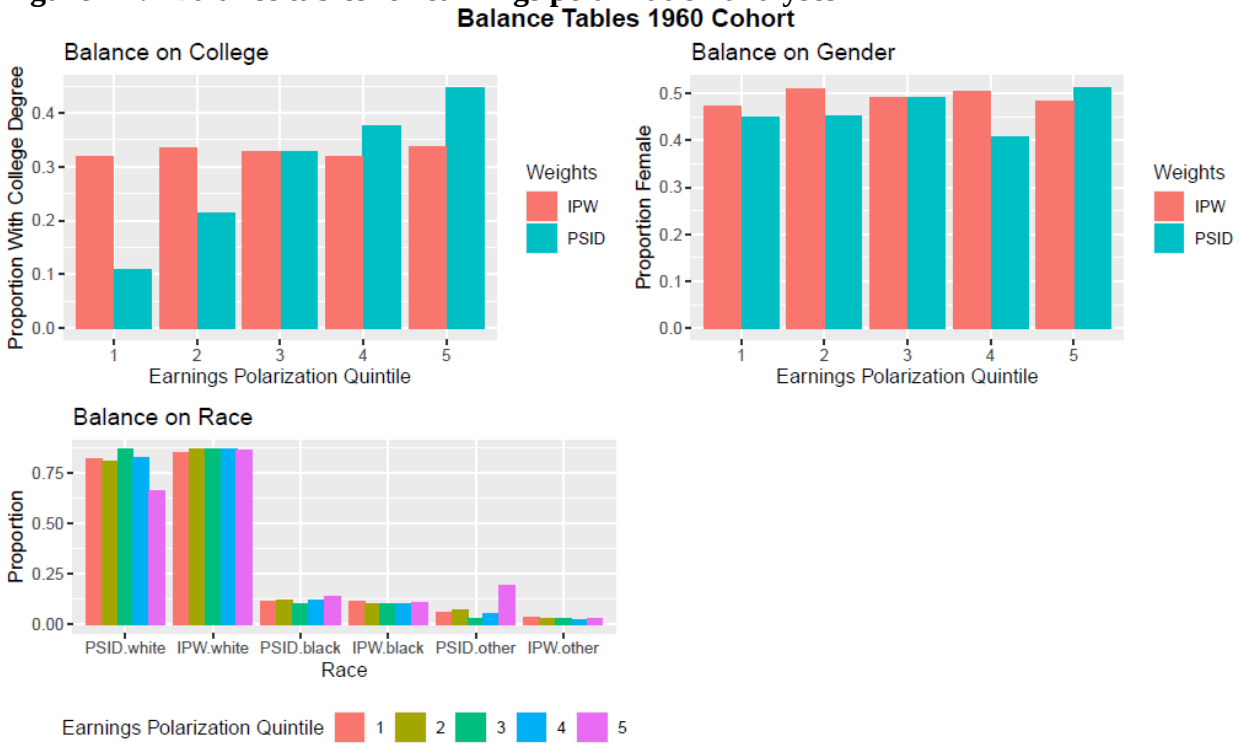
$$\omega_{ATT,i} = \mathbb{I}(Q_i = j) + e_{f,i} \sum_{j \neq f}^{p} \frac{\mathbb{I}(Q_i = j)}{e_{ji}}$$

