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 middle-paying occupations, 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 ACS, I demonstrate that polarization amplifies inequalities within and between local labor markets through its effect on workers' earnings when they enter the labor market and reduces inequalities as workers age by providing low earners with greater opportunity to increase their earnings over the career. The benefits of polarization disproportionately accrue to managers and professionals. Further, I show that while polarization was an equalizing force in older cohorts, it amplifies earnings inequality over the lifecycle in younger cohorts.

Introduction

Income inequality in the United States increased substantially over the last half-century, with much of that growth in inequality driven by growth at 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; Goos and Manning 2007; Autor et al. 2008; 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. Analyses of career 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. 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. 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 in privileged occupations.

I leverage variation in the 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 the 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 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. But polarization benefits earnings growth for low-earners more than high-earners, leading earnings trajectories to diverge less over the career in more polarized CZs compared to average CZs. Polarization also contributes to inequalities between CZs through its positive effect on earnings at the beginning of workers' careers. While average earnings between CZs converge as workers age, overall earnings inequality increases over workers' careers, and sorting into CZs of heterogeneous polarization explains a considerable proportion of inequality across the life course. This is especially the case in recent cohorts, where high-earners disproportionately benefit from high levels of polarization.

Background

Earnings inequality over the life course

Social scientists have long been concerned with the processes by which individuals move between 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 rising inequality within cohorts as they age (e.g. Mincer 1988; Rosenfeld 1992; Topel and Ward

1992; Kristen Keith and Abagail McWilliams 1995; Fuller 2008; Mouw and Kalleberg 2010a; Cheng 2014, 2021; Jarvis and Song 2017).

Intragenerational mobility is a fundamental mechanism underlying inequality. Individuals' income trajectories and occupational pathways over their careers reflect how 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). Variation in career wage profiles may result from myriad sources including differences 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), race and gender discrimination (Tomaskovic-Devey 1993; Thomas, Herring, and Horton 1994; Maume 2004a, 2004b; Tomaskovic-Devey, Thomas, and Johnson 2005; Fernandez-Mateo 2009), and variation in the jobs, firms, and occupations in which individuals are 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).

Connecting these strands of intragenerational mobility research is the key insight that earnings inequality is a life course phenomenon. Life course analyses of career processes 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). Inequality in wages and occupational attainment is understood to 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).

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 the aggregation of individual-level variation in earnings trajectories (e.g. Cheng 2014, 2021), cumulative exposure to racial and gender discrimination (e.g. Thomas et al. 1994; Maume 2004b; Tomaskovic-Devey et al. 2005), and differences in workers' employment histories (e.g. Mincer 1974; Spilerman 1977; Mortensen 1988; Petersen and Spilerman 1990; Rosenfeld 1992; Brand 2006).

Much less work has investigated how the linkage between individuals' earnings trajectories and macro-level inequality is shaped by the other side of the labor market: labor demand. 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 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).

The occupational structure, matching, and earnings mobility

Focusing our attention to the structural determinants of mobility and inequality, I argue that the structure of jobs in a labor market shapes inequality in opportunity for earnings mobility over the career. Sociologists and economists have developed many theories of how workers are matched to jobs, but most theories 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 lead 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 polarization for inequalities in how inequalities unfold over workers' careers. Most labor market flows occur at the local level – 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) – suggesting that workers career trajectories are primarily structured by their local labor market context. 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 should 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 amplify inequalities in earnings trajectories. I expect that polarization intensifies cumulative advantages in earnings growth associated with higher baseline earnings. First, I consider whether individual baseline earnings are positively associated with the steepness of individual earnings trajectories within similarly polarized local labor markets. We may expect this to be true in part because returns to occupation-specific experience are higher in high-paying occupations than in low-paying occupations (Sullivan 2010; Cortes 2016). Individuals who enter the labor market in higher-paying jobs will also experience higher rates of earnings growth on average insofar all workers remain in the same or similar occupations. Of course, individuals also experience earnings growth by changing occupations. However, occupational mobility 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. Mobility has also become 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). Altogether, these findings suggest that individuals with low early-career earnings may also experience slower earnings growth.

H3a: There is a positive association between individuals' baseline earnings and earnings growth rates within labor markets of similar polarization.

There is also reason to expect that such within-local-labor-market cumulative advantages are greater in highly polarized labor markets. Mechanically, employment polarization reduces the number of "middle-paying" vacancies available to promote upward mobility out of low-paying occupations. If more workers begin their careers in low-paying occupations that have high rates of within-class circulation and little access to mobility pathways, and the opportunities that might exist for upward mobility become even more scarce, we might expect lower rates of upward mobility for low-paid workers. Earnings polarization is also likely to amplify cumulative advantages from early-career earnings. 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.

H3b: The positive association between individuals' baseline earnings and earnings growth rates is greater in more polarized labor markets.

Because both employment and earnings polarization are primarily driven by growth at the top of the occupational distribution, I expect that higher levels of polarization are associated with both higher earnings at the beginning of workers' careers and higher average rates of earnings growth.

H4a: The association between polarization and baseline earnings is positive.

H4b: Polarization positively moderates the association between experience and earnings.

If it is the case that polarization creates unequal opportunities for earnings growth according to workers' occupations as described above, we would expect that workers in high-paying occupations experience cumulative advantages in earnings growth over the career.

H5a: Inequalities in baseline earnings between occupations increase with polarization.

H5b: The association between occupation and earnings growth rates increases with polarization.

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 to local labor market characteristics derived from the American Community Survey (ACS) obtained from IPUMS[2] using restricted-use state- and county-level identifiers for PSID respondents.

The PSID Sample

PSID rsepondents 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.

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[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

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, occupational coding schemes employed by the Census bureau changed significantly starting in 1980. As a result, measures of occupational polarization from before 1980 are not comparable to measures post-1980. Second, respondents born after 1980 are dropped because we cannot observe enough of their career to model their earnings trajectories. Only reference persons and their spouses/partners are included in the sample. Respondents who reported earning an income equivalent to less than 20 hours per week at minimum wage were dropped from the sample. Earnings growth is modeled for the first 25 years of workers' careers. Observations with missing data on earnings, geographic identifiers, and other variables used in these analyses are dropped from the sample. The final sample includes 31,092 observations of 4,493 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*. *Main occupation* is the occupation where respondents worked the most years over their career.

[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.

The American Community Survey

Measures of occupational polarization within local labor markets are constructed using data from the 5% sample ACS in 1980, 1990, 2000, 2010, and 2020. The ACS is a nationally representative cross-sectional survey of the United States. *Earnings* in the ACS is measured using labor income standardized to year-2000 dollars. The ACS 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 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.

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

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 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:

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

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:

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

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 is *occupational earnings polarization*. This measure describes earnings inequality between occupations within a local labor market. 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:

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

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:

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

Earnings growth curves

I use a two-level hierarchical linear model of occasions nested within individuals to estimate earnings growth curves for PSID respondents:

Level 1:

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

Level 2:

$$\begin{aligned}
\beta_{0i} = {} & \gamma_{01}\text{POL(Q1)}_i + \gamma_{02}\text{POL(Q2)}_i + \gamma_{04}\text{POL(Q4)}_i + \gamma_{05}\text{POL(Q5)}_i + u\text{(Q1)}_{0i} * \text{POL(Q1)}_i \\
& + u\text{(Q2)}_{0i} * \text{POL(Q2)}_i + u\text{(Q3)}_{0i} * \text{POL(Q3)}_i + u\text{(Q4)}_{0i} * \text{POL(Q4)}_i \\
& + u\text{(Q5)}_{0i} * \text{POL(Q5)}_i \\
\beta_{1i} = {} & \gamma_{11}\text{POL(Q1)}_i + \gamma_{12}\text{POL(Q2)}_i + \gamma_{14}\text{POL(Q4)}_i + \gamma_{15}\text{POL(Q5)}_i + u\text{(Q1)}_{1i} * \text{POL(Q1)}_i \\
& + u\text{(Q2)}_{1i} * \text{POL(Q2)}_i + u\text{(Q3)}_{1i} * \text{POL(Q3)}_i + u\text{(Q4)}_{1i} * \text{POL(Q4)}_i \\
& + u\text{(Q5)}_{1i} * \text{POL(Q5)}_i \\
\beta_2 = {} & \gamma_{21}\text{POL(Q1)}_i + \gamma_{22}\text{POL(Q2)}_i + \gamma_{24}\text{POL(Q4)}_i + \gamma_{25}\text{POL(Q5)}_i
\end{aligned} \tag{5}$$

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 grand-mean centered in pooled analyses and cohort-mean centered in cohort-specific analyses. 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 80$^{\text{th}}$ to 99$^{\text{th}}$ percentile levels of average exposure to polarization over their career). The middle 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 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).

β_{0i} is the random intercept and can be interpreted as average earnings when individuals begin their careers in a CZ with average polarization. Random slope β_{1i} and fixed slope β_2 describe the earnings growth rate in dollars for individuals in CZs with average polarization. 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).

I estimate separate level-2 errors for individuals within each quintile of polarization. This allows me to examine how baseline earnings, earnings trajectories, and their association vary by labor market polarization. $u(\mathrm{QN})_{0i} * \mathrm{POL}(\mathrm{QN})_i$ is only estimated for individuals in the Nth quintile of polarization, and it refers to the difference between an individual's baseline earnings and their quintile of polarization's average baseline earnings. $u(\mathrm{QN})_{1i} * \mathrm{POL}(\mathrm{QN})_i$ describes the difference between an individual's rate of earnings growth and the average rate of earnings growth within their polarization quintile. $corr(u(\mathrm{QN})_{0i} * \mathrm{POL}(\mathrm{QN})_i, u(\mathrm{QN})_{1i} * \mathrm{POL}(\mathrm{QN})_i)$ describes the association between baseline earnings and earnings growth within the Nth quintile 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 variance increases 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. H3a is tested by checking for positive $corr(u(\mathrm{QN})_{0i} * \mathrm{POL}(\mathrm{QN})_i, u(\mathrm{QN})_{1i} * \mathrm{POL}(\mathrm{QN})_i)$ at each level of polarization. A positive correlation indicates that within a quintile of polarization, earnings grow faster for individuals with higher baseline earnings. H3b is tested by determining if this correlation increases with polarization.

H4a predicts that polarization increases average baseline earnings and therefore that γ_{01} and γ_{02} will be negative and γ_{04} and γ_{05} will be positive. H4b predicts that polarization increases the steepness of average earnings trajectories. Positive coefficients γ_{14} and γ_{15} and negative coefficients γ_{11} and γ_{12} are consistent with H4b.

To examine how occupation interacts with polarization to shape individuals' earnings trajectories, I add interaction terms between each individual's main occupation and the intercept and slope terms at each level of polarization. Significant coefficients on these interactions indicate between-occupation inequalities in baseline earnings (H5a) and earnings growth rates (H5b) between levels of polarization.

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.

Propensity score weighting

Observed associations between polarization and workers' earnings trajectories may be biased by nonrandom selection into labor markets with different levels of polarization. For example, highly skilled workers may select into highly polarized labor markets if they expect doing so will increase their earnings over the career. 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 observables 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 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 at the national level grew significantly between 1980 and 2020. Figure 1 presents smoothed plots of standardized occupational employment by occupational earnings. In 1980, employment was highest in low-earning occupations and declined almost linearly through the 80th occupational earnings percentile. Employment in the highest-earning occupations was a bit higher. In 2000, employment in low- and middle-earning occupations became less common, with the greatest decline in employment occurring in occupations with 20th to 40th percentile average earnings. By 2000, many more workers held jobs in high-earning occupations than in 1980. Polarization increased even more in 2020. Employment grew in occupations with average earnings ranked below the 20th percentile and above the 80th percentile while employment in middle-earning occupations continued to shrink.

Polarization in occupation average earnings follows similar trends (Figure 2). Between 1980 and 2020, the national Theil index increased by about 30 percent. Much of this rise in inequality was driven by growing inequality in occupation average earnings. While the within-occupation component of earnings inequality grew from 0.26 to 0.28, the between-occupation grew from 0.09 to 0.17. The corresponding percentage of total inequality explained within occupations decreased from 72 percent to 60 percent and the between-occupation component grew from 26 percent to 36 percent. The proportion of inequality explained by differences in CZ-average earnings increased from 1.4 percent to 3.6 percent.

