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Intragenerational Mobility and Inequality in Local Labor Markets

By

Joshua Choper

A dissertation submitted in partial satisfaction of the

requirements for the degree of

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in

Sociology

in the

Graduate Division

of the

University of California, Berkeley

Committee in charge:

Professor Neil Fligstein, Chair

Professor Heather Haveman

Professor Daniel Schneider

Professor David Card

Spring 2024

Abstract

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By

Joshua Choper

Doctor of Philosophy in Sociology

University of California, Berkeley

Professor Neil Fligstein, Chair

One of sociology's longstanding concerns is understanding how individuals are allocated to positions in the system of social stratification. While sociology has devoted significant attention to understanding how one's economic position – their earnings, job, occupation, class, or other marker of economic status – depends on their origins, much less work in recent decades has considered how individuals change economic positions throughout their career, how individuals differ in their chances of changing positions, or how such patterns of intragenerational mobility contribute to economic inequality. Moreover, work that does examine intragenerational mobility often only studies how patterns of mobility and attainment differ according to the characteristics of individual workers, without accounting for the fact that mobility also depends on structural features of the labor market that provide opportunities for such mobility. In this dissertation, I make the case that intragenerational mobility research is essential for understanding the processes that produce economic inequality. I argue that theorizing and modeling intragenerational mobility requires accounting for the interaction between workers and the economic structure in which they are embedded. I then apply this perspective in three empirical chapters on intragenerational mobility.

Chapter 2 considers how economic polarization affects lifecycle earnings trajectories and contributes to inequality. 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 Panel Study of Income Dynamics (PSID), US Census, and American Community Survey (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.

Chapter 3 develops a novel empirical approach to modeling intragenerational mobility. Recent research on intragenerational earnings mobility has primarily focused on how workers' earnings change in real dollars over their careers. Much less work has considered relative mobility, or workers' chances of changing positions in the earnings distribution. While prior research on intragenerational relative earnings mobility is largely descriptive and atheoretical, I examine how well patterns of relative mobility can be explained by four mechanisms of labor market mobility: discrimination, matching, human capital investment, and job mobility. I develop a novel approach using conditional quantile regressions to model how these mechanisms shape the full distribution of earnings ranks workers may attain through selection effects and career processes. Using PSID data, I show that gender, education, and human capital investment are the most important drivers of relative earnings mobility patterns and their change over time. Yet early-career earnings also directly shape opportunities for mid-career attainment after accounting for selection effects and mediating labor market processes. Over time, downward mobility among high-earners increased largely due to women's growing representation at the top of the earnings distribution and their relatively high risk of downward mobility, while upward mobility remained stable due to a combination rising educational attainment among low-earners and rising returns to education.

Chapter 4 investigates Black-White inequalities in earnings and job-task mobility among displaced workers. While social scientists have devoted significant effort to understanding racial economic inequalities, surprisingly little work has examined inequalities in how Black and White workers recover from job loss. I make two contributions towards that end. First, I offer the first historical accounting since the mid-1990s of racial inequalities in job search and earnings changes following job displacement, providing a new trend through 2020. Second, I draw on matching models of the labor market and queueing theory to elaborate the labor market processes that disadvantage Black workers in recovering from job displacement. Using data from the 1984-2020 Displaced Worker Supplement, I demonstrate that Black-White inequality in job search and earnings recovery decreased from the 1980s to the mid-2000s before increasing again after the Great Recession. Further, I show that while White workers experience large earnings losses relative to Black workers due to losing high quality jobs, these effects are outweighed by Black workers' disadvantage in resorting in the labor market after being displaced. While White workers are typically reemployed in similar, albeit somewhat lower paying, jobs, Black workers sort into categorically distinct jobs characterized by relatively high manual task intensity and relatively low abstract task intensity, and lower wages. Racial inequalities in the types of jobs that workers re-sort into, and consequently racial earnings inequalities post-displacement, are exacerbated by declining demand for routine labor.

The final chapter offers some concluding thoughts on the importance of intragenerational mobility research, how the previous chapters advance the intragenerational mobility literature, and some future directions for the research program.

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Connecting with Danny was a pivotal moment in my academic career. Danny encouraged me to apply to Berkeley's sociology program and secured funding to support the first half of my graduate school career. Throughout graduate school, Danny was incredibly generous with his time and feedback. He always gave detailed, helpful, and supportive feedback on dissertation chapters, articles, revisions, and my master's paper. He also provided formative opportunities for me to work as a graduate student researcher on the Shift Project studying work scheduling and low-wage work and helped co-author my first publication. I would not be where I am today without Danny's mentorship.

I am also incredibly grateful for the mentorship I have received from Neil Fligstein, who chaired this dissertation. Neil helps me see the forest through the trees when it comes to developing my research ideas and research program. When I find myself struggling to figure out how to distill many complex ideas and findings into one coherent chapter, I can count on Neil to help me find clear stories to tell. Heather Haveman also played a huge role in my intellectual development and in helping me hone my research skills. Heather's incredibly detailed and thoughtful feedback on my work helped me sharpen up my writing, argumentation, and analyses. Our conversations during her office hours not only helped me think more critically about individual chapters and papers, but also more broadly about how to conduct rigorous research.

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I dedicate this dissertation to everyone who has been there for me throughout this journey. No matter where you are, whether it's a quarter mile away or halfway across the world, you'll always be with me.

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Chapter 1: Introduction

Inequality and Intragenerational Mobility

Economic inequality in the United States has risen dramatically since the mid-1970s. Income inequality as measured by the Gini index increased by roughly 30 percent between 1970 and present day (United States Census Bureau 2019), with much of that growth in inequality driven by income 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; Auten and Splinter 2023). At the same time, inequality in economic rewards between different levels of education, occupations, and firms has grown (Katz and Autor 1999; Autor, Katz, and Kearney 2006; Lemieux 2006b; Autor et al. 2008; Lemieux 2008; Mouw and Kalleberg 2010b; Card et al. 2017; Song et al. 2019), suggesting that the processes through which workers are allocated to positions in the labor market have become increasingly important determinants of the level and shape of economic inequality.

The rising stakes associated with how workers are allocated to positions in the economic structure has reinvigorated inequality scholars' interest in analyzing workers' ability to move between positions. The bulk of this work has been concerned with intergenerational mobility, or the strength of the association between parents' status and their children's adult economic outcomes. Typical analyses of intergenerational mobility compare point-in-time or smoothed-averages of parents and their children's adult outcomes (Torche 2015; Mazumder 2016, 2018; Cheng and Song 2019; DiPrete 2020), and often describe how parent status is transmitted to their children via mediating mechanisms that occur before entry into the labor market such as the child's educational attainment, neighborhood, social capital, cognitive and noncognitive skills, and the like (Blau and Duncan 1967; Sewell, Haller, and Portes 1969; Becker and Tomes 1979; Sewell and Hauser 1980; Bowles and Gintis 2002; Chetty, Hendren, Kline, and Saez 2014; Torche 2015; Chetty et al. 2017).

The main shortcoming of such an approach is that it characterizes individuals' economic outcomes as static and invariant, despite the fact that income and occupation vary substantially over the career. While much of the literature on intergenerational mobility considers fluctuation in individuals' earnings or jobs over the career to be a potential source of measurement error (see Solon 1992; Mazumder 2005, 2012, 2016; Lee and Solon 2009), intragenerational mobility is a fundamental causal mechanism underlying mobility because variations in individuals' income trajectories and occupational pathways over their career reflect the actual attainment processes that connect workers to economic rewards (Sørensen 1975; Rosenfeld 1992; Cheng 2014; Cheng and Song 2019). Intragenerational mobility rates are relatively high – by the mid-2000s, over 60 percent of prime working age adults had changed income quintiles within their cohort relative to the beginning of their careers, and about half of individuals who started their career in the bottom income quintile rose out of it (Acs and Zimmerman 2008). However, substantial upward mobility is rare – the probability of moving from the bottom 40th percentile to above the 80th percentile in earnings over one's career is just over 5 percent (Carr and Wiemers 2022).

Variation in intragenerational mobility patterns is a major determinant of how inequality develops over workers' careers. Inequality in wages and occupational attainment unfolds 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; Kalleberg and Mouw 2018a; Cheng 2021). From the perspective of life course theory, career processes are understood to be time dependent and self-referential, with analyses emphasizing

wage trajectories and job-to-job linkages as the main outcomes of interest and stressing the cumulative nature of economic rewards over the career (Spilerman 1977; Abbott 1983, 1995; Dannefer 1987; DiPrete and Eirich 2006). Wage inequality grows substantially within cohorts as they age, and over half of this growth in inequality can be attributed to variation in the pattern by which individuals' wages develop over the life course (Cheng 2014, 2021). 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), heterogeneous 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).

While these strands of research highlight important factors that may affect rates of wage growth or occupational mobility, they largely neglect the macro-level processes by which individuals come to occupy positions in the labor market that inhibit or facilitate intragenerational mobility. Proponents of the life course perspective argue that life course theory offers a micro-macro link between individuals and social structures and institutions that shape inequality (Elder 1985; Huber 1990; Mayer 2004), but without attending to the labor market structures through which inequality in attainment is realized over the career, the macro-level mechanisms that relate early conditions to later life outcomes remain poorly understood. 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 features of the labor market that make up their opportunity structure for attainment.

While some sociologists have investigated mobility processes over the career and their consequences of inequality, very little of this work has managed to link individual career trajectories to concrete structural features of the economy that shape attainment processes, 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). Returning our attention to these processes that shape macro-level trends in inequality, I argue that it is through the matching process by which individuals are connected to firms and jobs that inequality is realized. These processes unfold over workers' careers, both providing opportunities for individuals to change their position in the social structure and giving rise to variation in inequality as workers age and as labor market processes change. I argue that heterogeneity in labor market structure and matching processes, and hence heterogeneity in the opportunity for mobility, are central mechanisms driving inequality over workers' careers.