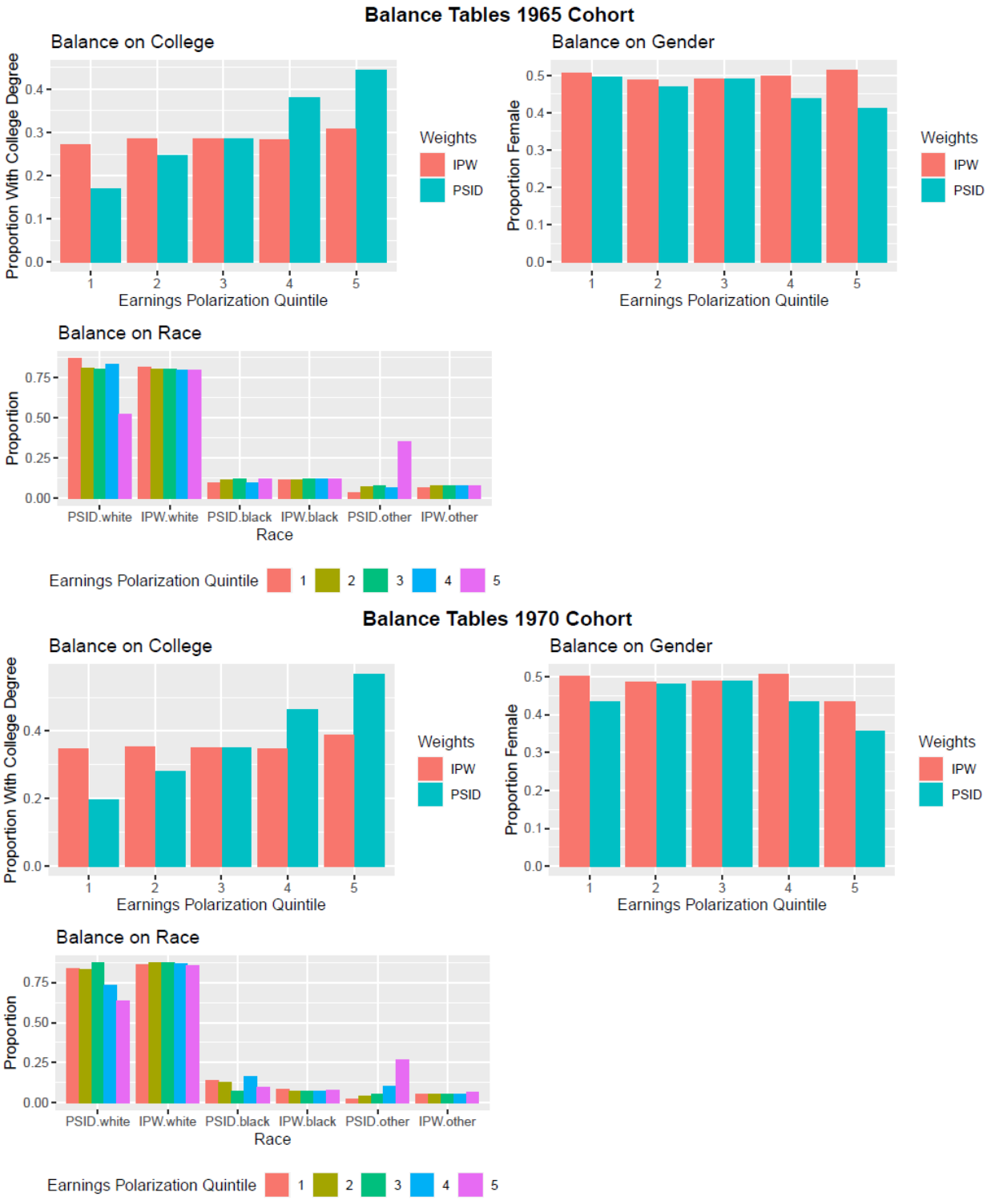
where Q_i represents the quintile of polarization and j indicates an individual's level of polarization and f indexes the third quintile of polarization. e_{ji} describes an individual's estimated probability of belonging to polarization quintile j, also known as the propensity score. Weights are equal to 1 for all individuals in the middle polarization quintile. For all other individuals, weights are equal to their predicted probability of belonging to the middle polarization quintile divided by their predicted probability of belonging to their own polarization quintile. Propensity scores are estimated by obtaining predicted values from multinomial regressions for each level of polarization $j \neq f$ (quintiles 1, 2, 4, and 5):

$$\log\left(\frac{p_j(x)}{p_f(x)}\right) = \beta_{0j} + \beta_{1j}(\text{college}) + \beta_{2j}(\text{female}) + \beta_{3j}(\text{black}) + \beta_{4j}(\text{hispanic})$$

Below, I present plots that demonstrate how the IPW weights effectively achieve balance on education, gender, and race across polarization quintiles for each cohort.