Figure 3 presents distributions of CZ-level employment and earnings polarization in 1980, 2000, and 2020. Both measures of polarization increased considerably between 1980 and 2020. The distribution of CZ-level employment polarization also grew wider between 1980 and 2020, meaning that CZs became more unequal in the extent to which their labor markets had relatively high levels of employment in low- and high-paying jobs and low employment in middle-paying jobs. CZ-level between-occupation earnings inequality also increased between 1980 and 2020. However, inequality between CZs in earnings polarization grew only slightly.

While occupational polarization increased throughout the US, the largest increases were in large cities with high concentrations of educated workers and high-skill occupations and industries. CZs like the San-Francisco-Oakland and New York City experienced tremendous increases in polarization, largely due to rising employment and earnings in high-paying jobs in industries like finance and tech which was accompanied by rising employment in low-paying service jobs.

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. In the analytic sample, just over half of respondents are white and about one-third are Black (Table 2). The sample is about evenly split by gender. Just over half the sample is married and a similar proportion have children. About 28 percent of the sample holds a college degree. The average age is about 32 years old and average income is about $33,000. The measures of occupational employment and earnings polarization are standardized to means of approximately zero and standard deviations of approximately 1.

Table 3 presents coefficients and variance components from earnings growth curve models where log earnings is regressed on potential experience and its square, interacted with measures of earnings and employment polarization. Average predicted log earnings trajectories for individuals in each quintile of polarization are presented in Figure 4. These predicted values incorporate estimates of both fixed and random effects. In both models, baseline earnings increase substantially with polarization. Compared to individuals in CZs with moderate levels of polarization, average baseline earnings for individuals in the most polarized CZs are about 33 percent higher. The positive slopes on potential experience and negative slopes on its square indicate that earnings grow at a decelerating rate over the career. The effects of earnings polarization and employment polarization on earnings growth differ. Higher earnings polarization is associated with slower average rates of earnings growth while higher employment polarization is associated with faster average earnings growth.

Figure 5 presents average earnings trajectories for individuals in the bottom, middle, and top quintiles of baseline earnings conditional on their CZ's level 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 $Var(u(\text{QN})_{0i})$ and increases steadily with polarization, indicating that inequality in baseline earnings is greater among individuals in more highly polarized labor markets. In Figure 5, we see that inequality in average bottom and top quintile baseline earnings in the least polarized labor markets is about $10,800 (exp(9.75)-exp(8.75). In CZs with high levels of earnings polarization, the same inequality in baseline earnings is about $25,900 (exp(10.5)-exp(9.25)). Models of employment polarization produce similar results. The second hypothesis predicts that earnings trajectories vary within similarly polarized CZs. The positive variances on the slopes support this hypothesis.

Hypothesis 3a predicts that within similarly polarized CZs, individuals with higher baseline earnings also experience faster earnings growth. A positive correlation between the intercept and the slope would suggest that individuals with above-average baseline earnings experience faster earnings growth rates. This hypothesis is rejected at all levels of polarization.

Next, I examine how this relationship within CZs changes with polarization. Hypothesis 3b predicts that cumulative advantages from higher baseline earnings are greater in more polarized labor markets. I find that the association between baseline earnings and earnings growth is weakest in labor markets with moderate polarization and relatively strong in the second quintile of polarization. However, the association between baseline earnings and earnings growth is similar in CZs with low and high polarization. It appears that within local labor markets, high earners' advantage is largely set at the beginning of their career and diminishes somewhat over the career.

Hypotheses 4a and 4b predict that employment and earnings polarization create cumulative advantages associated with sorting between labor markets. In support of hypothesis 4a, the positive slope on indicators for higher exposure to polarization indicates that average baseline earnings are higher in more polarized labor markets. Consistent with hypothesis 4b and consistent with cumulative advantages in earnings growth due to employment polarization, I find that earnings growth curves are steeper in CZs with high employment polarization. Together, these results suggest that sorting between local labor markets on employment polarization is associated with inequalities in early-career earnings that get amplified over the career. However, I do not find evidence of cumulative advantages due to earnings polarization.

Next, I consider how the advantages from polarization may amplify cumulative advantages between occupations. Table 4 presents results from growth curve models where log earnings is regressed on four-way interactions between potential experience, its square, earnings and employment polarization, and indicators for workers' main occupation. First, I find evidence that managers experience cumulative advantages in earnings growth in CZs with moderate polarization. Negative coefficients on occupation dummies and on interactions between occupation and potential experience indicate that managers and professionals experience both higher baseline earnings and faster earnings growth than other occupations.

Polarization may amplify cumulative advantages by occupation through its effect on occupational inequalities in baseline earnings or earnings growth. Hypothesis 5a predicts that inequalities in baseline earnings by occupation will be greater in more polarized labor markets. I find evidence that earnings polarization is associated with greater increases in baseline earnings for managers and professionals than it is for workers in technical, sales, and admin, farming and agriculture, or production craft and repair occupations. I find no evidence for a similar effect of employment polarization.

Hypothesis 5b predicts that between-occupation inequalities in earnings trajectories will increase with polarization. Significant positive coefficients for interactions between occupation dummies, potential experience, and indicators for low earnings polarization suggest that moving from low-polarization to average-polarization CZs improves earnings growth more for managers and professionals than it does for non-managers or professionals. Moving into CZs with high earnings polarization decreases earnings growth rates for managers. Earnings growth rates decrease less for farmers and for production craft and repair workers. Again, I find no effect for employment polarization. In general, these results suggest that earnings polarization, and particularly moving from low- to mid- levels of polarization, amplifies managers' cumulative advantages in earnings growth.

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 heterogeneity in earnings trajectories within CZs. How does variation in workers' earnings trajectories stemming from sorting into CZs with different levels of polarization shape how earnings inequality develops as workers age? 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 with average levels of earnings polarization.

The sorting of workers across CZs with different levels of polarization increases earnings inequality at the beginning of workers' careers. Sorting between CZs is associated with more rapid growth in earnings inequality earlier in workers' careers and slower growth later in their careers. In the counterfactual where all workers are exposed to the same level of polarization, earnings inequality increases more slowly at the start of workers' careers and approaches observed levels of earnings inequality around 20 years of potential experience. The advantages in baseline earnings due to polarization and in earnings growth rates for high-earners appear to increase baseline inequality and accelerate within-cohort inequality in earnings earlier in workers' careers. Later on, individuals with low baseline earnings appear to catch up and reduce the rate at which inequality grows over the career. Without the convergence in earnings between low- and high-earners that is driven by polarization, inequality would continue to rise as workers age.

Cohort trends

It is possible that analyses of the pooled sample of PSID respondents mask differences between cohorts in how polarization shapes inequality in earnings trajectories. Table 5 presents results from regressions by 5-year birth cohorts starting in 1960, 1965, 1970, and 1975. The cohort-specific analyses reveal that the average effects of occupational polarization on earnings trajectories have not changed substantially. For each cohort, earnings and employment polarization are generally associated with higher log earnings and average earnings growth rates are typically highest in CZs with moderate earnings and employment polarization.

The major change in the relationship between occupational polarization and career earnings mobility has to do with its effect on inequality in earnings trajectories within labor markets. These effects can be observed by comparing the estimates of variance components across cohorts. In the 1960 cohort, the variance of the intercept increases substantially with polarization (0.146 in CZs with the lowest earnings polarization vs. 0.474 in CZs with the highest). This means that inequality in earnings when workers enter the labor market is much greater in CZs with relatively high polarization than those with relatively low polarization. While baseline earnings inequality decreases at all levels of polarization across cohorts, it decreases the most in CZs with relatively high polarization. In the 1975 cohort, baseline earnings inequality does not change substantially between levels of polarization.

At the same time, the relationship between polarization and within-CZ inequalities in earnings growth reversed between the 1960 and the 1975 cohort. In the 1960 cohort, the correlation between baseline earnings and earnings growth was -0.215 in CZs with the least earnings polarization and -0.447 in CZs with the greatest polarization. For the 1960 cohort, even though earnings inequality was high in highly polarized CZs, workers with low earnings enjoyed much faster earnings growth and inequality diminished substantially over the career. This relationship is weaker for the 1975 cohort. For this cohort, earnings equalize much faster in CZs with low levels of polarization than in those with high polarization.

It is possible that these trends may be driven by cohort differences in how workers select into levels of polarization. Table 6 presents results from the same regressions but with IPW weights to account for selection into levels of polarization on education, race, and gender.

Results from the fixed components of the model do not change substantially – that is, the average effects of polarization, experience, and their interaction remain relatively stable. However, the trends observed in the analysis of the variance components are amplified considerably. First, after accounting for selection, the positive relationship between polarization and baseline earnings inequality is much stronger in the older cohorts and much weaker in the younger cohorts, particularly in models of employment polarization. The starkest change occurs in the correlation between baseline earnings and earnings growth. In older cohorts, polarization is associated with even greater equalization in earnings over the career. In younger cohorts, the negative relationship between baseline earnings and earnings growth rates is much weaker. For the 1975 cohort, baseline earnings and earnings growth rates are actually positively correlated in the most polarized CZs, suggesting that polarization provides high-earners with significant opportunities for earnings growth in younger cohorts.

Conclusions

A defining feature of the economic transformation in the US over the last half century has been the polarization of the labor market 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 opportunity over their career. Those concerned with inequality in intragenerational mobility may worry that occupational polarization creates barriers to career advancement for low-earners and creates new and more rewarding opportunities for earnings growth for high-earners, resulting in a cumulative advantage process that amplifies inequality in earnings trajectories and reproduces workers' economic position over their career.

I find that occupational polarization affects inequalities in earnings trajectories within local labor markets and between local labor markets through mechanisms that combine to amplify earnings inequalities over the career. I find that earnings inequality when workers begin their careers is greater in CZs with higher levels of polarization. On average, workers with relatively low baseline earnings within their CZ experience faster earnings growth than those with higher baseline earnings. This negative dependence between baseline earnings and earnings growth is strongest among workers in CZs with the greatest employment polarization and moderately low levels of earnings polarization. Across CZs, more polarized CZs have higher baseline earnings on average, but also lower average rates of earnings growth, leading average earnings trajectories to converge between CZs over workers' careers.

These patterns contribute to inequalities between workers in different occupations. The benefits of occupational polarization are primarily enjoyed by managers and professionals, who experience disproportionate gains both in baseline earnings and in earnings growth. These patterns also combine to increase overall levels of inequality when workers enter the labor market and amplify that inequality over the first 20 or so years of their career. Later in workers' careers, the higher earnings growth rates in low-polarization CZs and lower growth rates for high earners in high-polarization CZs outweigh high earners' overall advantage in earnings growth to cancel out the effect of sorting by polarization on inequality.

Crucially, sorting between CZs with different levels of polarization amplifies lifecycle earnings inequality more in more recent cohorts. In older cohorts, polarization was associated with economic mobility and opportunity. In highly polarized CZs, individuals who entered the labor market with low earnings experienced much faster earnings growth on average than individuals with high earnings. The reverse is true for more recent cohorts. Low-earners experience relatively fast earnings growth in less polarized CZs while higher polarization provides more of a relative advantage for high-earners by providing more opportunity for earnings growth. This reversal may be explained by a number of factors. It is possible that polarization benefits high earners in more recent cohorts 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). It is also possible that upward earnings mobility for low earners in older cohorts is explained by internal labor markets, where compensation schemes structured around deferred earnings were common (Lazear 1979).

These results speak more broadly to the rising importance of local labor market context 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). These results suggest that polarization's combined effect on within-CZ and between-CZ inequalities over the life course may play an important role in shaping regional inequalities. Regions with high levels of polarization have both greater opportunity for high-earners to achieve very high levels of early-career earnings and for low-earners to increase their earnings over the career. But while a rising tide may lift all ships within these CZs, the rest of the country falls further behind as opportunities for meaningful earnings growth become scarcer. As sorting across labor markets becomes stronger, earnings inequalities are increasingly determined by where workers begin their careers and we see less convergence in earnings over the life course.