Labor Market Structure, Matching, and Inequality

This dissertation is primarily concerned with the matching processes in the labor market through which workers are matched to jobs and firms and their associated economic rewards. This matching process involves heterogeneous populations of firms and workers simultaneously choosing between one another. Inequality in outcomes occurs not just because individuals differ in their characteristics, but also because heterogeneous individuals interact with important social

forces that determine the distribution of positions in the social structure, the rewards attached to those positions, and the extent to which different individual characteristics are weighed when allocating individuals to those positions. Understanding inequality in the context of workers' careers thus requires a conception of the labor market that not only accounts for a worker and the job they currently occupy, but also all the alternative jobs the worker could have taken and workers the firm could have hired. Therefore, analyses of inequality in the labor market must account for *population level* phenomena for both the populations of firms and workers in a labor market.

I conceive of labor markets as fields comprised of populations of firms and workers whose actions are oriented towards one another and aimed towards matching workers to jobs in exchange for wages in deeply institutionalized patterns of interaction characterized by shared rules and collective understandings and structured competition and cooperation (DiMaggio and Powell 1983; Fligstein 1996; Fligstein and McAdam 2012). Labor markets embody shared understandings of, and are structured by, property rights governing ownership of capital and labor, governance structures such as professional associations and common practices of identifying potential job matches, selecting matches, and ending matches, rules of exchange like minimum wage laws and laws barring the employment of children, and conceptions of control that structure perceptions of how the market works including the status orderings of both workers and firms and expectations about typical job match pairings and compensation (Fligstein and Fernandez 1988). Firms in a labor market compete for market share, profits, capital, legitimacy, survival, and the like. The population of firms in a labor market can be characterized by its demographic features, including vital rates such as founding and disbanding as well as by the diversity of firms according to their structure, composition, quality, and industry (Hannan and Freeman 1977, 1989; Carroll and Hannan 2004; Sørensen 2007; Sørensen and Sorenson 2007).

Much of this dissertation leverages matching models of the labor market to understand how geographic and historical variation in the job structure and labor pool shape patterns of intragenerational mobility and inequality. Models of labor market matching in sociology (e.g. White 1970; Berg 1981; Sørensen and Kalleberg 1981; Coleman 1991; Berg and Kalleberg 2012) and economics (e.g. Mortensen 1978, 1988; Jovanovic 1979b, 1979a; Mincer and Jovanovic 1981; Barron, Black, and Loewenstein 1989; Pissarides 1994) start from similar basic premises. Each firm contains a set of job openings that it seeks to fill from the labor pool, and workers in the labor pool compete for their most desired jobs. Matching between workers and jobs occurs through simultaneous competition between firms for workers and between workers for jobs. Workers leverage their personal resources (e.g. human, social, and cultural capital) to compete for jobs with their most preferred bundle of characteristics including wages, hours, flexibility, benefits, activities, etc. Firms compete for employees primarily through their wage offers but also through other benefits and compensating differentials.

In sociological variants of labor market matching models, wages and benefits are attached to jobs and the set of jobs is relatively fixed, at least in the short-run (White 1970b; Sørensen 1977; Sørensen and Kalleberg 1981). Because positions and their associated wages are fixed, the set of jobs in a labor market determines the level and structure of economic inequality and it provides an opportunity structure for workers to receive economic rewards and to experience upward or downward mobility over their careers. Therefore, understanding the changing nature of inequality requires examining how changes to the structure of labor demand (the distribution of jobs, occupations, firms, etc.) influence workers' patterns of attainment and mobility.

Situating Labor Markets and Mobility Patterns in Place and Time

The importance of local labor markets

We must empirically observe the labor market in order to analyze inequality-generating matching processes within it, but it is not obvious what level of analysis constitutes a labor market. The vast majority of studies of the structure of labor demand in the United States treat the country as a single homogenous unit. While it is true that most jobs can accept applicants from across the country and most workers can, at least in theory, apply to work in any locale, a growing literature has demonstrated that labor markets vary geographically and give rise to variation in employment outcomes (Topel 1994; Beggs and Villmez 2001; Fernandez and Su 2004; Sørensen and Sorenson 2007; Dorn 2009; Moretti 2010). Focusing our analysis of labor markets at the local or regional level is necessary to capture heterogeneity in both labor supply and demand. On the supply side, 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). Populations of workers also vary substantially in their demographic traits and human capital characteristics across geographies (see Moller, Alderson, and Nielsen 2009). On the demand side, regional labor markets vary substantially in the types of jobs, firms, and industries that define them (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; Moller et al. 2009; Connor and Storper 2020; Thiede et al. 2020).

Economic restructuring since 1980 and its consequences for mobility

A central theme of this dissertation is that historical changes in structural features of the labor market have had a meaningful impact on the patterns of inequality that emerge over the course of workers' careers. From the 1970s to present, the economic structure changed substantially. Economic activity shifted away from the production of goods to services, high- and low-end jobs grew in number while middle-class jobs became less common, and inequality between firms rose substantially (Osterman 1999; Autor et al. 2006, 2020; Kalleberg 2011; Card et al. 2017; Song et al. 2019). At the same time as inequalities between economic locations – firms, jobs, occupations, industries – became increasingly important determinants of inequality, upward mobility became less common. Although mobility between occupations has increased since 1970 (Kambourov and Manovskii 2008; Jarvis and Song 2017), occupational mobility among lower-skilled workers increased largely within their origin class, reducing upward mobility and reinforcing inequalities between classes (Kim 2013). Similarly, while earnings mobility was relatively steady through the 1970s (Acs and Zimmerman 2008; Kopczuk et al. 2010), recent decades have seen a marked decline in earnings mobility and a heightened persistence of early-career earnings rank across the career (Bradbury and Katz 2009; Western et al. 2012a; Carr and Wiemers 2016). Throughout this dissertation, I seek to describe how the structure of labor demand has changed in ways that meaningfully affect workers' labor market opportunities and relate those changes to emerging patterns of inequality and mobility.

Intragenerational Mobility and Inequality in Local Labor Markets

So far, I have argued that intragenerational mobility is an important and under-studied feature of economic life. Workers spend their careers moving between levels of earnings, jobs, firms, occupations, and industries. Mobility over the career allocates workers to different positions in the system of economic stratification. Economic inequality is therefore a phenomenon that is produced over the course of workers' careers through their heterogeneous patterns of mobility. Mobility is achieved through labor market processes that match workers to jobs, where worker-job matches are determined by workers' characteristics, the characteristics of others against whom they are competing, firms' demand for labor, and workers' and firms' simultaneous evaluations of their options. Importantly, the structure of labor demand, i.e. the types of jobs firms wish to fill and their willingness to pay to fill them, creates an opportunity for structure and determines the shape of inequality in a labor market. Geographic and historical variation in each of these elements of labor market matching processes give rise to different forms of economic inequality that develop over workers' careers.

In what follows, I apply this perspective to make three contributions to our understanding of the relationship between intragenerational mobility, inequality, and labor market structure. These empirical chapters investigate inequalities in earnings mobility over workers' careers, the extent to which workers' opportunity for mobility is constrained by their initial position in the labor market, and how the association between present and future earnings is structured by workers' local labor market context.

Chapter 2 focuses on how occupational polarization – that is, rising employment at the top and bottom of the labor market and shrinking employment in the middle, as well as rising inequality in occupation average earnings – structures the relationship between early-career earnings, mid-career earnings, and earnings inequality. I demonstrate that in local labor markets with higher levels of polarization, earnings inequality is greater at the beginning of workers' careers, low-earners' chances of “catching up” to high-earners over the career are substantially diminished, and inequality over the life course is much greater, primarily because polarization amplifies inequality at the beginning of workers' careers. I also find some evidence that polarization disproportionately benefits highly educated workers.

Chapter 3 develops a new empirical approach to examine how workers' economic position when they enter the labor market shapes their future earnings opportunities. While previous research investigates how labor market entry shapes future average earnings, this chapter models how full distribution of earnings that workers attain changes depending on where they enter the labor market. I show that even after accounting for selection into different levels of early-career earnings, upward mobility from the bottom of the earnings distribution and downward mobility from the top are both significantly constrained. Over time, downward mobility among high-earners increased largely due to women's growing representation at the top of the earnings distribution and their relatively high risk of downward mobility, while upward mobility remained stable due to a combination rising educational attainment among low-earners and rising returns to education.

Chapter 4 shifts our attention to job displacement, an important and highly disruptive event in workers' economic lives that typically results in substantial short- and long-term downward earnings mobility. I investigate how racial inequalities in the earnings consequences of job displacement have varied over time due to the changing incidence of job displacement, and between places due to variation in local labor markets' demand for labor. I demonstrate that while displaced White workers experience disproportionate earnings losses due to losing high quality jobs, these losses are significantly outweighed by Black workers' substantial

disadvantage in finding high quality employment after displacement. Black workers' disadvantage in finding reemployment are exacerbated by declining demand for routine labor in their state. Chapter 5 offers some concluding thoughts.

Chapter 2: Local Labor Market Polarization and Inequality in Career Earnings Mobility

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 et al. 2008; Lemieux 2008; Kopczuk et al. 2010; Piketty et al. 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 et al. 2006, 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 et al. 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 *intragenerational* 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; Kalleberg and Mouw 2018a; Cheng 2021). 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), heterogeneous returns to human capital (Mincer 1996; Heckman et al. 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 et al. 1994; Maume 2004a, 2004b; Tomaskovic-Devey et al. 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 heterogeneous populations of firms and workers simultaneously choose between one another (Jovanovic 1979c; 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 1970a; 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 2006b) 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 2006c). 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 Dynamics¹ (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 IPUMS².