Figure A1.1 Balance tables for earnings polarization analyses




Balance Tables 1965 Cohort
Balance on College
Proportion With College Degree
0.0
0.1
0.2
0.3
0.4
1
2
3
4
5
Earnings Polarization Quintile
Weights
IPW
PSID
Balance on Gender
Proportion Female
0.0
0.1
0.2
0.3
0.4
0.5
1
2
3
4
5
Earnings Polarization Quintile
Weights
IPW
PSID
Balance on Race
Proportion
0.00
0.25
0.50
0.75
PSID.white
IPW.white
PSID.black
IPW.black
PSID.other
IPW.other
Race
Earnings Polarization Quintile
1
2
3
4
5
Balance Tables 1970 Cohort
Balance on College
Proportion With College Degree
0.0
0.2
0.4
1
2
3
4
5
Earnings Polarization Quintile
Weights
IPW
PSID
Balance on Gender
Proportion Female
0.0
0.1
0.2
0.3
0.4
0.5
1
2
3
4
5
Earnings Polarization Quintile
Weights
IPW
PSID
Balance on Race
Proportion
0.00
0.25
0.50
0.75
PSID.white
IPW.white
PSID.black
IPW.black
PSID.other
IPW.other
Race
Earnings Polarization Quintile
1
2
3
4
5