These analyses are not without limitations. Perhaps most importantly, these analyses do not account for selection on unobservables into CZs or into mobility between CZs. Bias due to endogenous mobility between CZs throughout the career is less of a concern because over 97 percent of individuals in this sample remain in the same CZ throughout their career. Selection into CZs at the beginning of the career is a greater concern when considering whether these results have causal implications. Results from analyses using IPW weights account for selection on observables and, if anything, suggest that within-CZ inequality in earnings trajectories is less than it would be with random assignment to labor markets. 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	Yes
H2: Earnings growth rates vary among individuals in similarly polarized local labor markets.	$u(\mathrm{QN})_{0i} > 0$	Yes
H3a: There is a positive association between individuals' baseline earnings and earnings growth rates within labor markets of similar polarization.	$corr(u(\mathrm{QN})_{0i} * \mathrm{POL(QN)}_i, u(\mathrm{QN})_{1i} * \mathrm{POL(QN)}_i) > 0$	No
H3b: The positive association between individuals' baseline earnings and earnings growth rates is greater in more polarized labor markets.	$corr(u(\mathrm{QN})_{0i} * \mathrm{POL(QN)}_i, u(\mathrm{QN})_{1i} * \mathrm{POL(QN)}_i)$ increases with N	Earnings polarization: no Employment polarization: no
H4a: The association between polarization and baseline earnings is positive.	$\gamma_{01} < 0$ $\gamma_{02} < 0$ $\gamma_{04} > 0$ $\gamma_{05} > 0$	Yes
H4b: Polarization positively moderates the association between experience and earnings.	$\gamma_{11} < 0$ $\gamma_{12} < 0$ $\gamma_{14} > 0$ $\gamma_{15} > 0$	Earnings polarization: no Employment polarization: yes
H5a: Inequalities in baseline earnings by occupation increase with polarization.	Significant interactions with $\mathrm{POL(QN)}_i$	Earnings polarization: yes Employment polarization: no
H5b: The association between occupation and earnings growth rates increases with polarization.	Significant interactions with $\mathrm{POL(QN)}_i * \mathrm{EXP}_{ti}$	Earnings polarization: yes Employment polarization: no
H6: In more recent cohorts, polarization disproportionately benefits earnings growth for high-earners.	$corr(u(\mathrm{QN})_{0i} * \mathrm{POL(QN)}_i, u(\mathrm{QN})_{1i} * \mathrm{POL(QN)}_i)$ increases with N more in younger cohorts than older cohorts	Yes

Figure 1. National Employment Polarization

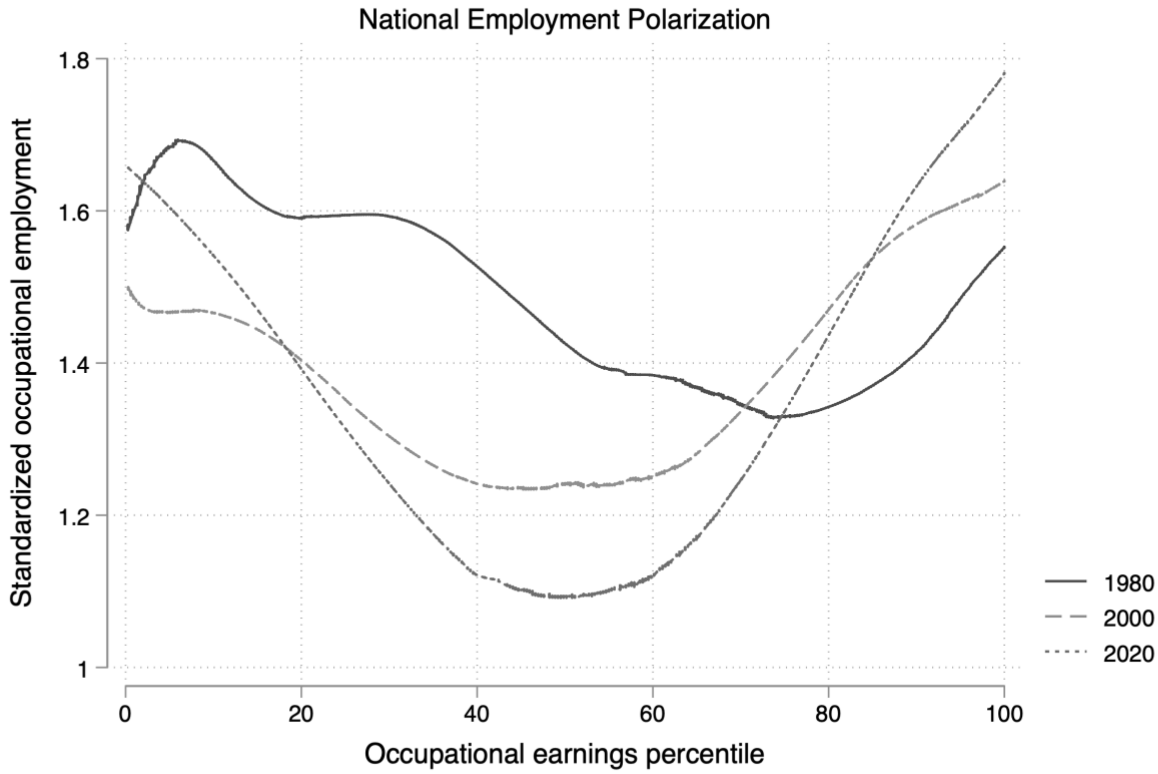


Figure 2. National Earnings Polarization

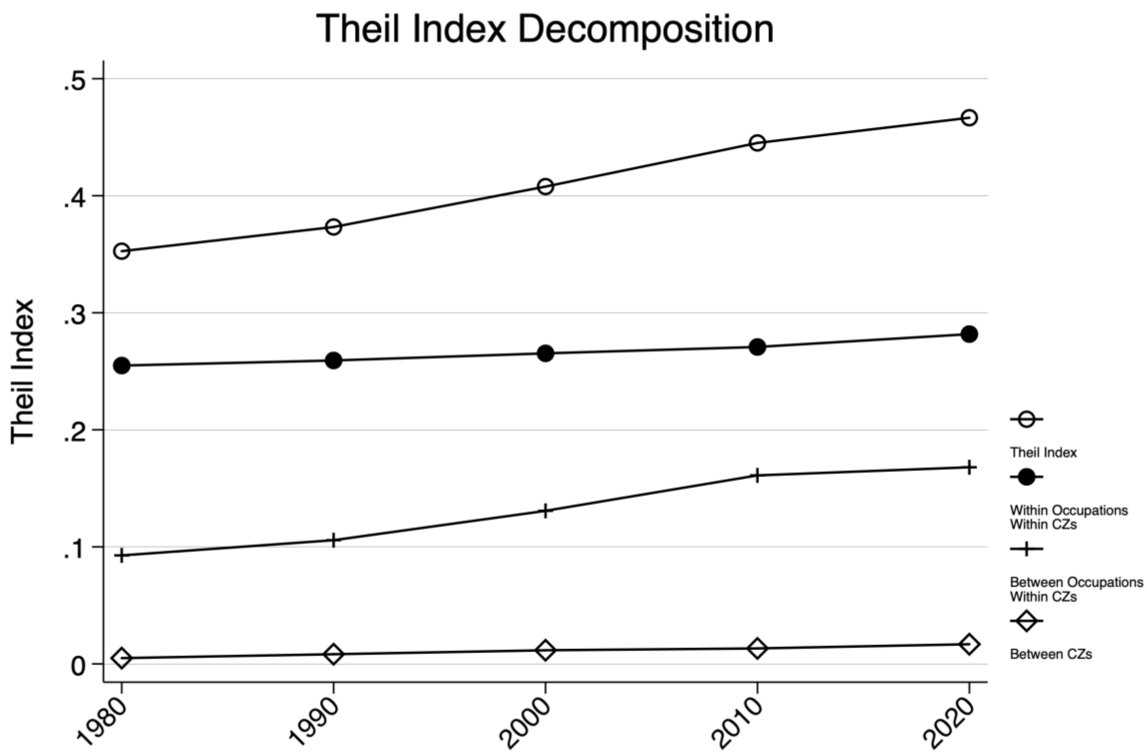


Figure 3. CZ-level variation in polarization

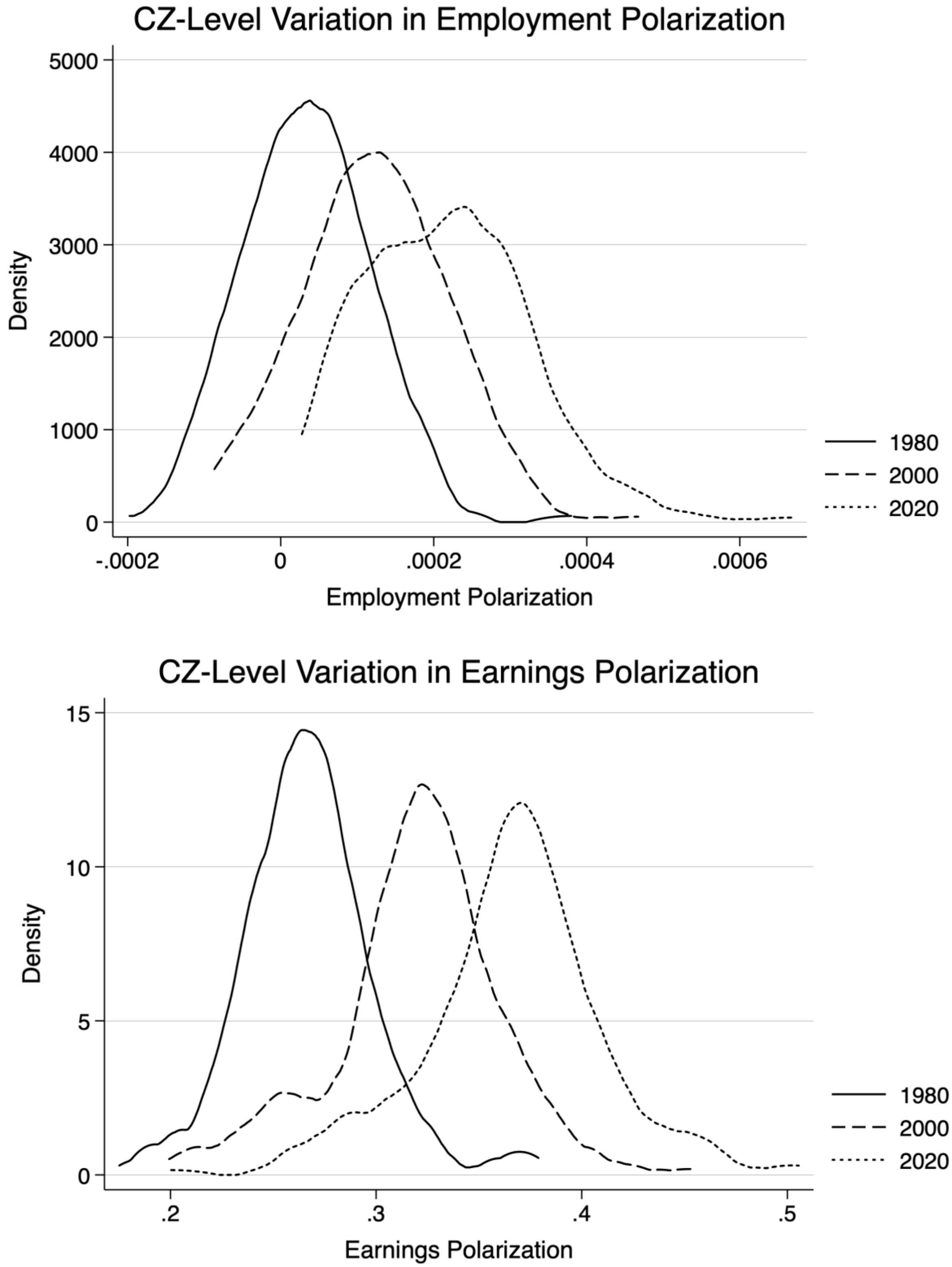


Table 2. Descriptive statistics

Variable	Mean or %
Birth cohort	
1960-1964	37.42
1965-1969	23.66
1970-1975	19.76
1975-1980	19.16
Age	31.58
Race	
White	54.45
Black	34.75
Other	10.81
Female	50.96
Married	57.7
Has kids	55.72
College degree	28.05
Occupation	
Managerial and professional specialty	36.39
Technical, sales, and administrative support	24.21
Service	13.81
Farming, forestry, and fishing	2.74
Precision production, craft, and repair	6.53
Operators, fabricators, and laborers	16.32
Industry	
Agriculture, forestry, and fisheries	1.74
Mining	0.23
Construction	5.75
Manufacturing	16.18
Transportation, communications, and other public utilities	7.58
Wholesale trade	3.96
Retail trade	13.85
Finance, insurance, and real estate	6.95
Business and repair services	8.18
Personal services	3.55
Entertainment and recreation services	1.41
Professional and related services	23.66
Public administration	6.98
Income (2000 $)	$ 33,370.62
N	
Occassions	31092
Individuals	4493