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 Members³ 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 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 age – years of education – 6. If the respondent has less than 12 years of education, potential experience is recorded as 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

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.

dollars. The sample is limited to individuals between 18 and 65 years old who are employed, are not missing non-imputed⁴ 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. 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:

$$\text{Standardized occupational employment}_{oct} = \frac{\text{total employment}_{oct}}{\text{total employment}_{ct} / \text{number of occupations}_{ct}} \quad (1)$$

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:

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

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

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:

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

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

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:

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

Level 2:

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

$$\beta_2 = \gamma_{20}$$

(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 $u(Q1)_{0i} * POL(Q1)_i$ through $u(Q5)_{0i} * POL(Q5)_i$. 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 $u(QN)_{1i} * POL(QN)_i$ 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 ($corr(u(QN)_{0i} * POL(QN)_i, u(QN)_{1i} * POL(QN)_i)$) 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 $u(QN)_{0i}$ 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 $u(QN)_{0i}$ at each quintile of polarization. H3 predicts that polarization disproportionately benefits earnings mobility for high earners. It is tested by examining $corr(u(QN)_{0i} * POL(QN)_i, u(QN)_{1i} * POL(QN)_i)$. 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.

⁵ Experience-earnings profiles are typically fit with quadratic terms to account for declining rates of earnings growth over the career (Mincer 1974; Lemieux 2006c). 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 2008a; Cheng 2014)

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 ($corr(u(QN)_{0i} * POL(QN)_i, u(QN)_{1i} * POL(QN)_i)$) 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.

Table 2.1. Hypotheses and tests

Hypothesis	Test	Supported?
H1: Polarization increases inequality in earnings at the beginning of workers' careers.	$var(u(QN)_{0i})$ increases with N	1965, 1970: yes 1960, 1975: no
H2: Earnings growth rates vary among individuals in similarly polarized local labor markets.	$var(u(QN))_{1i} > 0$	Yes
H3: The association between individuals' baseline earnings and earnings growth rates is greater in more polarized labor markets.	$corr(u(QN)_{0i} * POL(QN)_i, u(QN)_{1i} * POL(QN)_i)$ 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.	$corr(u(QN)_{0i} * POL(QN)_i, u(QN)_{1i} * POL(QN)_i)$ increases with N more in younger cohorts than older cohorts	No

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.

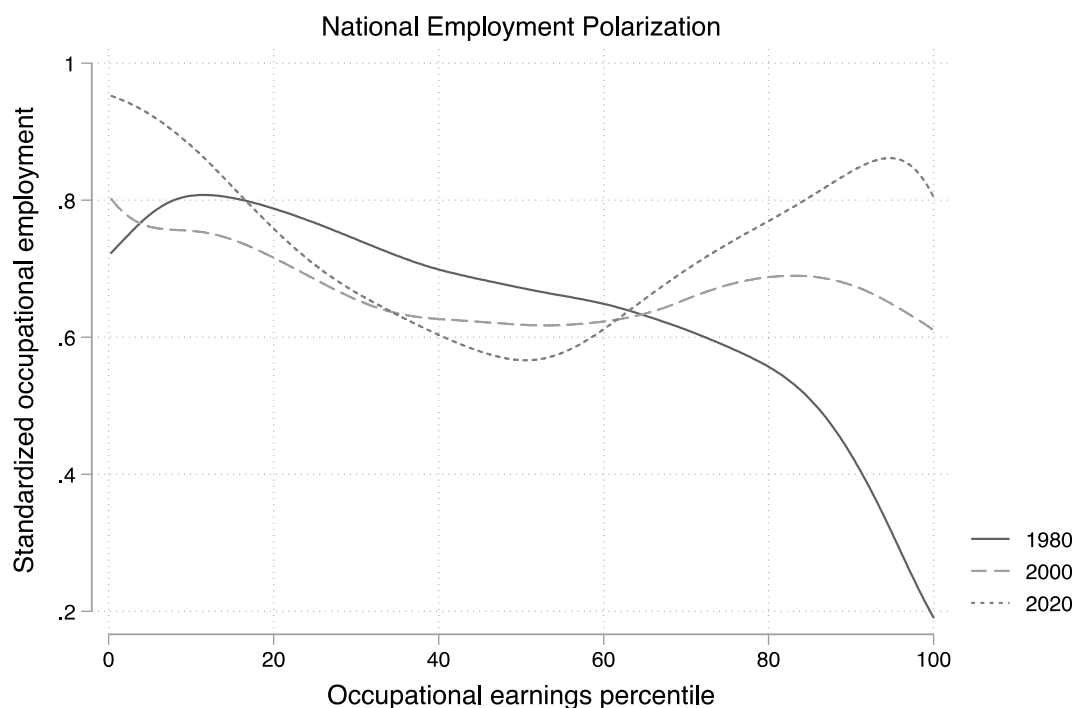
I account for selection on observable individual traits by using inverse probability weighting (IPW). IPW weights are constructed to achieve balance on a set of covariates across levels of a treatment. For these analyses, I construct weights for each cohort such that within each level of polarization, 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.

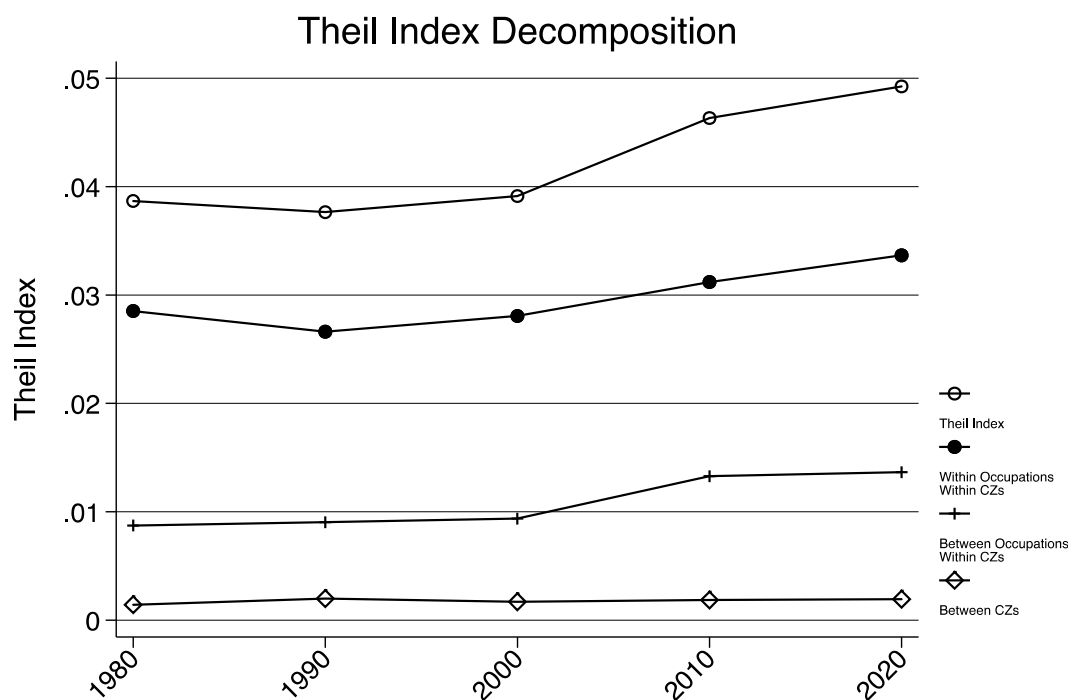
Results

Occupational polarization across the US

Occupational polarization in CZs grew significantly between 1980 and 2020. The top panel of Figure 2.1 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.