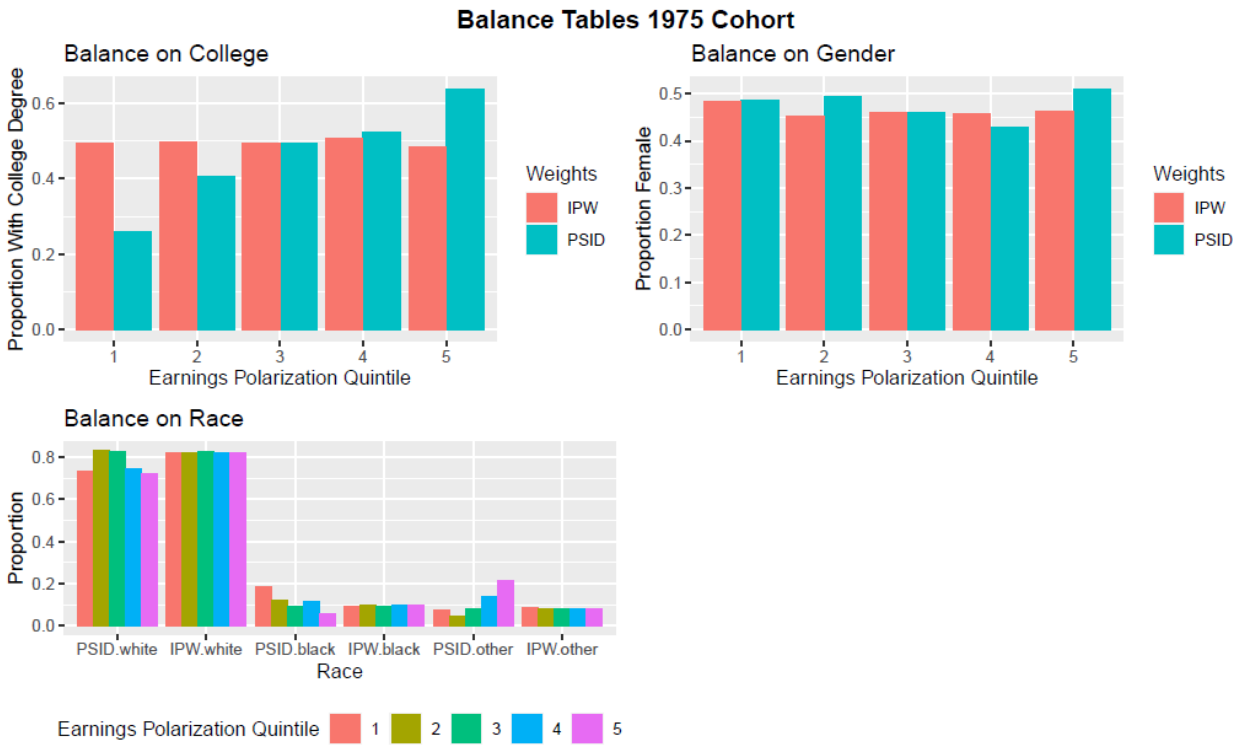
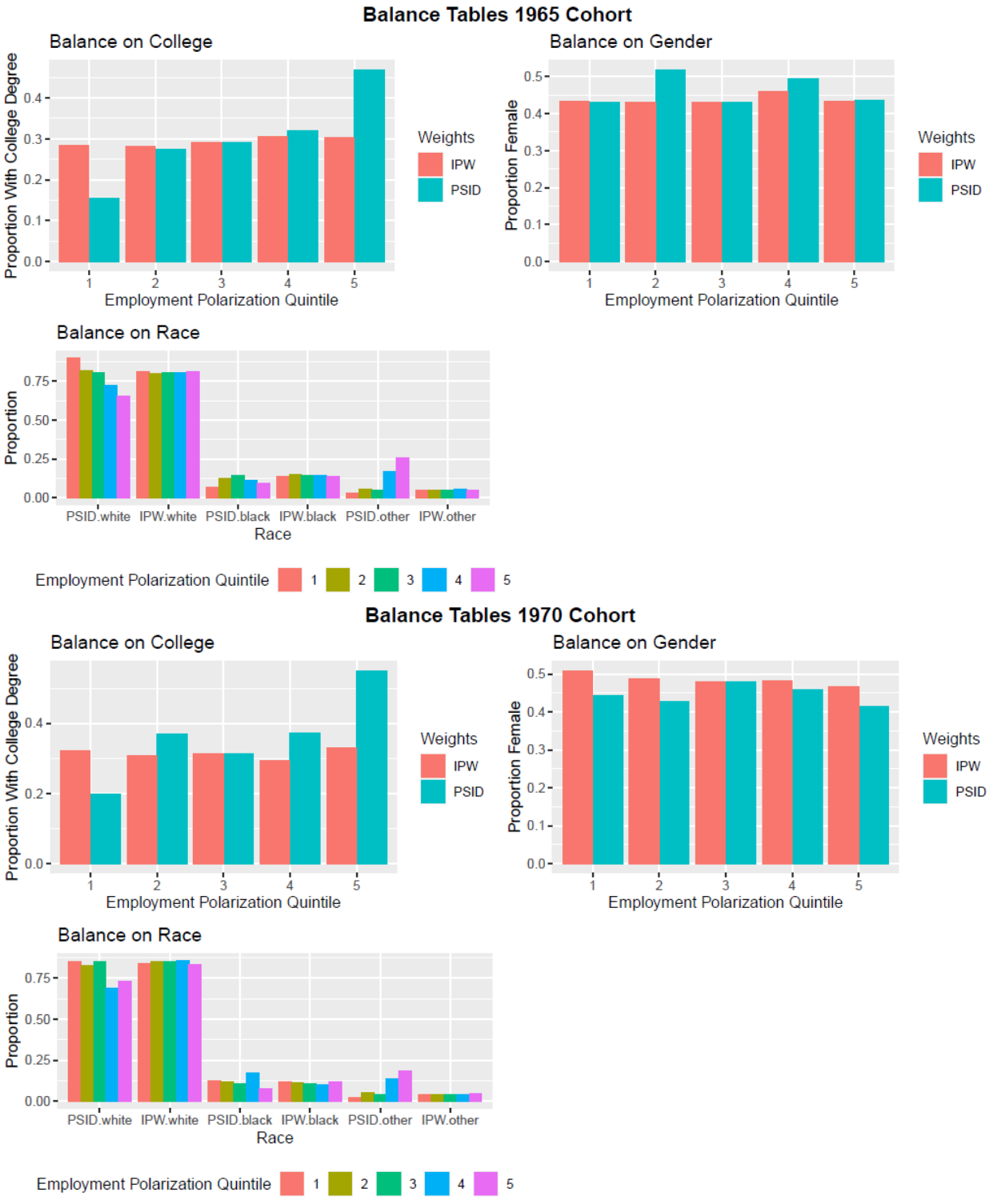