Note: descriptive statistics are unweighted

Table 3. Estimated coefficients from growth curve model of earnings

	Earnings polarization	**Employment polarization**
Fixed effects		
Constant	9.343***	9.309***
Potential experience	0.0947***	0.0905***
Potential experience^2	-0.00184***	-0.00161***
Polarization quintile (base=3)		
1 (Lowest)	-0.157***	-0.132***
2	-0.128***	-0.0217
4	0.143***	0.146***
5 (Highest)	0.337***	0.341***
Polarization quintile X potential experience		
1 (Lowest)	-0.00136	-0.00022
2	0.00821+	0.002
4	-0.00067	0.00916*
5 (Highest)	-0.01731***	0.00271
Polarization quintile X potential experience^2		
1 (Lowest)	0.000136	0.00013
2	-0.0000108	0.0000265
4	0.0000326	-0.00049**
5 (Highest)	0.000465**	-0.00028+
Variance components		
Var(intercept)		
1 (Lowest)	0.192	0.189
2	0.235	0.264
3	0.275	0.228
4	0.286	0.284
5 (Highest)	0.373	0.384
Var(slope)		
1 (Lowest)	0.00106	0.000879
2	0.00112	0.00108
3	0.000896	0.000903
4	0.00126	0.00141
5 (Highest)	0.00128	0.00133
Corr(intercept, slope)		
1 (Lowest)	-0.297	-0.331
2	-0.42	-0.385
3	-0.259	-0.209
4	-0.334	-0.339
5 (Highest)	-0.317	-0.394
N occassions	31092	31092
N individuals	4493	4493

***p<0.001 **p<0.01 *p<0.05 +p<0.10

Figure 4. Average earnings trajectories by level of polarization

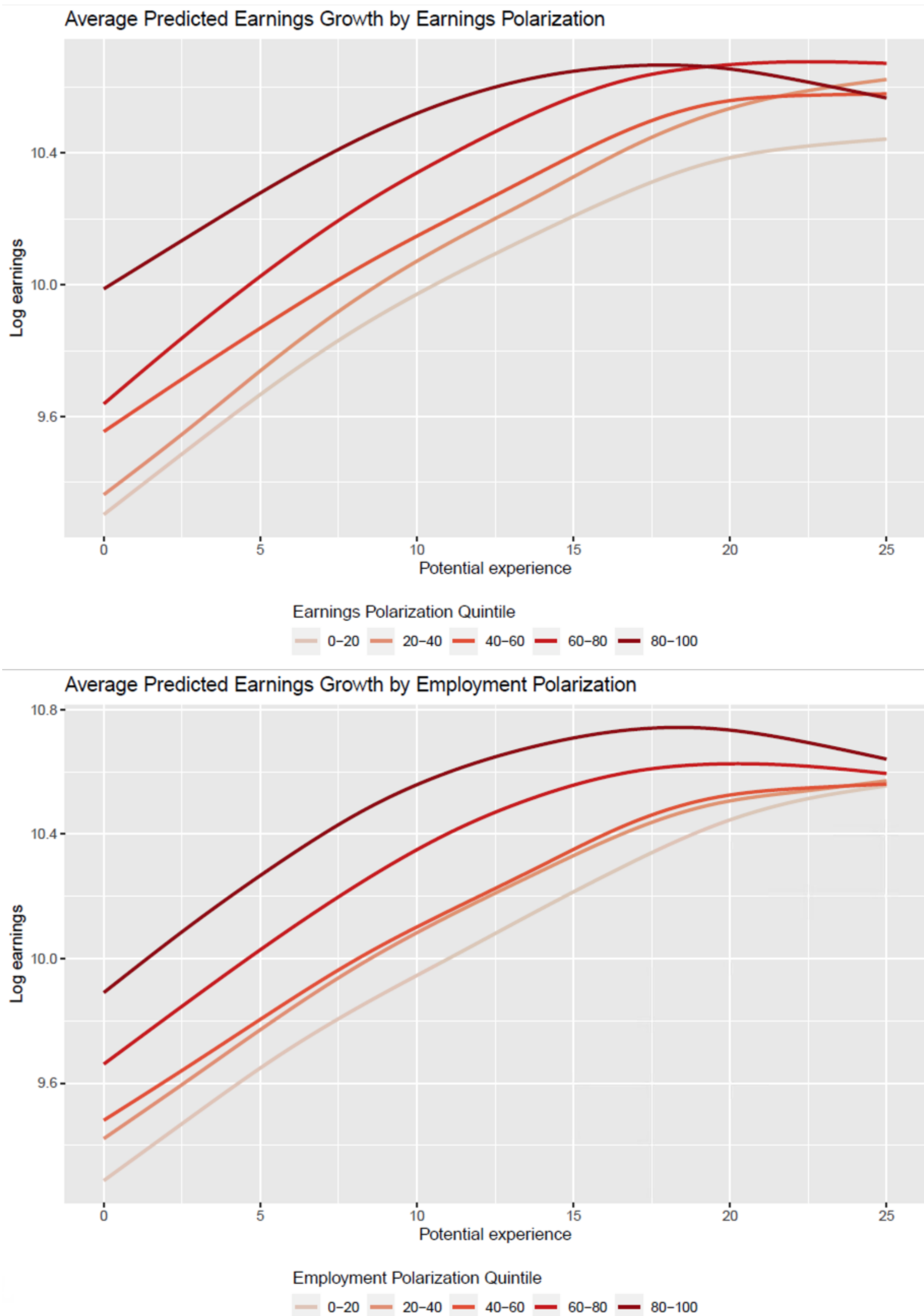


Figure 5. Predicted earnings trajectories for low, mid, and high earners by polarization

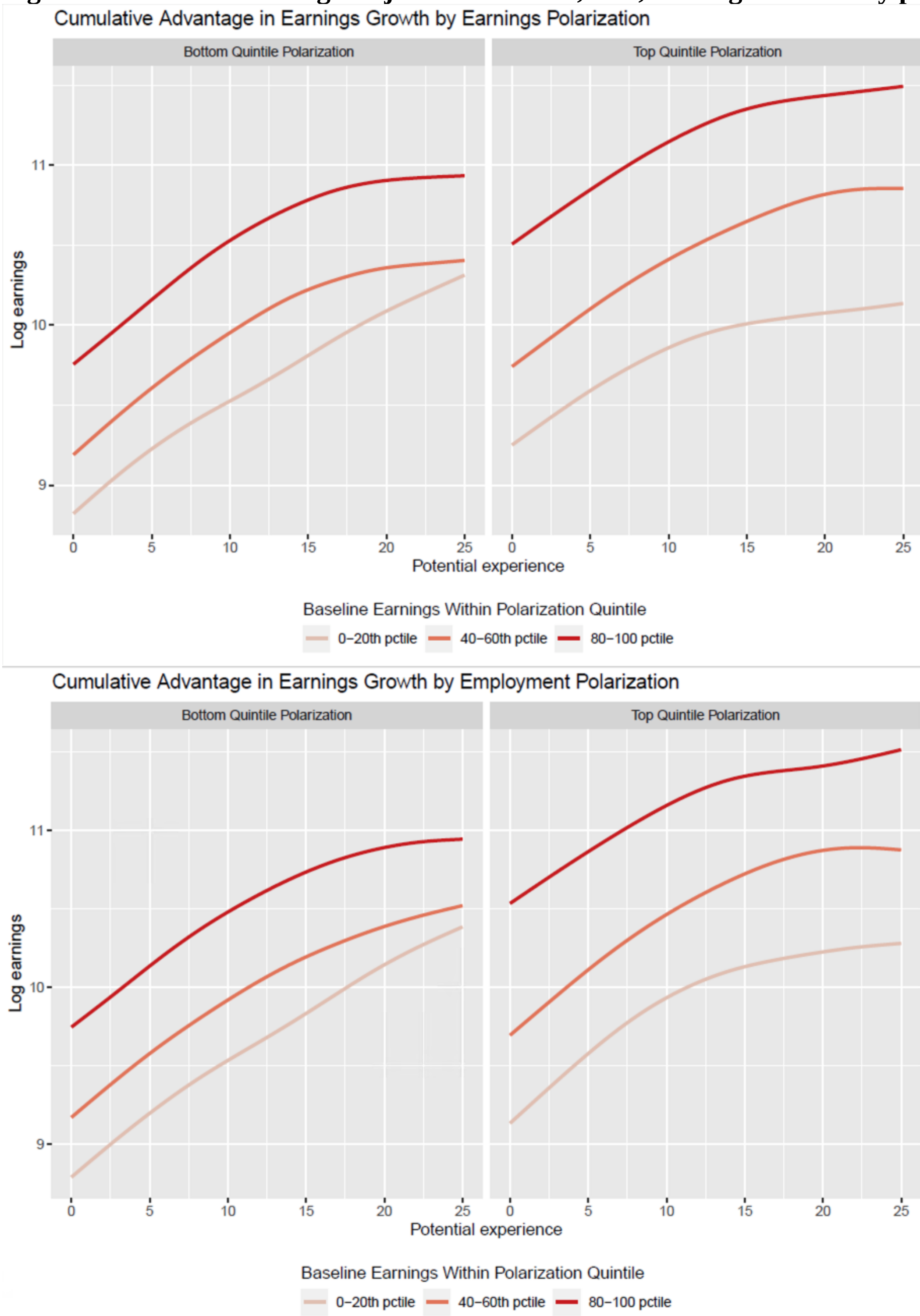


Table 4. Estimated coefficients from growth curve model of earnings by occupation

			Earnings polarization				
Occupation	Managers and Professionals		Technical, Sales, Admin	Service	Farm and Agriculture	Production, Craft, Repair	Operators, Fabricators, Laborers
Fixed effects		**Interactions with occupation**					
Constant	9.429***		-0.0985	-0.274**	0.0919	0.0349	-0.0871
Potential experience	0.121***		-0.0488***	-0.0622**	-0.0666**	-0.0741***	-0.0427***
Potential experience ^2	-0.00261***		0.00147***	0.00195***	0.00217**	0.00207**	0.00140***
Polarization quintile (base=3)							
1 (Lowest)	-0.192***		-0.00185	0.198	-0.362	-0.247	0.103
2	-0.207***		0.0976	0.311*	-0.0847	-0.255	0.201+
4	0.172**		-0.0696	0.163	-0.0745	-0.460+	-0.0263
5 (Highest)	0.428***		-0.215+	0.0651	-0.842*	-0.894**	-0.214
Potential experience X polarization quintile							
1 (Lowest)	-0.0162***		0.0412***	0.0116	0.0887**	0.0727**	0.0316*
2	0.0110+		0.00242	-0.0370*	0.0633*	0.0367	-0.00202
4	-0.00927		0.0186+	-0.024	-0.0101	0.0960**	0.00986
5 (Highest)	-0.0386***		0.0607	-0.0112	0.145***	0.0941*	0.0203
Potential experience^2 X polarization quintile							
1 (Lowest)	0.000717*		-0.00176***	-0.0006	-0.00245*	-0.00226*	-0.00085
2	-0.0000107		-0.00019	0.00104+	-0.00283**	-0.001	-0.00014
4	0.000408*		-0.0006	0.000402	0.00106	-0.00365***	-0.006
5 (Highest)	0.00118***		-0.00216***	0.0000717	-0.00475***	-0.00261*	-0.00099+