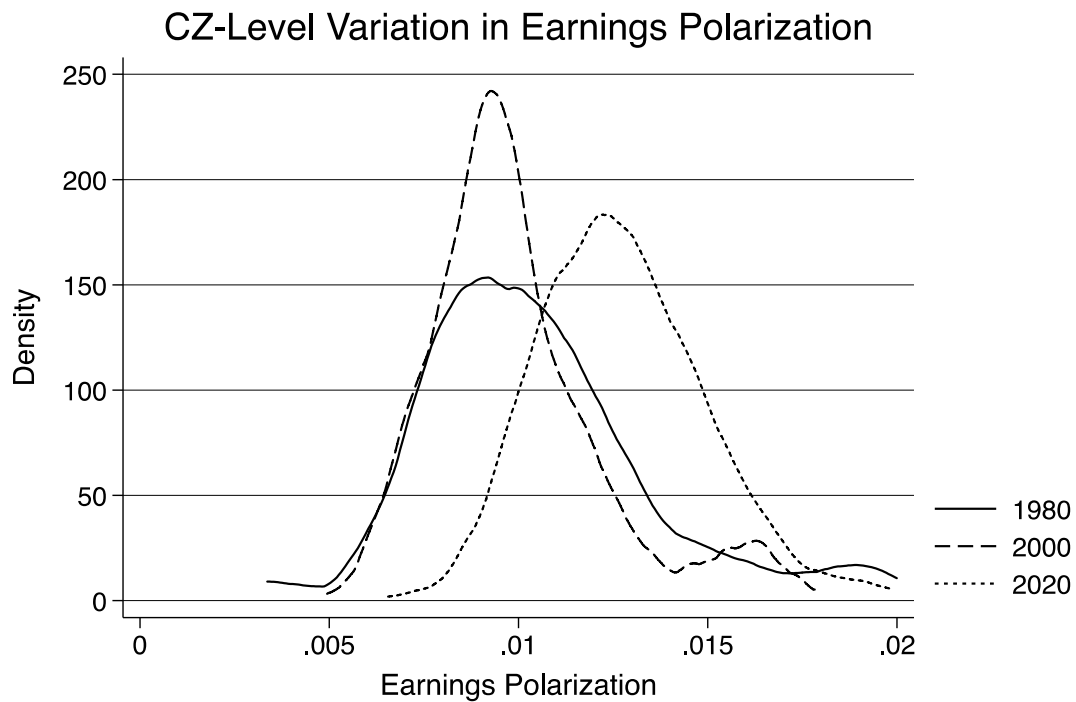
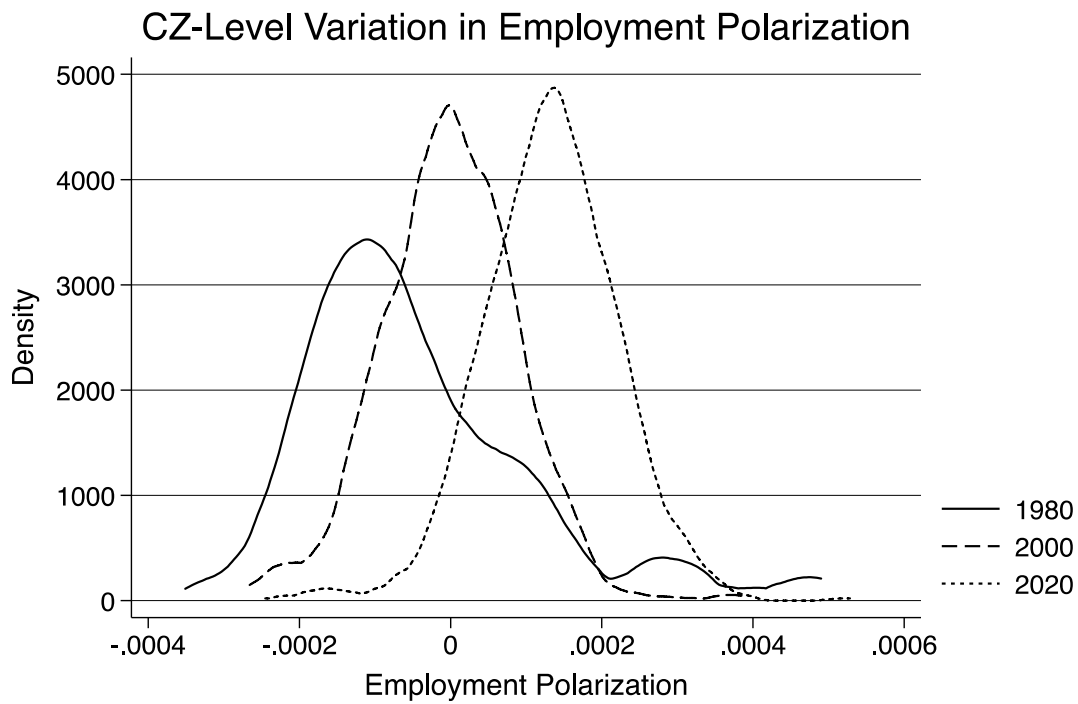
Figure 2.1. National employment and earnings polarization





Polarization in occupation average earnings follows similar trends (Figure 2.1 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 2.2 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.

Figure 2.2. CZ-level variation in polarization



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 2.2). 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).

Table 2.2. 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

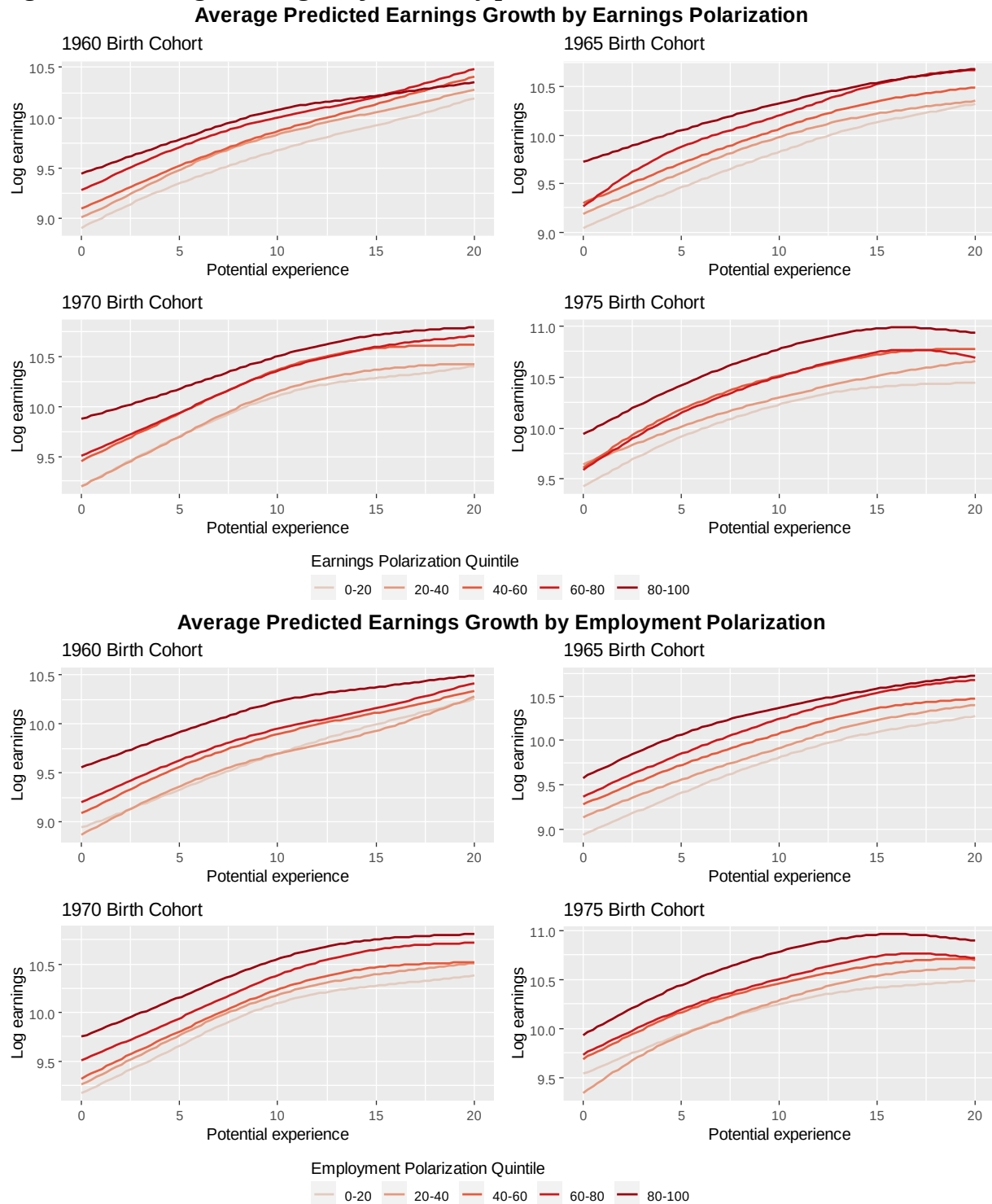
Table 2.3 presents coefficients and variance components from growth curve models where log earnings is regressed on measures of earnings and employment polarization, their interaction with potential experience, and potential experience squared. Average best linear unbiased predictions (BLUPs) of log earnings trajectories for individuals in each quintile of

polarization are presented in Figure 2.3. These BLUPs incorporate estimates of both fixed and random effects.

Table 2.3. Estimated coefficients and variance components from growth curve models of log earnings by cohort

Fixed effects	Earnings polarization					Employment polarization		
	1960-1964	1965-1969	1970-1974	1975-1980	1960-1964	1965-1969	1970-1974	1975-1980
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

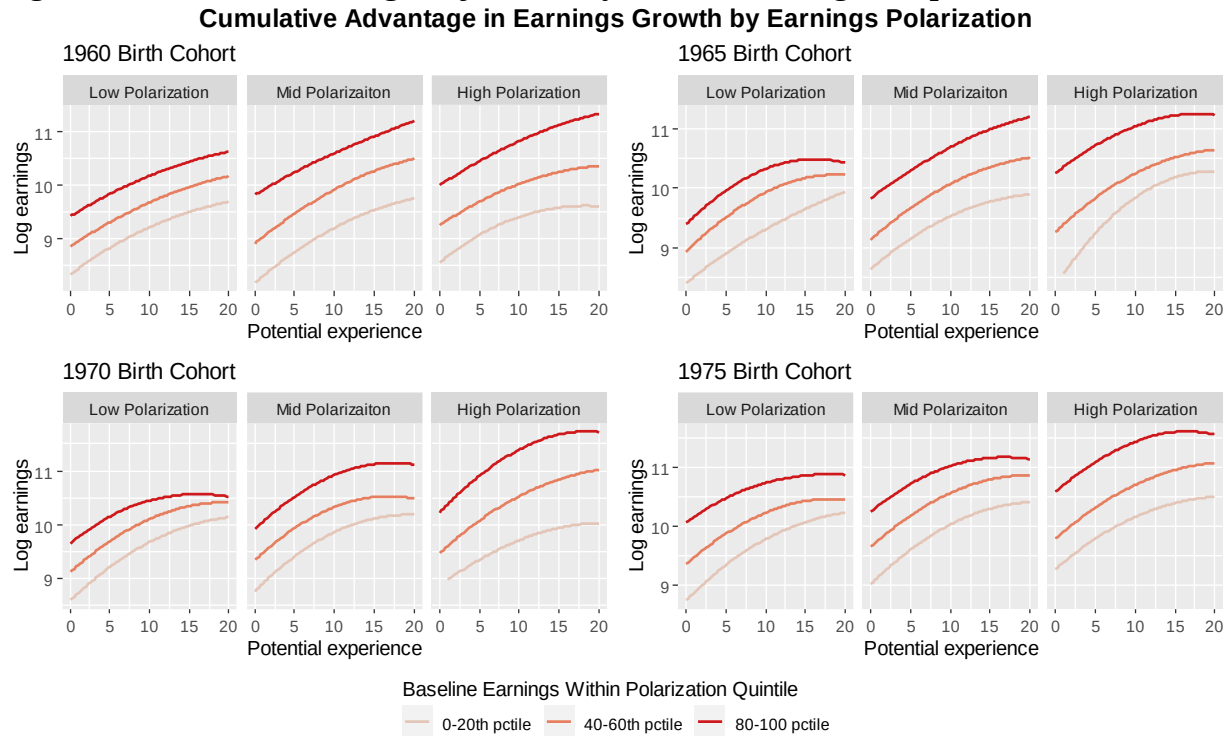
***p<0.001 **p<0.01 *p<0.05 +p<0.10. Stars indicating significant difference from coefficient at polarization quintile=1 as determined by Wald test.