Figure A1.2 Balance tables for employment polarization analyses


Balance Tables 1965 Cohort
Balance on College
Proportion With College Degree
0.0
0.1
0.2
0.3
0.4
1
2
3
4
5
Employment Polarization Quintile
Weights
IPW
PSID
Balance on Gender
Proportion Female
0.0
0.1
0.2
0.3
0.4
0.5
1
2
3
4
5
Employment Polarization Quintile
Weights
IPW
PSID
Balance on Race
Proportion
0.00
0.25
0.50
0.75
PSID.white
IPW.white
PSID.black
IPW.black
PSID.other
IPW.other
Race
Employment Polarization Quintile
1
2
3
4
5
Balance Tables 1970 Cohort
Balance on College
Proportion With College Degree
0.0
0.2
0.4
1
2
3
4
5
Employment Polarization Quintile
Weights
IPW
PSID
Balance on Gender
Proportion Female
0.0
0.1
0.2
0.3
0.4
0.5
1
2
3
4
5
Employment Polarization Quintile
Weights
IPW
PSID
Balance on Race
Proportion
0.00
0.25
0.50
0.75
PSID.white
IPW.white
PSID.black
IPW.black
PSID.other
IPW.other
Race
Employment Polarization Quintile
1
2
3
4
5


Balance Tables 1975 Cohort
Balance on College
Proportion With College Degree
0.0
0.2
0.4
0.6
1
2
3
4
5
Employment Polarization Quintile
Weights
IPW
PSID
Balance on Gender
Proportion Female
0.0
0.2
0.4
1
2
3
4
5
Employment Polarization Quintile
Weights
IPW
PSID
Balance on Race
Proportion
0.00
0.25
0.50
0.75
PSID.white
IPW.white
PSID.black
IPW.black
PSID.other
IPW.other
Race
Employment Polarization Quintile
1
2
3
4
5

Table A1.2. Estimated coefficients and variance components from growth curve models of log earnings by cohort (IPW)