			Employment polarization				
Occupation	Managers and Professionals		Technical, Sales, Admin	Service	Farm and Agriculture	Production, Craft, Repair	Operators, Fabricators, Laborers
Fixed effects		**Interactions with occupation**					
Constant	9.408***		-0.110+	-0.177*	-0.0329	-0.457**	-0.0546
Potential experience	0.110***		-0.0339***	-0.0730***	-0.00323	-0.018	-0.0373***
Potential experience ^2	-0.00202***		0.000766**	0.00207***	-0.00071	-0.00013	0.000968**
Polarization quintile (base=3)							
1 (Lowest)	-0.203***		0.0497	0.0959	0.0217	0.466*	0.03
2	-0.0695		0.0238	0.0211	-0.236	0.113	0.135
4	0.147**		-0.0288	0.0671	0.245	-0.247	-0.0405
5 (Highest)	0.386***		-0.189+	0.175	-0.276	-0.317	0.00796
Potential experience X polarization quintile							
1 (Lowest)	-0.00047		0.00364	0.00854	-0.0411	-0.00871	0.0276*
2	-0.00301		0.0144	0.0262	0.035	0.0147	0.00813
4	0.0112+		-0.00597	-0.014	-0.0775	0.0949**	-0.0115
5 (Highest)	-0.00418		0.0293*	-0.0347+	-0.00741	0.0127	-0.00908
Potential experience^2 X polarization quintile							
1 (Lowest)	0.0000333		-0.00021	-0.00025	0.00255*	0.000868	-0.00063
2	0.0000799		-0.00026	-0.00111+	-0.0000938	0.00027	-0.00015
4	-0.00064**		0.000367	0.00042	0.00349*	-0.00359**	0.000331
5 (Highest)	-0.0003		-0.00069	0.00129*	0.000908	0.000533	0.000395

***p<0.001 **p<0.01 *p<0.05 +p<0.10; Coefficients obtained from one regression where managers/professionals are the base category. Coefficients for non-managers/professionals represent interaction terms

Figure 6. Effect of sorting by polarization on lifetime earnings inequality

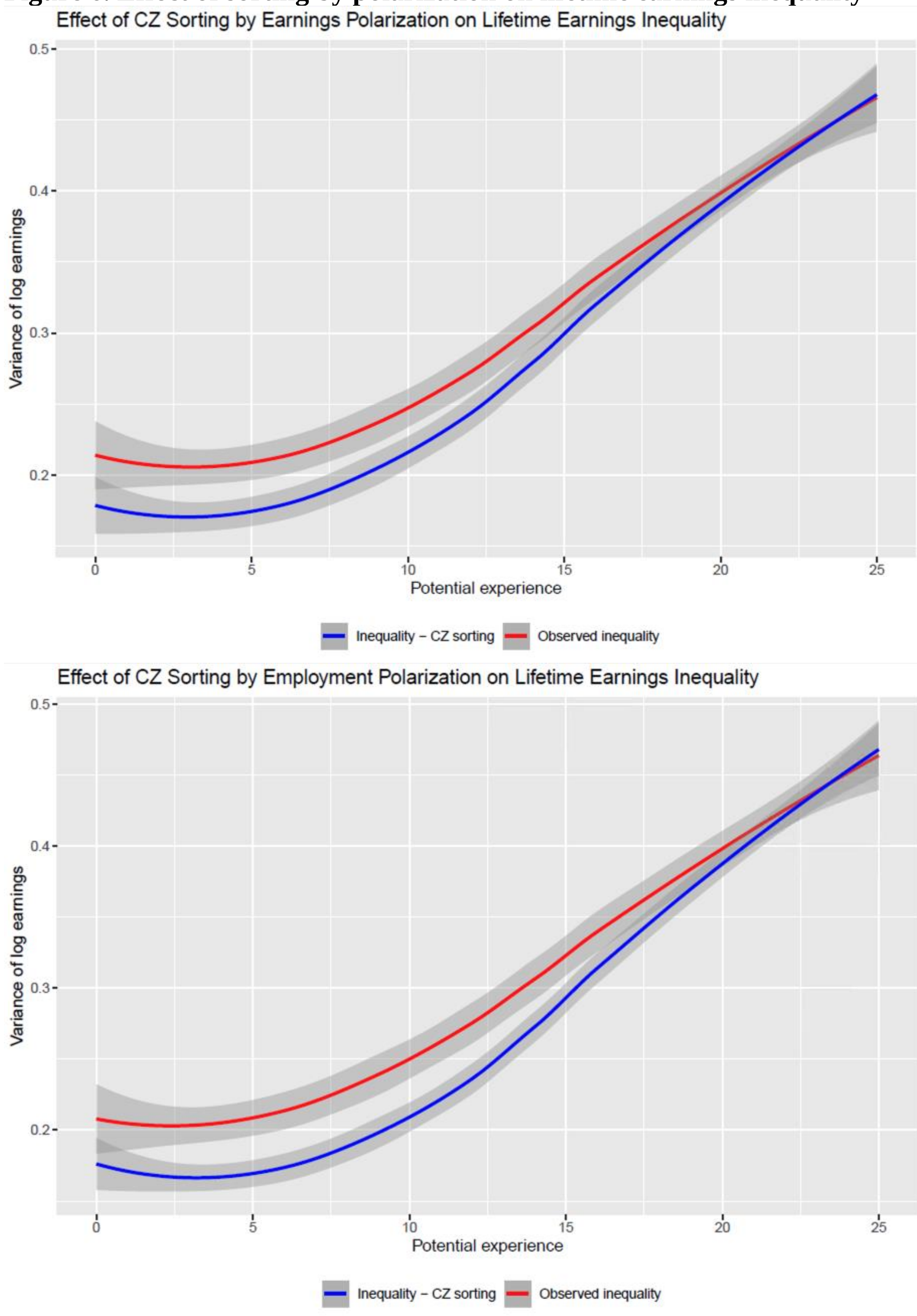


Table 5. Estimated coefficients from growth curve model of earnings by cohort

	Earnings polarization				Employment polarization			
	1960-1964	1965-1969	1970-1974	1975-1980	1960-1964	1965-1969	1970-1974	1975-1980
Fixed effects								
Constant	8.949***	9.224***	9.338***	9.915***	9.003***	9.277***	9.420***	9.802***
Potential experience	0.113***	0.0995***	0.130***	0.0671***	0.119***	0.0967***	0.119***	0.0853***
Potential experience^2	-0.00195***	-0.00183***	-0.00312***	-0.00097**	-0.00244***	-0.00193***	-0.00275***	-0.00187***
Polarization quintile (base=3)								
1 (Lowest)	0.0504	-0.0131	0.0606	-0.283***	-0.00444	-0.0891	-0.0648	-0.105
2	0.118+	0.0847	0.0899	-0.158*	-0.0366	0.0473	0.00438	-0.114
4	0.171*	0.131*	0.283***	-0.223**	0.197***	0.136+	-0.00897	0.00299
5 (Highest)	0.176+	0.211*	0.184*	0.0681	-0.137	0.096	0.338***	0.195***
Polarization quintile X potential experience								
1 (Lowest)	-0.0178*	0.00311	-0.0367***	0.00193	-0.0319***	-0.00091	-0.0154	-0.0186+
2	-0.00999	-0.00352	-0.0273**	-0.00059	-0.0253***	-0.01396	-0.0355***	-0.0253*
4	-0.0182*	-0.00323	-0.0457***	0.0405***	-0.0389***	-0.00368	-0.00492	-0.00308
5 (Highest)	-0.0307***	-0.0127	-0.0309***	0.00505	0.00861	0.0155	-0.0347**	0.00124
Polarization quintile X potential experience^2								
1 (Lowest)	0.000361	-0.0005	0.00127***	0.000178	0.00129***	-0.0000397	0.000498	0.000999*
2	0.000162	0.0000143	0.00109**	-0.00014	0.00105***	0.000627+	0.00134***	0.00127**
4	0.000261	-0.0000651	0.00166***	-0.00174***	0.00125***	0.000341	0.000357	0.000316
5 (Highest)	0.000617*	0.000251	0.00125**	-0.00025	-0.0003	-0.00055+	0.00114**	-0.0000181
Variance components								
Var(intercept)								
1 (Lowest)	0.146	0.137	0.114	0.247	0.175	0.136	0.113	0.253
2	0.275	0.171	0.237	0.178	0.215	0.175	0.13	0.161
3	0.284	0.223	0.167	0.145	0.286	0.202	0.231	0.185
4	0.31	0.322	0.245	0.249	0.275	0.263	0.276	0.248
5 (Highest)	0.474	0.345	0.452	0.332	0.564	0.378	0.361	0.258
Var(slope)								
1 (Lowest)	0.00124	0.00104	0.001	0.000898	0.000841	0.00108	0.00103	0.000992
2	0.00121	0.000682	0.000985	0.000978	0.00126	0.000667	0.000627	0.00093
3	0.00105	0.000825	0.000858	0.00117	0.00126	0.000737	0.000765	0.00157
4	0.00109	0.00132	0.000863	0.00175	0.00103	0.00165	0.00119	0.00113
5 (Highest)	0.00115	0.00113	0.00142	0.00135	0.00153	0.000978	0.00141	0.00155
Corr(intercept, slope)								
1 (Lowest)	-0.215	-0.289	-0.324	-0.413	-0.297	-0.282	-0.228	-0.374
2	-0.475	-0.338	-0.254	-0.157	-0.327	-0.331	-0.217	-0.00504
3	-0.28	-0.105	-0.0291	-0.275	-0.409	-0.201	-0.0623	-0.407
4	-0.436	-0.444	-0.0784	-0.364	-0.396	-0.468	-0.277	-0.38
5 (Highest)	-0.447	-0.392	-0.499	-0.306	-0.514	-0.327	-0.379	-0.315

***p<0.001 **p<0.01 *p<0.05 +p<0.10

Table 6. Estimated coefficients from IPW growth curve model

	Earnings polarization				Employment polarization			
	1960-1964	1965-1969	1970-1974	1975-1980	1960-1964	1965-1969	1970-1974	1975-1980
Fixed effects								
Constant	8.994***	9.239***	9.351***	9.925***	9.027***	9.279***	9.42***	9.807***
Potential experience	0.110***	0.0990***	0.129***	0.0674***	0.118***	0.0967***	0.118***	0.0850***
Potential experience^2	-0.00185***	-0.00182***	-0.0031***	-0.00097**	-0.00237***	-0.00192***	-0.00275***	-0.00185***
Polarization quintile (base=3)								
1 (Lowest)	0.042	-0.0211	-0.00356	-0.315***	-0.017	-0.108+	-0.0739	-0.136+
2	0.0786	0.0668	0.0831	-0.162*	0.0225	0.0475	-0.0253	-0.0957
4	0.157*	0.184*	0.295***	-0.191*	0.176*	0.146+	0.0478	0.0381
5 (Highest)	0.0248	0.303**	0.272*	0.0278	-0.260***	0.0599	0.244***	0.161+
Polarization quintile X potential experience								
1 (Lowest)	-0.0156	0.00498	-0.0181+	0.00692	-0.0281**	0.00421	-0.0144	-0.0111
2	-0.00739	-0.00085	-0.02238*	-0.00104	-0.0260***	-0.0143	-0.0300***	-0.0275*
4	-0.0213*	-0.00781	-0.0447***	0.0301*	-0.0395***	-0.00588	-0.00918	-0.00508
5 (Highest)	-0.0140+	-0.0241*	-0.0383**	0.0113	0.0267**	0.0185+	-0.0402***	0.0129
Polarization quintile X potential experience^2								
1 (Lowest)	0.000257	-0.00053	0.000524	-0.0000237	0.00110***	-0.00027	0.00045	0.000732*
2	0.000116	-0.0000466	0.000897**	-0.00016	0.000956**	0.000663+	0.00112***	0.00135**
4	0.000383	0.000125	0.00162***	-0.00138*	0.00129***	0.000415	0.000436	0.000363
5 (Highest)	0.000159	0.000582+	0.00132**	-0.0005	-0.00094***	-0.00066*	0.00131***	-0.00052
Variance components								
Var(intercept)								
1 (Lowest)	0.103	0.139	0.155	0.259	0.151	0.146	0.136	0.305
2	0.221	0.181	0.258	0.212	0.191	0.173	0.177	0.145
3	0.236	0.21	0.141	0.115	0.248	0.204	0.229	0.176
4	0.284	0.318	0.227	0.128	0.288	0.235	0.208	0.197
5 (Highest)	0.622	0.434	0.334	0.235	0.704	0.499	0.337	0.164
Var(slope)								
1 (Lowest)	0.000504	0.00104	0.00189	0.0019	0.000667	0.00098	0.00119	0.00156
2	0.000834	0.000737	0.00115	0.00128	0.000923	0.000746	0.000715	0.000862
3	0.000891	0.000777	0.000736	0.000917	0.00108	0.000726	0.000752	0.00147
4	0.00097	0.00147	0.000769	0.000333	0.001	0.00157	0.000921	0.000806
5 (Highest)	0.00156	0.00152	0.00119	0.000333	0.00237	0.00132	0.00121	0.000514
Corr(intercept, slope)								
1 (Lowest)	0.17	-0.289	-0.418	-0.409	-0.24	-0.26	-0.3	-0.493
2	-0.383	-0.378	-0.321	-0.28	-0.246	-0.347	-0.329	0.0619
3	-0.189	-0.0739	0.0271	-0.142	-0.341	-0.205	-0.0548	-0.383
4	-0.406	-0.476	0.0277	0.649	-0.433	-0.4336	-0.168	-0.268
5 (Highest)	-0.589	-0.558	-0.424	0.116	-0.629	-0.498	-0.338	0.217