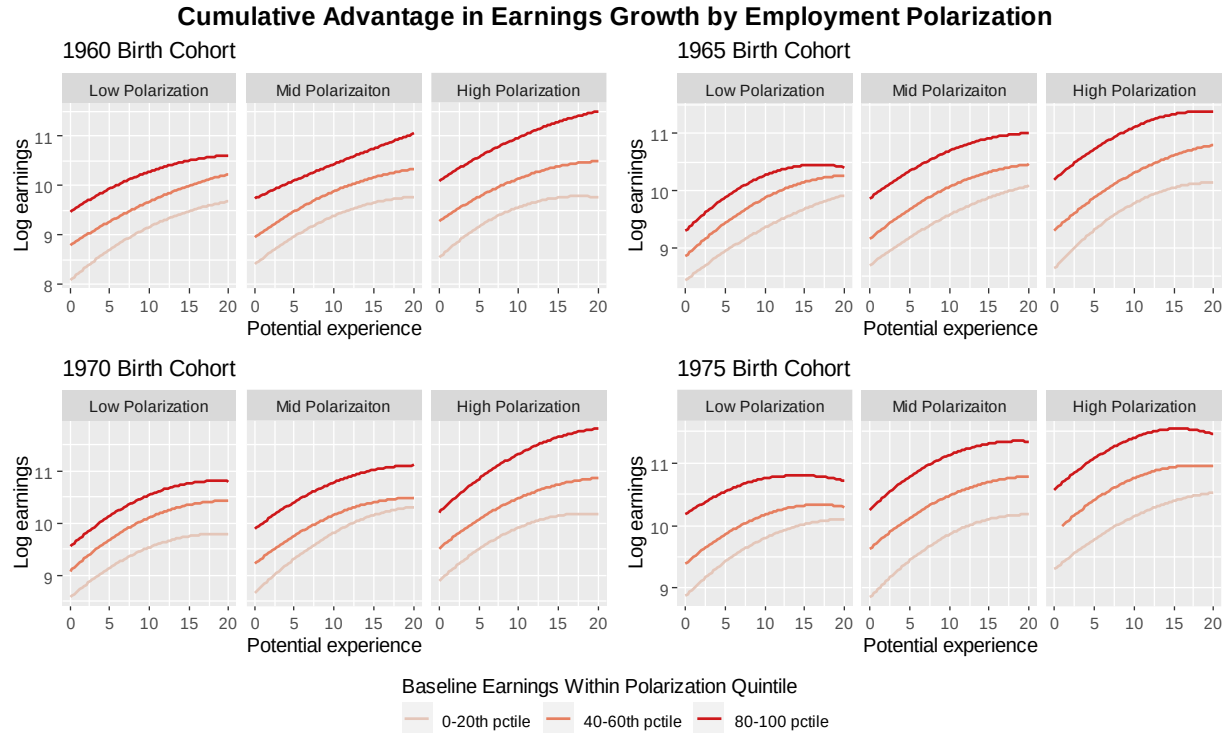
Figure 2.3. Average earnings trajectories by polarization

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 2.3 suggest that polarization has a strong effect on inequalities within CZs. Figure 2.4 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 2.3, the variance component labeled $\text{Var}(\text{intercept})$ corresponds to $\text{Var}(u(\text{QN})_{oi})$ 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 2.4, 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.

Figure 2.4. Predicted earnings trajectories by baseline earnings and polarization





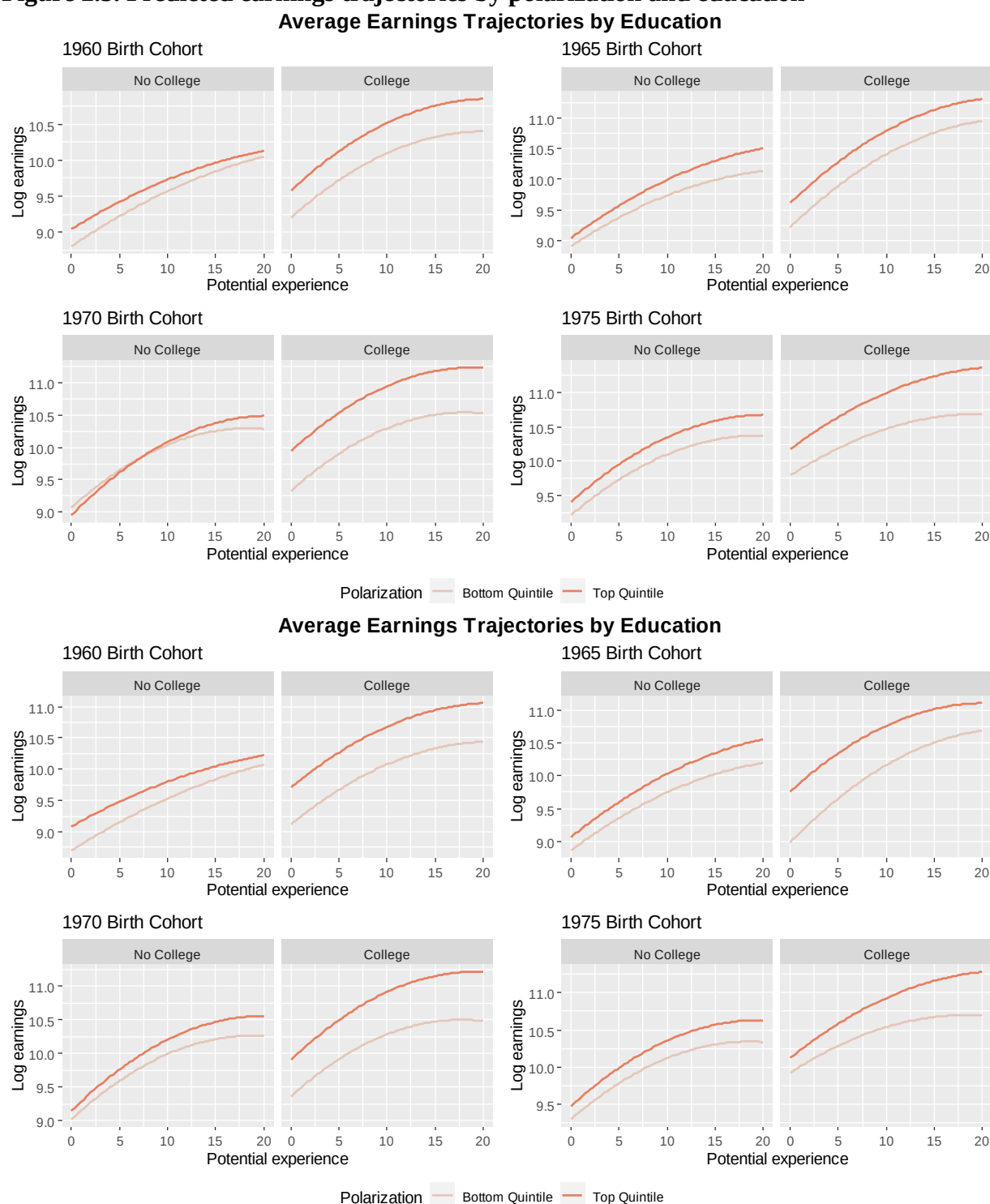
Hypothesis 3 predicts that polarization disproportionately benefits earnings growth for high earners. The correlation between the intercept and slope describes the relationship between baseline earnings and earnings growth within similarly polarized CZs. A positive correlation would suggest that individuals 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 2.4 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-

	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	9.197	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	0.094	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+	0.124	0.138	0.105+	0.105+
Potential experience ²	-0.00143	-0.00297	-0.00216	-0.00327	-0.00365	-0.00365	-0.00305	-0.00231
				Employment polarization				
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*	9.1028	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	0.104*	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 2.5. Predicted earnings trajectories by polarization and education

The cumulative advantages in earnings that college educated workers experience from polarization can be observed in Figure 2.5. Figure 2.5 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