	Earnings polarization				Employment polarization			
	1960-1964	1965-1969	1970-1974	1975-1980	1960-1964	1965-1969	1970-1974	1975-1980
Fixed effects								
Polarization quintile								
1 (Lowest)	8.822	8.938	9.120	9.360	8.722	8.860	9.053	9.419
2	8.854	9.040	9.055	9.432	8.755	8.997+	9.092	9.310
3	8.836	9.111*	9.315*	9.616***	8.980***	9.156***	9.201+	9.562+
4	9.072***	9.205***	9.267+	9.563**	9.039***	9.246***	9.243*	9.599*
5 (Highest)	9.233***	9.274**	9.424**	9.772***	9.272***	9.330***	9.467***	9.808***
Polarization quintile X potential experience								
1 (Lowest)	0.105	0.116	0.133	0.005	0.113	0.119	0.138	0.109
2	0.113	0.117	0.142	0.005	0.111	0.113	0.140	0.121*
3	0.115+	0.117	0.137	0.005	0.107	0.116	0.137	0.113
4	0.108	0.122	0.143	0.005	0.109	0.121	0.148+	0.115
5 (Highest)	0.099	0.122	0.140	0.005	0.105	0.122	0.140	0.118
Potential experience^2	-0.002	-0.003	-0.004	-0.003	-0.002	-0.003	-0.004	-0.003
Variance components								
Var(intercept)								
1 (Lowest)	0.269	0.250	0.258	0.369	0.364	0.231	0.220	0.364
2	0.448	0.286	0.393	0.407	0.361	0.282	0.550	0.413
3	0.514	0.280	0.309	0.314	0.299	0.303	0.335	0.358
4	0.314	0.412	0.369	0.323	0.341	0.379	0.370	0.258
5 (Highest)	0.316	0.676	0.471	0.359	0.365	0.459	0.296	0.395
Var(slope)								
1 (Lowest)	0.00177	0.00129	0.00209	0.00150	0.00119	0.00094	0.00098	0.00196
2	0.00253	0.00067	0.00156	0.00157	0.00210	0.00142	0.00213	0.00142
3	0.00208	0.00086	0.00131	0.00141	0.00236	0.00098	0.00199	0.00121
4	0.00173	0.00137	0.00129	0.00142	0.00190	0.00220	0.00131	0.00126
5 (Highest)	0.00139	0.00350	0.00133	0.00095	0.00154	0.00164	0.00071	0.00125
Corr(intercept, slope)								
1 (Lowest)	-0.423	-0.119	-0.518	-0.529	-0.469	-0.210	-0.332	-0.543
2	-0.503	-0.180	-0.472	-0.453	-0.441	-0.183	-0.626	-0.564
3	-0.359	-0.282	-0.416	-0.516	-0.301	-0.392	-0.451	-0.361
4	-0.174	-0.538	-0.255	-0.357	-0.362	-0.596	-0.295	-0.216
5 (Highest)	-0.376	-0.727	-0.410	-0.329	-0.313	-0.597	-0.100	-0.424

***p<0.001 **p<0.01 *p<0.05 +p<0.10 . Stars indicating significant difference from coefficient at polarization quintile=1 as determined by Wald test.

REFERENCES

Ruggles, Steven, Sarah Flood, Matthew Sobek, Danika Brockman, Grace Cooper, Stephanie Richards, and Megan Schouwiler. 2023. "IPUMS USA: Version 13.0."

Appendix 2. Constructing Earnings Inequality Counterfactuals

To assess the contribution of occupational polarization to earnings inequality over the life course, I compare observed levels of earnings inequality at each year of potential experience against counterfactual levels of earnings inequality under the assumption that all workers operate in CZs with similar levels of polarization. I design the counterfactual to account for how polarization affects two components of workers' earnings trajectories: 1) the effect of polarization on average baseline earnings and average earnings growth and 2) the effect of polarization on the relationship between individual baseline earnings and individual earnings growth.

I construct a counterfactual scenario where the distribution of random intercepts (baseline earnings), random slopes (earnings growth rates), and their correlation mimics that found in the bottom quintile of earnings polarization for each cohort. I assign each individual a new random intercept β_0^* and random slope β_1^* that is randomly drawn from a multivariate normal distribution whose parameters are defined by the means, variances, and covariances of the estimated random intercepts and slopes in the bottom quintile of polarization:

$$\begin{bmatrix}\beta_0^* \\ \beta_1^*\end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix}\bar{\hat{\beta}}_{0,Q1} \\ \bar{\hat{\beta}}_{1,Q1}\end{bmatrix}, \begin{bmatrix}\sigma^2_{\bar{\hat{\beta}}_{0,Q1}} & \rho\sigma_{\bar{\hat{\beta}}_{0,Q1}}\sigma_{\bar{\hat{\beta}}_{1,Q1}} \\ \rho\sigma_{\bar{\hat{\beta}}_{0,Q1}}\sigma_{\bar{\hat{\beta}}_{1,Q1}} & \sigma^2_{\bar{\hat{\beta}}_{1,Q1}}\end{bmatrix}\right)$$

I then use these newly defined random intercepts and slopes to generate counterfactual levels of earnings for each observation of each individual:

$$y_{it}^* = \beta_0^* + \beta_1^* \mathrm{EXP} + \beta_2 \mathrm{EXP}^2$$

Earnings inequality is measured using the variance of the logarithm of earnings.