***p<0.001 **p<0.01 *p<0.05 +p<0.10

Appendix 1. 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:

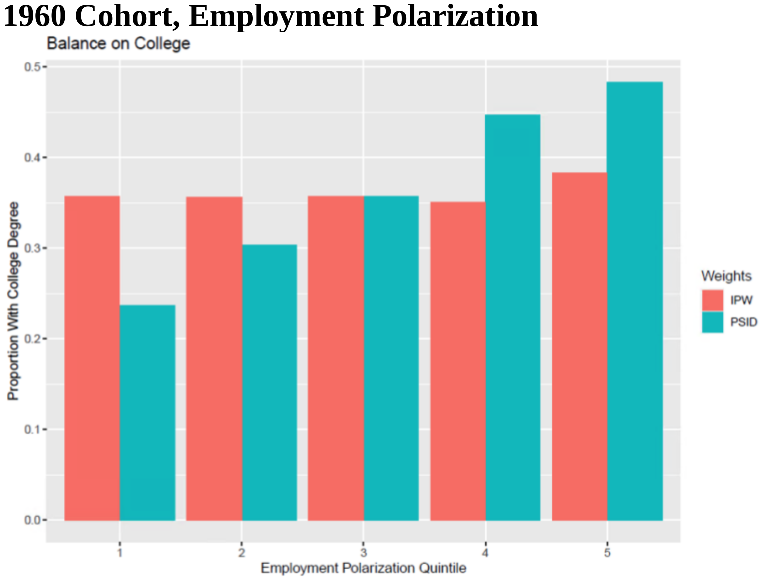
$$\omega_{ATT,i} = \mathbb{I}(Q_i = j) + e_{f,i} \sum_{j \neq f}^{p} \frac{\mathbb{I}(Q_i = j)}{e_{ji}}$$

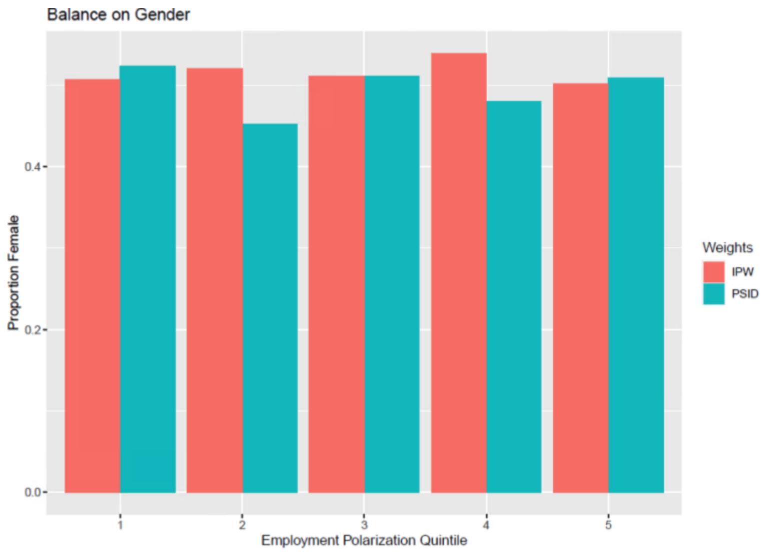
where Q_i represents the quintile of polarization and j indicates an individual's level of polarization and f indexes the third quintile of polarization. e_{ji} describes an individual's estimated probability of belonging to polarization quintile j, also known as the propensity score. Weights are equal 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):

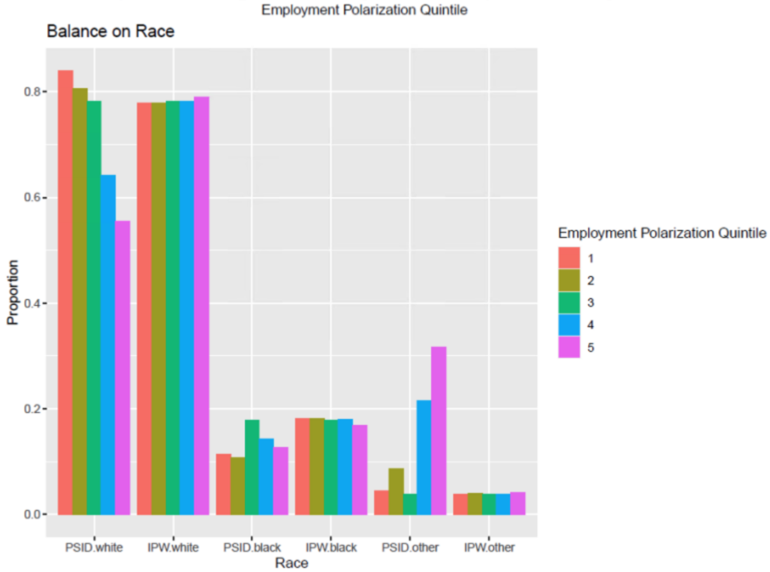
$$\log\left(\frac{p_j(x)}{p_f(x)}\right) = \beta_{0j} + \beta_{1j}(\text{college}) + \beta_{2j}(\text{female}) + \beta_{3j}(\text{black}) + \beta_{4j}(\text{hispanic})$$