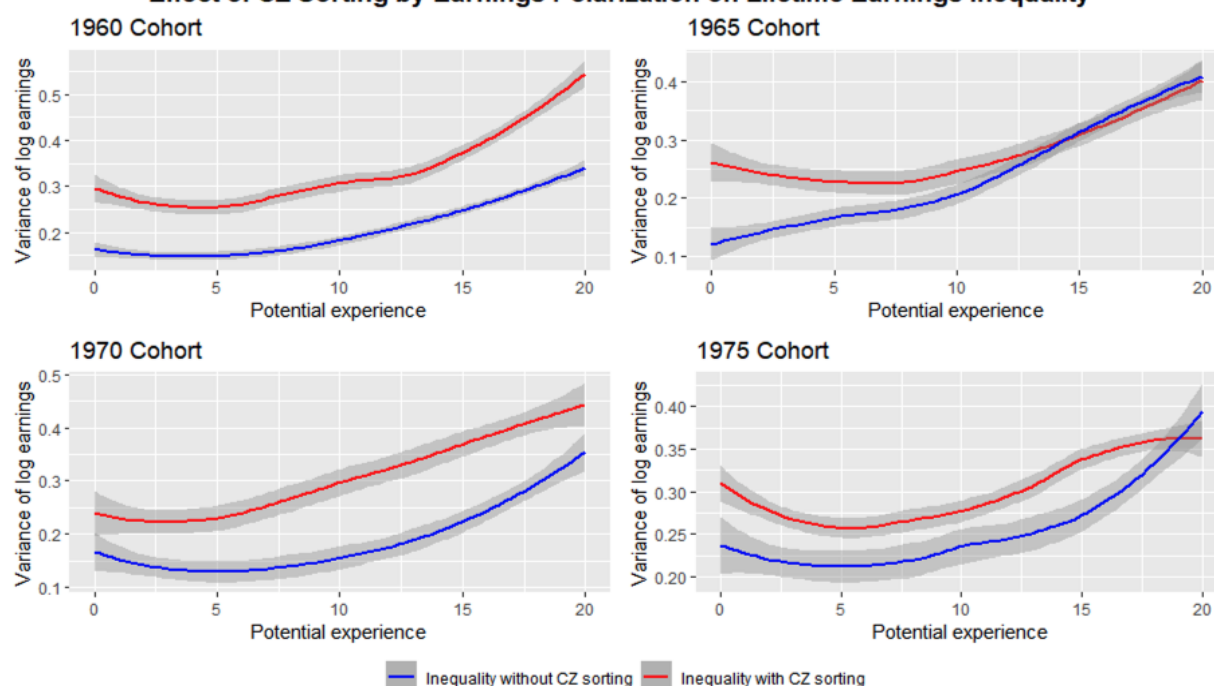
1975 cohort, we see that earnings trajectories diverge between college-educated workers in the least and most polarized CZs.

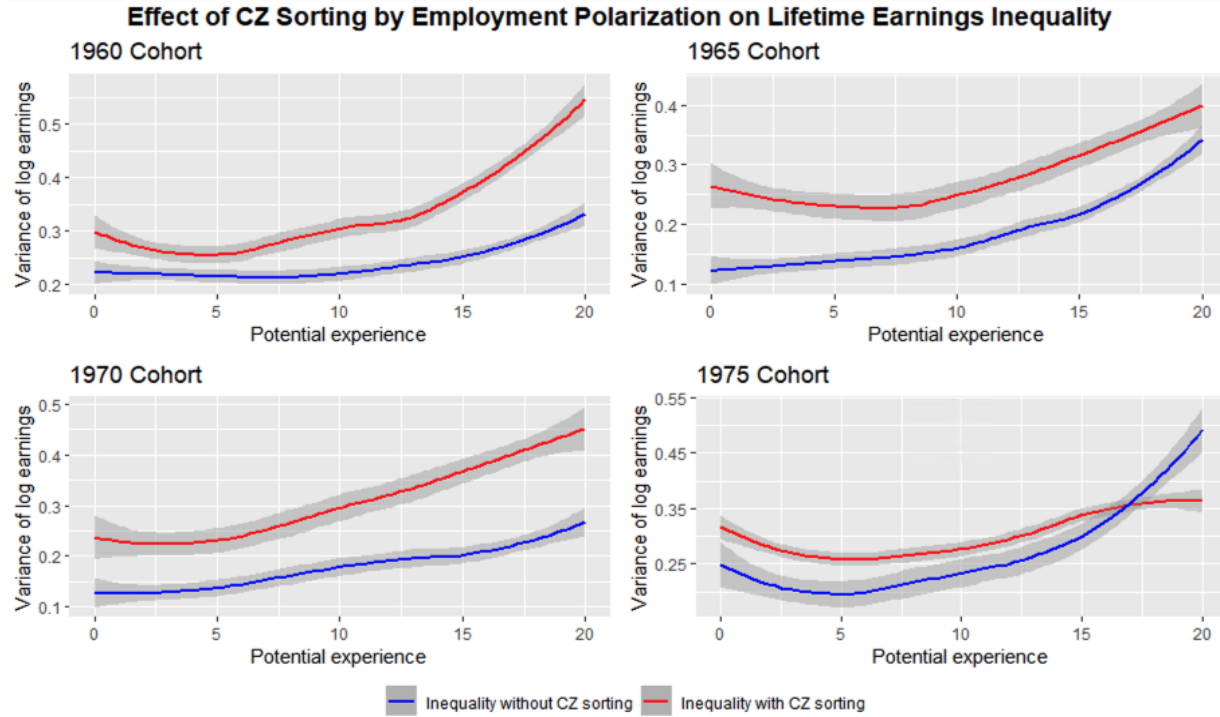
Hypothesis 6 predicts that polarization has a stronger effect on inequality in earnings trajectories in more recent cohorts. I do not find evidence in support of this hypothesis. The relationship between polarization and workers' earnings trajectories is consistent between the 1960, 1970, and 1975 birth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

Figure 2.6. Observed and counterfactual lifecycle earnings inequality
Effect of CZ Sorting by Earnings Polarization on Lifetime Earnings Inequality





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.

Chapter 3: Moving Between the Ranks: The Determinants of Relative Earnings Mobility Over the Career and Change Between Cohorts

Introduction

Scholars of mobility and stratification have long been interested in characterizing the relative “openness” or equality of opportunity in a society by examining how individuals differ in their chances of attaining positions in a system of stratification (Sorokin 1927). Historically, most mobility research has considered economic opportunity through an intergenerational lens and investigated the strength of the association between parents and their children’s economic status (e.g. Coleman 1966; Blau and Duncan 1967; Sewell and Hauser 1975; Hout 1988; Erikson and Goldthorpe 1992; Breen and Jonsson 2005; Torche 2015). Recently, however, there has been renewed interest in investigating intragenerational mobility over the career (e.g. Tomaskovic-Devey, Thomas, and Johnson 2005; Fuller 2008; Cheng 2014, 2021; Yaish et al. 2021; Berman 2022). This work follows from the observation that earnings attainment is fundamentally a change process (Sørensen 1975) – pay raises, promotions, and job changes all cause meaningful variation in a worker’s earnings over the course of their career. Inequality in how workers experience these labor market processes produces variation in both the level of stratification among workers and in workers’ position within the stratification system as they progress through their careers. Developing a full understanding of social fluidity or economic opportunity in a society therefore requires examining patterns of how labor market processes shape individuals’ opportunities for earnings attainment over the career.

Most of the research on intragenerational earnings mobility has focused on absolute mobility, or how individuals’ earnings in real dollars change over time (e.g. Loprest 1992; Keith and McWilliams 1997; Tomaskovic-Devey et al. 2005; Fuller 2008; Cheng 2014, 2021; Maume and Wilson 2015; Cheng and Song 2019; Doren and Lin 2019; Yaish et al. 2021; Berman 2022). Absolute mobility is clearly an essential element of stratification because it describes the real income dynamics that directly affect inequality in consumption and savings. But analyses of earnings mobility conducted in real dollars cannot distinguish between earnings mobility due to changes in the shape of the earnings distribution (e.g., rising inequality or rising earnings levels) and mobility due to individuals changing positions in the distribution relative to one another. This distinction is akin to the difference between occupational mobility due to changes to the occupational structure versus changes to mobility rates between occupations (Featherman, Jones, and Hauser 1975; Hauser 1978; Goodman 1979; Logan 1983; Sobel 1983; Erikson and Goldthorpe 1992; Breen 1994). Similar to analyses of occupational mobility, “relative” mobility between positions or ranks in the earnings distribution describes how individuals get ahead of or fall behind one another in economic rank and can be interpreted as an indicator of social fluidity or the openness of the economic stratification system within the labor market.

While recent analyses of absolute earnings mobility over the career have revealed much about how career and life course dynamics give rise to inequality, relative mobility between positions in the earnings distribution remains less well understood. I address three basic sociological questions surrounding relative earnings mobility: 1) how do individuals’ early-career earnings shape their opportunity for mobility into different positions in the earnings distribution later in their career? 2) how well do prominent theories of earnings attainment identify the “‘holes,’ ‘staircases,’ ‘elevators,’ and ‘channels’” (Sorokin 1927: 164) through which mobility between earnings ranks occurs? and 3) how have historical changes in the economic and institutional forces that structure mobility in the labor market reshaped patterns of

relative mobility over the last half century? Surprisingly little work attempts to assess how well different theories of the labor market can explain intragenerational relative earnings mobility (but see Schiller 1977). Instead, the literature has remained largely atheoretical and focused on describing mobility patterns and historical trends but taken less interest in identifying the mechanisms that underlie movement between positions in the earnings distribution.

I examine the mechanisms that drive mobility between positions in the earnings distribution over the career and how they have changed across cohorts using conditional quantile regressions (CQRs). This new approach to the empirical analysis of relative earnings mobility accounts for three properties of mobility not fully captured by the two methods typically employed in previous studies – the descriptive analysis of transition matrices and ordinary least squares (OLS) regressions of rank earnings on past rank earnings. These properties are: 1) *mobility opportunity*, which describes the full distribution of earnings rank outcomes that individuals may attain (rather than just the average outcomes), 2) *rank-dependence*, or the extent to which the distribution of ranks that individuals may attain in their career depends on their initial earnings rank, and 3) inequality in mobility patterns due to *selection* into early-career earnings levels and due to *career processes* that link early- and mid-career earnings.

While some recent work has examined rank-dependence at the mean in a regression framework (e.g. Bradbury 2018; Carr and Wiemers 2022), this paper is the first to the author's knowledge to examine rank dependence across the full distribution of rank mobility outcomes and characterize variation in mobility opportunity while distinguishing between selection effects and career processes. I use regression adjustment with covariates and instrumental variables to assess the extent to which patterns of relative earnings mobility can be attributed selection into positions in the early-career earnings distribution versus by processes within the labor market. I then decompose between-cohort differences in relative earnings into components due to changes in the labor force and changes in the structural association between early- and mid-career earnings.

Using data from the Panel Study of Income Dynamics (PSID), I demonstrate that the median earnings rank workers attain at age 45 is highly dependent on their earnings rank at age 25, while the lowest and highest earnings rank outcomes are somewhat less dependent on early-career earnings. Much of this association is explained by selection into early-career earnings ranks by gender and education and by the unequal accumulation of valuable work experience and mobility between jobs among low- and high-earners. Female and non-college-educated workers experience limited upward mobility from low ranks and more severe downward mobility from high ranks, while the accumulation of labor market experience and firm tenure primarily protects high earners from downward mobility. Frequently changing employers both reduces upward mobility for low earners and increases downward mobility for high earners, and these effects are amplified when job changes occur within the service sector. After accounting for selection into early-career earnings ranks using IVs, I find that there remains a strong association between early-career earnings and mid-career earnings ranks primarily due to highly compressed mobility from the upper and lower tails of the earnings distribution. Analyses of changes in relative mobility patterns between cohorts reveal marked stability over time. However, I find evidence that in recent cohorts, greater downward mobility from high early-career earnings ranks is largely due to the growing proportion of women among high earners and high earners' diminishing advantage in accumulating general and specific human capital. Apparent stability in the relationship between early-career earnings and upper-tail earnings rank outcomes is

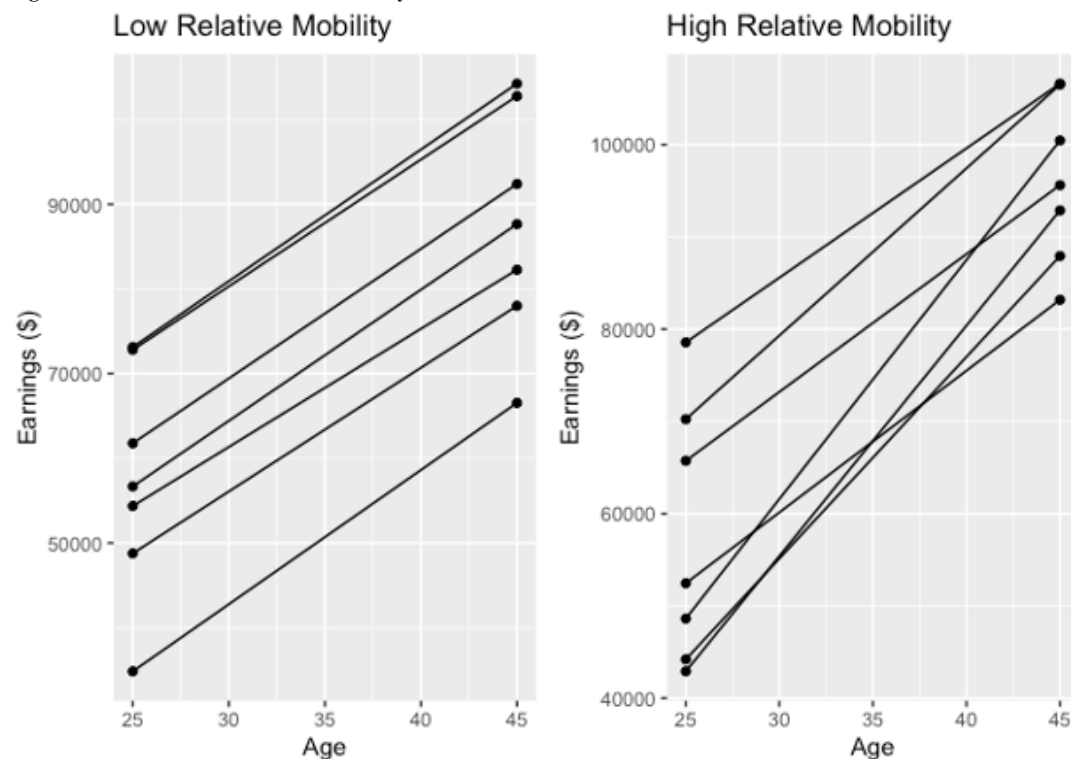
undergirded by a simultaneous rise in educational attainment across the earnings distribution and increase in mobility returns to higher education.

Relative Earnings Mobility and Labor Market Opportunity

Research on intragenerational earnings mobility is broadly concerned with how individuals' earnings change over their careers. Most research on intragenerational earnings mobility examines how individuals' earnings trajectories vary due to differences in their exposure to labor market processes such as pay raises, promotions, job changes, and the accumulation of skills and experience, as well as life course events like marriage, childbearing, incarceration, and personal injury (Granovetter 1974; Sørensen 1975, 1977; Spilerman 1977; Abbott 1983; Elder 1985; Dannefer 1987; Huber 1990; Rosenfeld 1992; Mayer 2004, 2009; Western et al. 2012b). Heterogeneity in earnings growth causes inequality within cohorts to grow substantially as workers progress through their careers and tends to exacerbate inequalities by educational attainment, gender, race, parental status, and other major dimensions of stratification (Ryder 1965; Borjas 1981; Riley 1987; Loprest 1992; Keith and McWilliams 1997; Alon and Tienda 2005; Tomaskovic-Devey et al. 2005; Lemieux 2006b; Fuller 2008; Kopczuk et al. 2010; Miller 2011; Cheng 2014; Maume and Wilson 2015; Doren and Lin 2019; Cheng 2021; Berman 2022).

While research on earnings trajectories has considerably deepened our understanding of how earnings inequalities unfold over the career, it remains less well understood how such variation in earnings trajectories might correspond to change or stability in individuals' standing relative to one another as they progress in their careers. Labor markets with the same level of absolute mobility may have very different levels of relative mobility (see Figure 3.1). In labor markets with low relative mobility, those who begin their careers at the top of the earnings distribution remain near the top as they age and those who earn comparably little remain near the bottom. Such immobility is possible even if all workers experience absolute earnings growth, so long as growth among low earners does not sufficiently outpace growth among high earners. Labor markets with high relative mobility will exhibit many "crossovers" (Mincer 1974; Schiller 1977) where individuals move ahead of or fall behind other workers over the course of their careers.

Figure 3.1. Absolute versus relative mobility



Analyses of the association between absolute earnings levels measured over time cannot distinguish between these regimes of earnings mobility because this association is affected by both relative mobility between positions in the earnings distribution and by changes in the shape of the earnings distribution (Chetty, Hendren, Kline, and Saez 2014; Chetty, Hendren, Kline, Saez, et al. 2014; DiPrete 2020). In analyses of earnings mobility that do not account for changing levels of earnings or earnings inequality, it is unclear whether the association between earnings levels at different points in the career is driven by changes in the earnings distribution or changes in individuals' position in the distribution.

Analyses of mobility between earnings ranks isolate relative mobility from changes in the shape of the earnings distribution. Standardizing earnings into percentile ranks allows analysts to compare patterns of earnings mobility over time and across contexts. Relative earnings mobility captures the extent to which individuals' economic status relative to others in the labor market is systematically reproduced over the course of their careers by describing the extent to which individuals tend to maintain their rank in the earnings distribution over their careers. Relative mobility reflects social fluidity, equality of opportunity, or competition for positions in the social structure by describing how an individual's economic position changes over time (Erikson and Goldthorpe 1992; Goldthorpe 2007; Brown 2013). Examining relative earnings mobility reveals the opportunity for individuals to change their economic status over their careers and provides an avenue to test theories of mechanisms that may enhance or diminish the rigidity of stratification within the labor market.