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

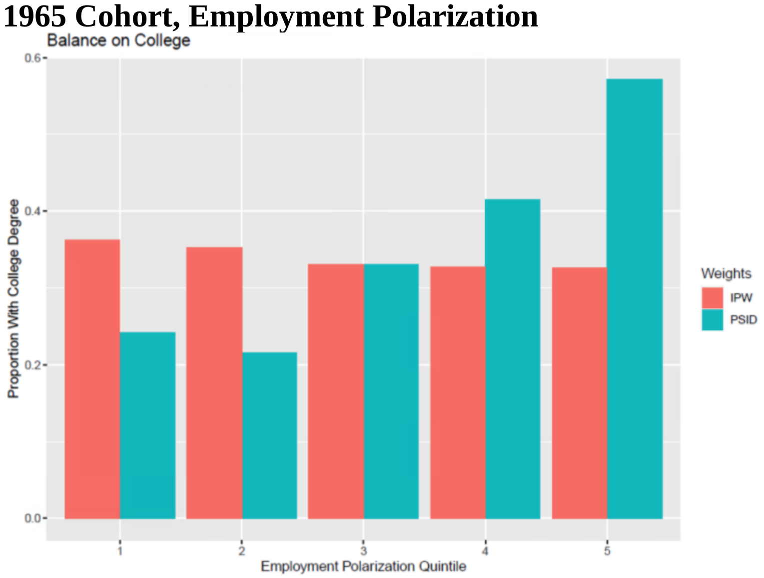
1960 Cohort, Employment Polarization

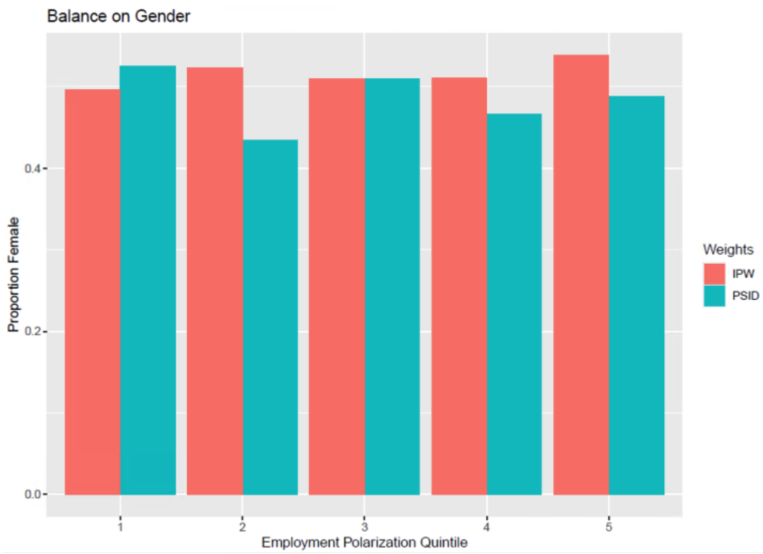


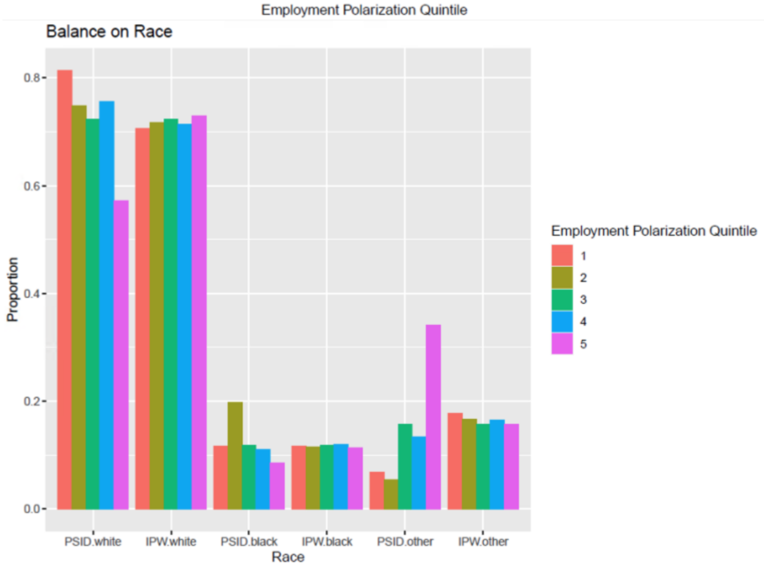




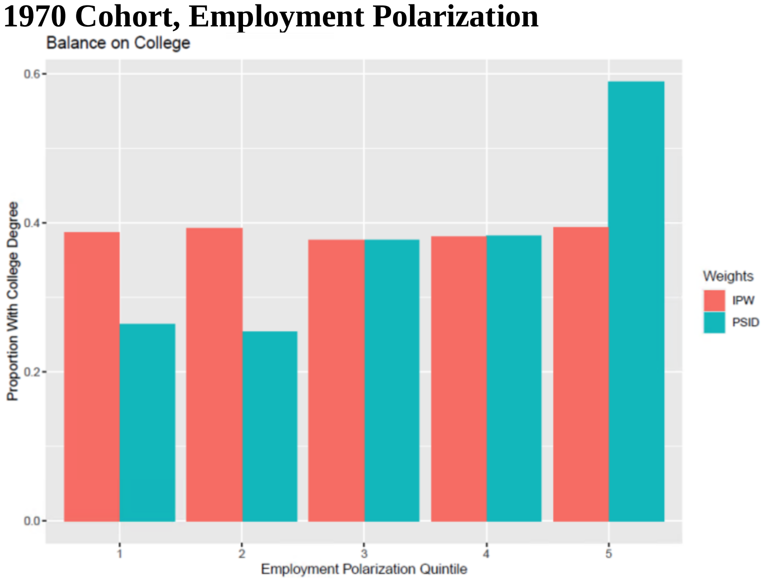
1965 Cohort, Employment Polarization

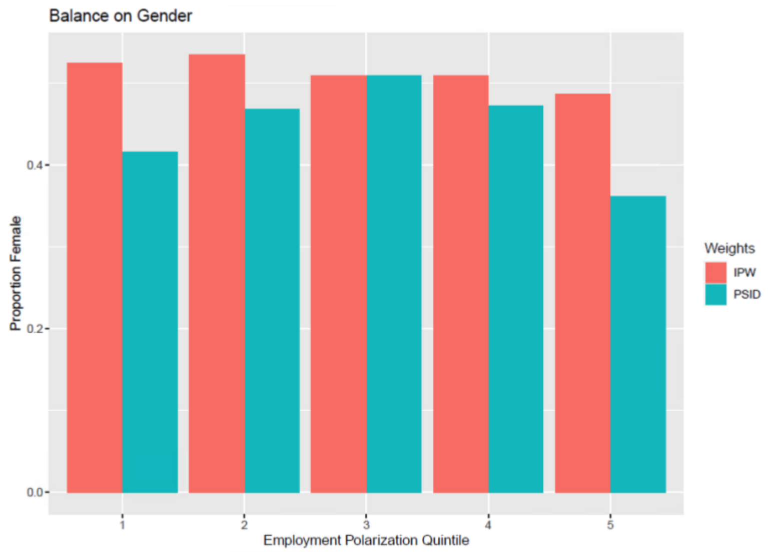


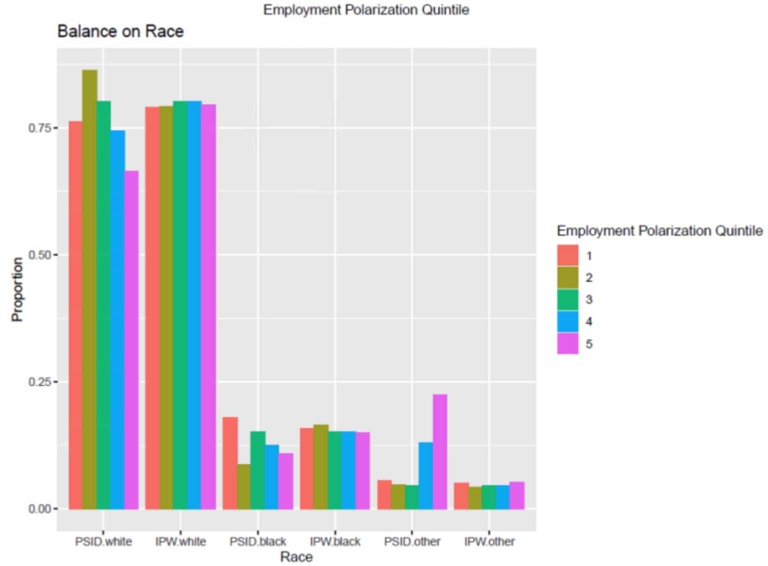




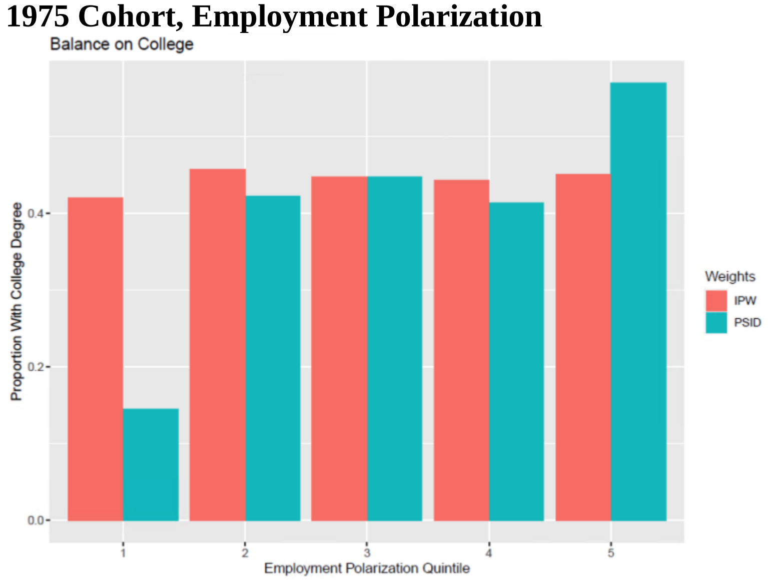
1970 Cohort, Employment Polarization

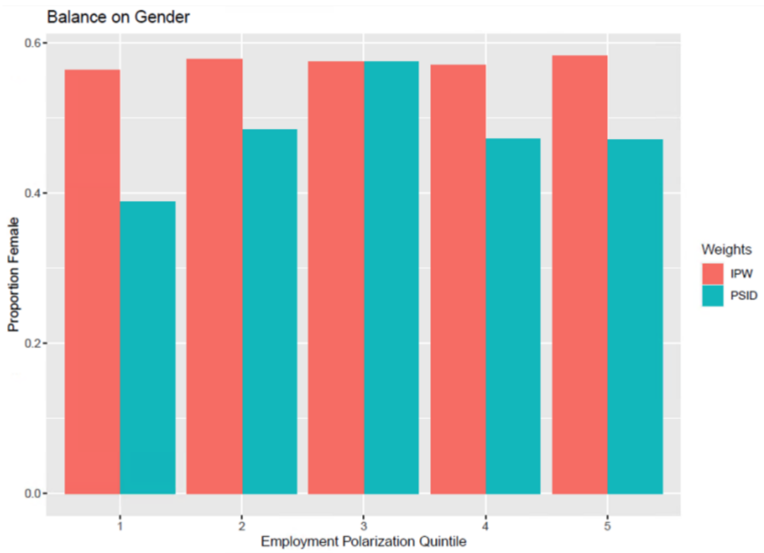


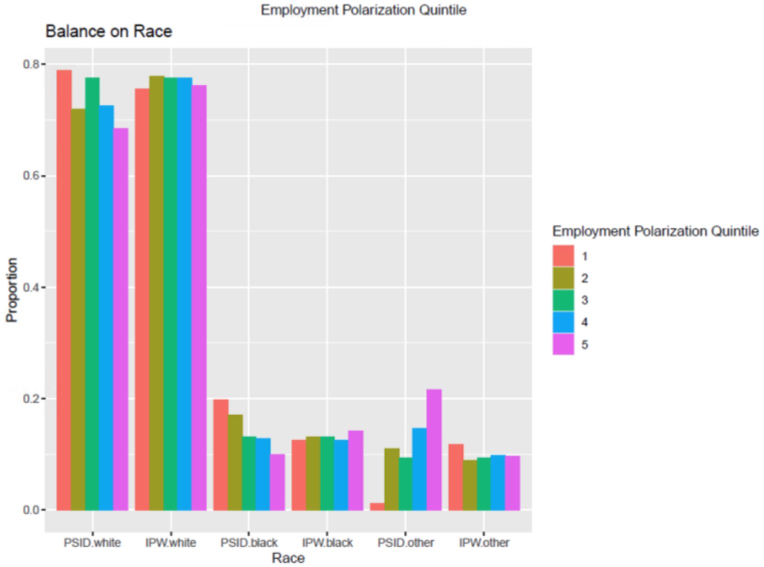




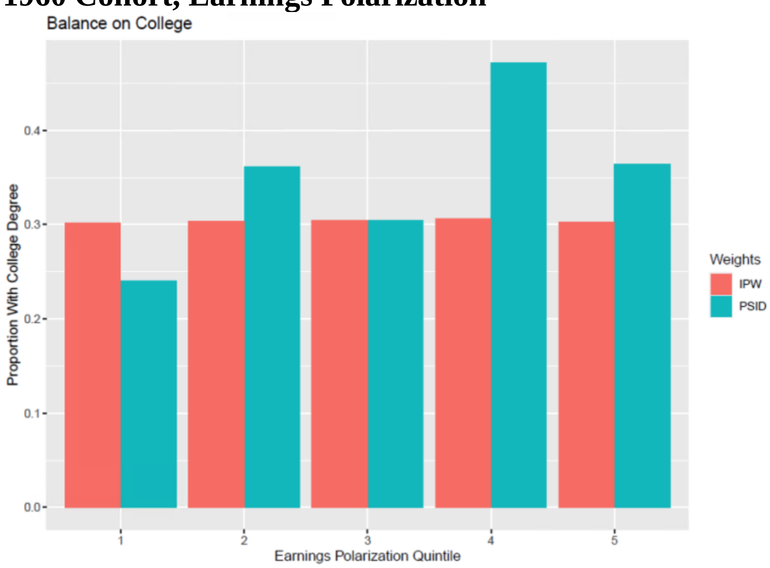
1975 Cohort, Employment Polarization

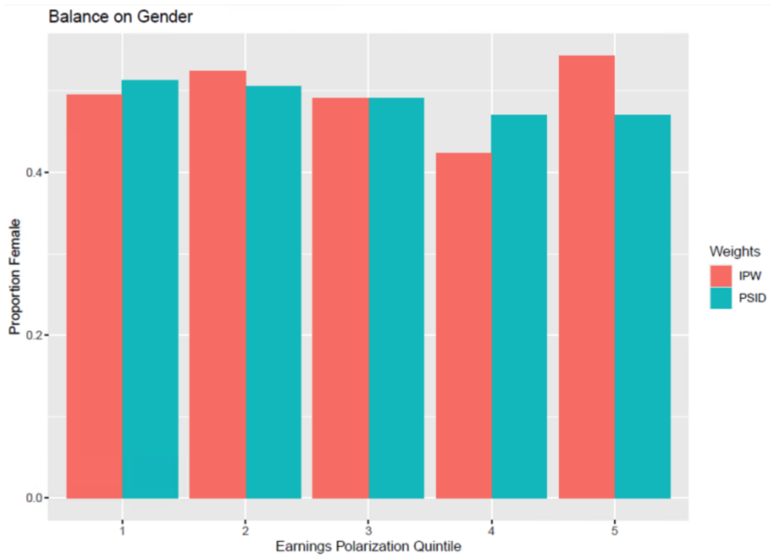


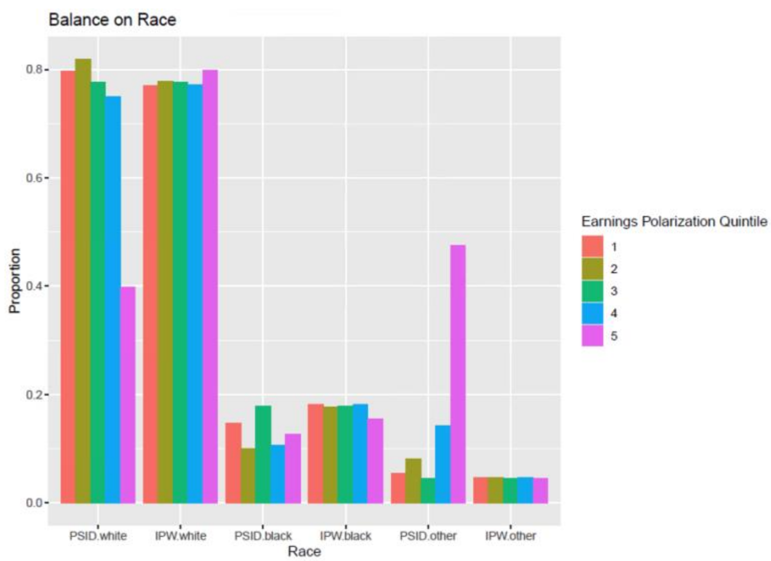




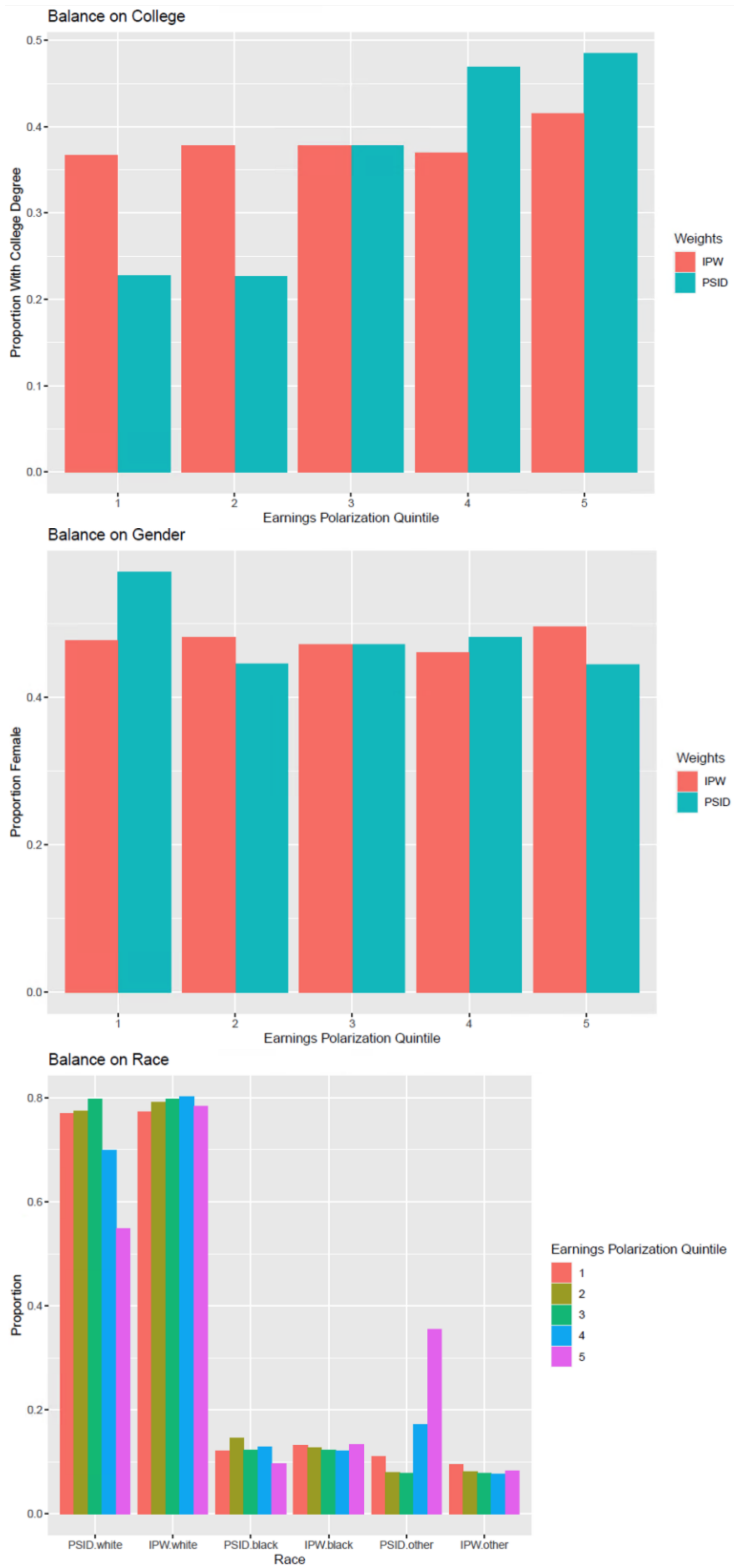
1960 Cohort, Earnings Polarization



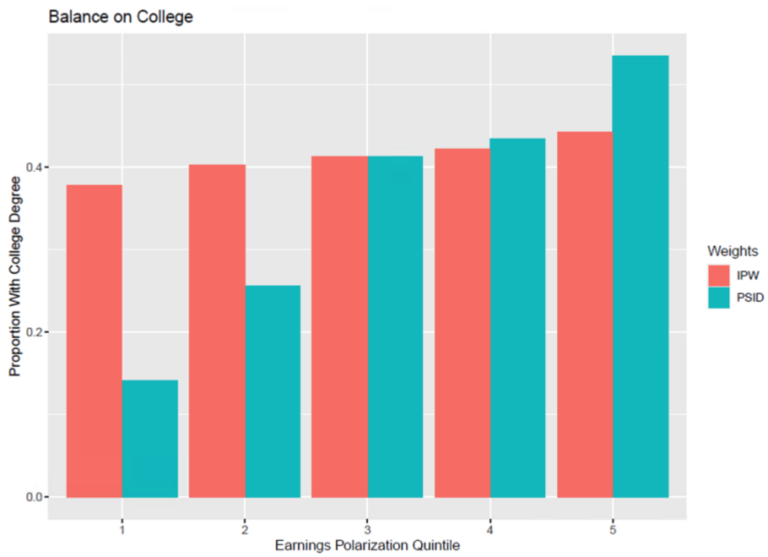


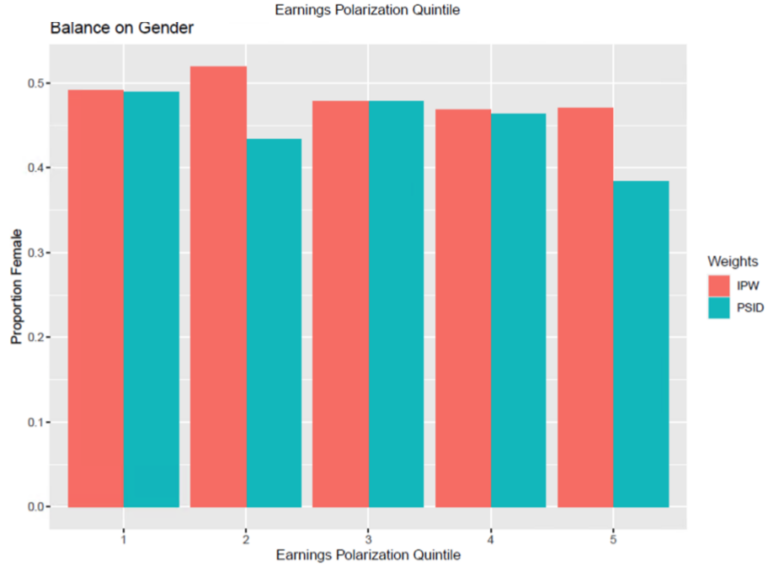


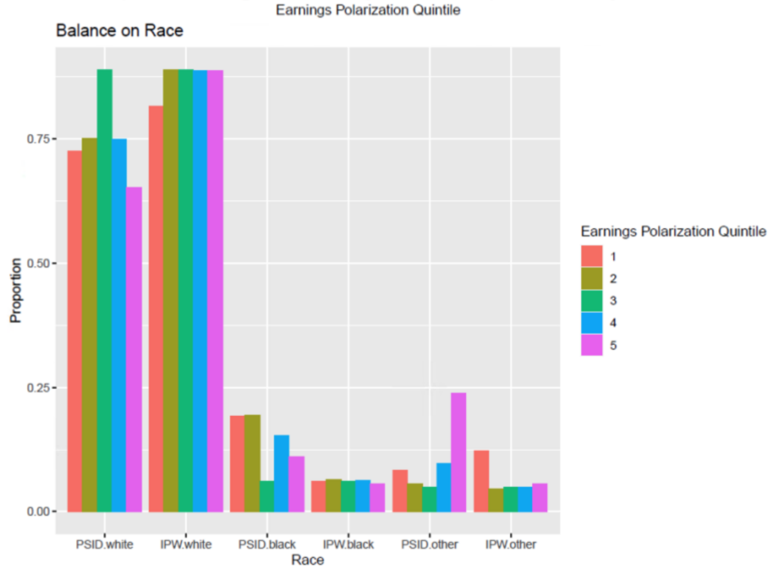
1965 Cohort, Earnings Polarization



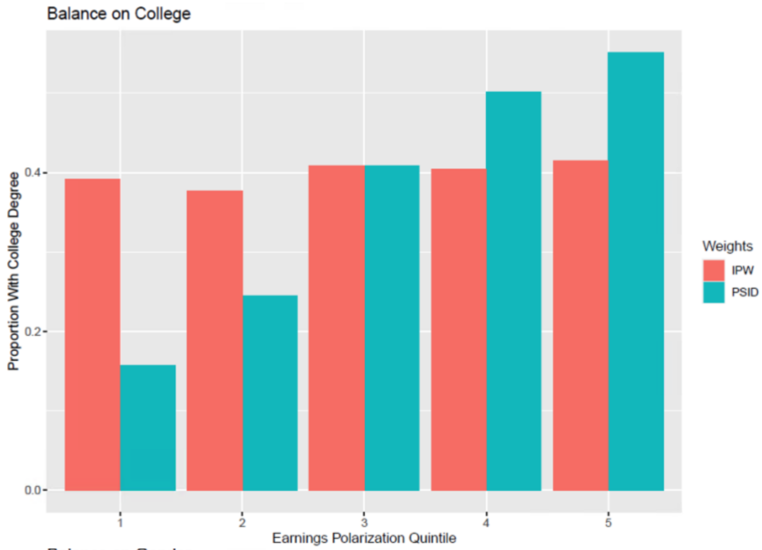
1970 Cohort, Earnings Polarization

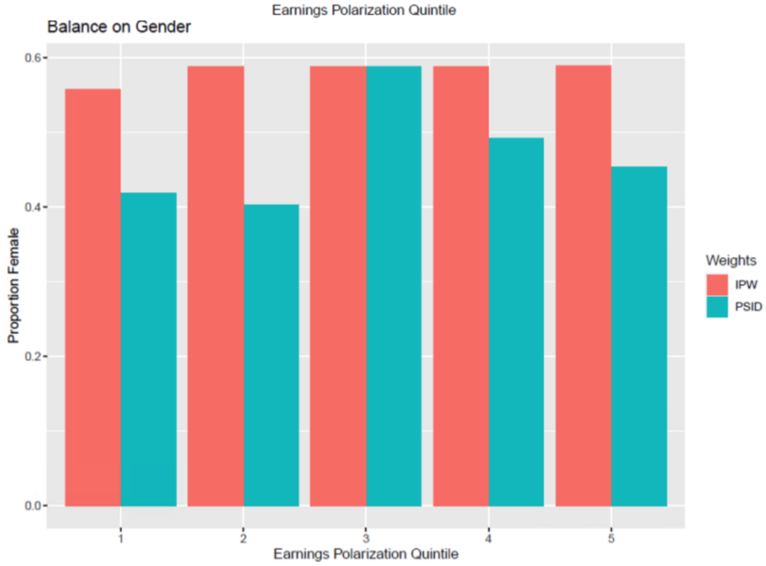


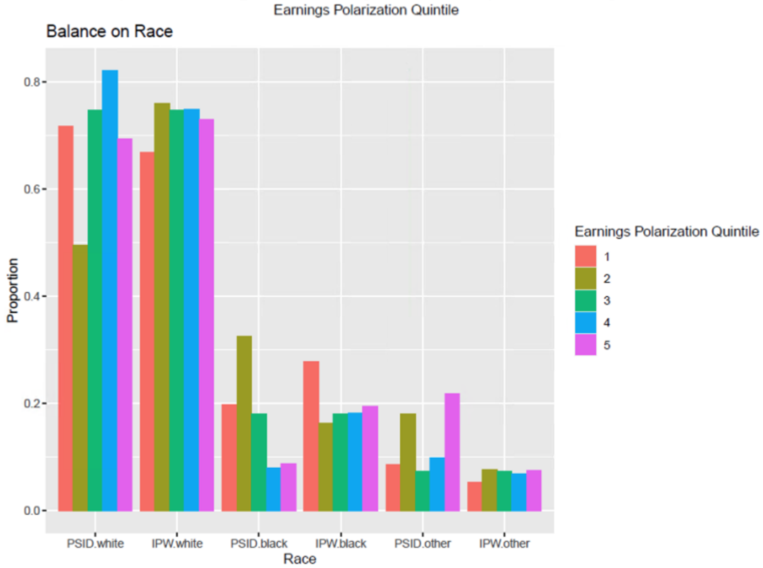




1975 Cohort, Earnings Polarization


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
0.2
0.4
0.6
1
2
3
4
5
Earnings Polarization Quintile
Weights
IPW
PSID


Balance on Race
Proportion
0.0
0.2
0.4
0.6
0.8
PSID.white
IPW.white
PSID.black
IPW.black
PSID.other
IPW.other
Race
Earnings Polarization Quintile
1
2
3
4
5