Although relative earnings mobility has received little empirical attention, evidence from prior studies suggests the relationship between average early- and mid-career earnings ranks is both strong and intensifying over time. Estimates of the correlation between workers' earnings

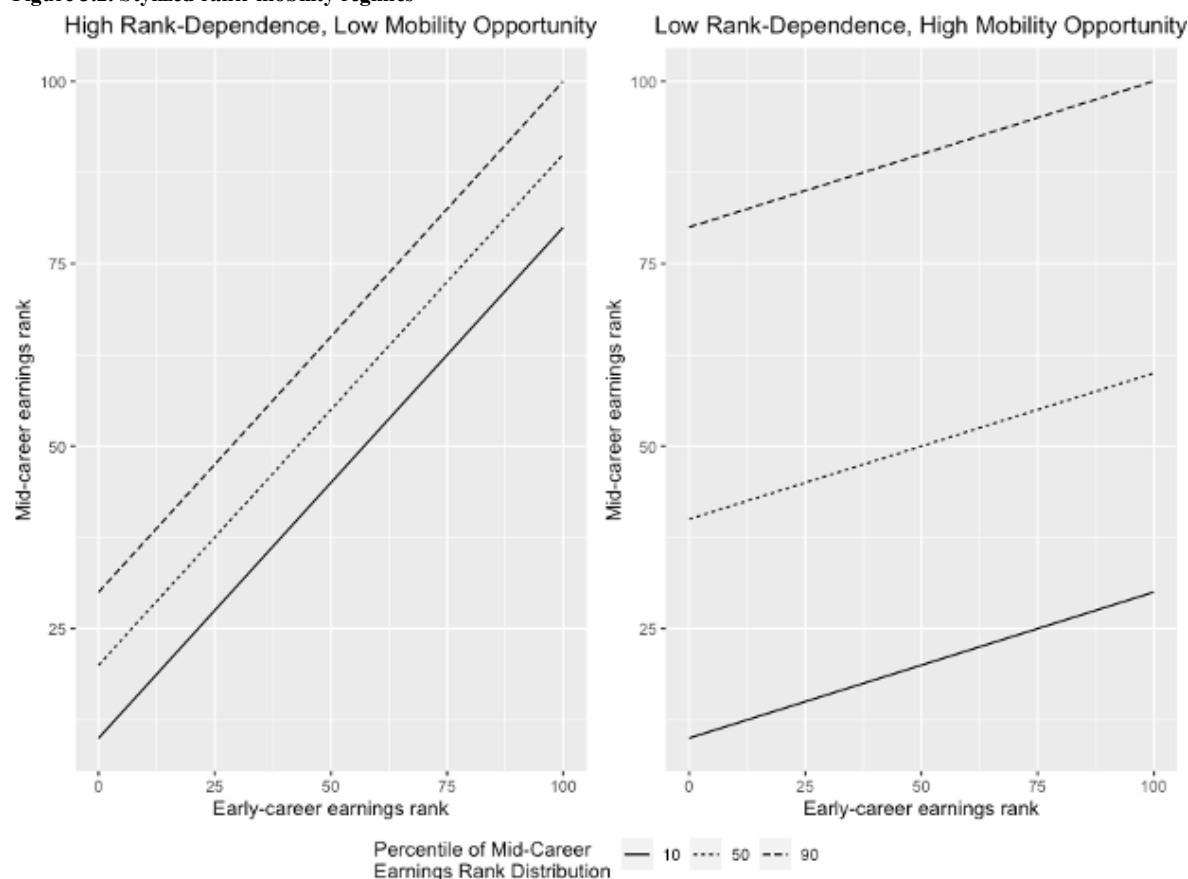
ranks measured a decade or more apart tend to fall around 0.65, roughly double the typical estimate of intergenerational rank-rank correlation (Chetty, Hendren, Kline, Saez, et al. 2014; Gregg et al. 2017; Carr and Wiemers 2022). Earnings rankings are especially sticky at the top and the bottom of the earnings distribution. Around 60 percent of individuals who start in the top or bottom earnings quintile remain in that quintile later in their careers, compared to roughly 35 percent of workers who remain immobile from the 2nd through 4th quintiles (Acs and Zimmerman 2008; Auten and Gee 2009; Bradbury and Katz 2009; Carr and Wiemers 2022). Historical trends in relative earnings mobility are less clear. While some studies find no change over time in persistence within earnings quintiles (Acs and Zimmerman 2008; Auten and Gee 2009), others show rising stickiness at the tails of the earnings distribution (Carr and Wiemers 2022).

The Changing Opportunity Structure for Mobility: Mechanisms and Consequences

Earnings attainment over the career is determined through the interaction of individual workers and firms in the labor market, where workers' opportunity for mobility depends on the set of available jobs and on workers' ability to mobilize their individual resources in competition to fill those jobs (Sørensen 1975, 1977). Over the last 40 years, both the resources held by workers and the sets of jobs available to them have changed considerably. The composition of the labor force changed substantially as more women and nonwhite workers entered the labor market and workers' educational attainment significantly increased. At the same time, employment relations shifted away from stable, long-term, and full-time employment towards weaker attachments between firms and employees and more part-time and contingent labor, and the occupational structure became more polarized between high- and low-earning occupations.

How have these major economic transformations affected relative earnings mobility? While some research has found that relative earnings mobility declined in recent decades and in more recent cohorts (Bradbury and Katz 2009; Bradbury 2018; Carr and Wiemers 2022), little of this work investigates the mechanisms driving observed mobility patterns or how the role of those mechanisms has changed over time. Moreover, prior research has not examined whether the association between earnings ranks over workers' careers is driven by *selection* where individuals with high-demand skills or traits command higher earnings at both the beginning and middle of their careers versus *career processes* within the labor market that create a structural connection between past and future earnings. Without distinguishing between relative mobility due to selection versus career processes, it is not clear whether high earnings rank correlations and decreasing mobility should be interpreted as changes in how workers are sorted into starting positions at the beginning of their careers versus inequality in economic opportunity for workers at different parts of the earnings distribution.

Figure 3.2. Stylized rank-mobility regimes



In what follows, I consider how four prominent explanations of labor market mobility – race and gender discrimination, worker-firm matching, human capital investment, and job mobility – may contribute to relative earnings mobility through selection and career processes and how economic restructuring in recent decades may have changed the role of each mechanism in shaping mobility. I develop hypotheses about two components of relative earnings mobility (see Figure 3.2). The first is *mobility opportunity*. Mobility opportunity describes the range of earnings ranks that workers may attain by the middle of their career conditional on the rank where they enter the labor market. The second component is *rank-dependence*, which describes the association between workers' early- and mid-career earnings rank. While mobility opportunity describes the distribution of outcomes for workers of the same rank, rank-dependence describes inequality in mobility opportunity for workers of different starting ranks. Rank-dependence may vary over the distribution of mid-career earnings ranks. For example, median mid-career earnings may be strongly tied to early-career earnings but the top outcomes for workers of all levels of early-career earnings could be more similar.

Race and gender discrimination

Race and gender discrimination may affect earnings mobility through both selection effects and career processes. Discrimination may create a spurious link between early- and mid-career earnings where we observe relatively low rates of upward earnings mobility not due to a lack of pathways through which low earners can increase their earnings, but rather because low earners are disproportionately nonwhite and female, and these workers have lower earnings on average

than otherwise similar white and male workers (Neal and Johnson 1996a; Grodsky and Pager 2001; Carneiro, Heckman, and Masterov 2005; Lang and Lehmann 2012; Fryer, Pager, and Spenkuch 2013). Racial and gender discrimination may also moderate the relationship between early- and mid-career earnings through discriminatory career processes. Discrimination within the labor market accumulates over the career to flatten the earnings trajectories of marginalized workers (Tomaskovic-Devey et al. 2005). Upward mobility within firms is limited for women and nonwhite workers because they often allocated to lower paying jobs, promoted at lower rates, and evaluated less favorably than their colleagues (Greenhaus, Parasuraman, and Wormley 1990; Greenhaus and Parasuraman 1993; Landau 1995; Petersen and Morgan 1995; Baldi and McBrier 1997; Maume 1999; Cotter et al. 2001; Elvira and Town 2001; Petersen and Saporta 2004; Tomaskovic-Devey et al. 2006; Heilman 2012). Nonwhite and female workers also tend to realize smaller earnings gains from changing jobs than their white male counterparts (Bartel 1980; Ruhm 1987; Alon and Tienda 2005; Pearlman 2018) and are at greater risk of downward mobility from high-earning occupations (Gabriel 2003; McBrier and Wilson 2004; Wilson and Roscigno 2010; Wilson, Roscigno, and Huffman 2013).

Together, these dynamics suggest that some of the association between early- and mid-career rank earnings may be explained by selection on race and gender into earnings ranks. To the extent that nonwhite and female workers are disproportionately represented at the bottom of the early-career earnings distribution, racial and gender earnings inequalities may spuriously suppress upper tail earnings and further diminish lower-tail earnings, resulting in upwardly biased estimates of rank-dependence upper-tail rank earnings and downwardly biasing estimates of rank-dependence in lower-tail rank earnings. If discrimination within the labor market also disproportionately constrains nonwhite and female workers' chances of changing earnings ranks, we should observe that nonwhite and female workers are less likely than white and male workers to climb earnings ranks from low positions in the earnings distribution and are more likely to fall from high positions in the earnings distribution.

It is possible that the effect of gender on relative earnings mobility has declined in recent cohorts. Women are now more likely to occupy the same economic positions as men than in the past. Labor force participation among women has risen (Bureau of Labor Statistics 2021) and the gender pay gap has decreased since 1970, in part due to women's increased educational and occupational attainment (Blau, Brummund, and Liu 2013; DiPrete and Buchmann 2013; Mandel and Semyonov 2014), perhaps improving women's mobility opportunity. However, it is possible that occupational integration may lead to higher rates of downward mobility from the top of the earnings distribution simply because more women begin their careers towards the top in recent cohorts and highly paid women experience especially large penalties to motherhood (England et al. 2016).

The effect of race has likely either remained the same or grown over time. Educational attainment in the Black population is rising but not at the same rate as among whites (McDaniel et al. 2011; Nichols 2013; National Center for Education Statistics 2022). Racial segregation between occupations has been fairly stagnant since 1980 (Tomaskovic-Devey et al. 2006; Stainback and Tomaskovic-Devey 2012; Mandel and Semyonov 2016), the Black-white earnings gap has held steady among men and grown among women (Mandel and Semyonov 2016), and racial discrimination in hiring has remained fairly stable (Quillian et al. 2017). As changing jobs and employers has become an increasingly important avenue for increasing earnings in recent decades, the race gap in earnings returns to job changes has grown among college graduates (Kronberg 2014). Altogether, this suggests that both selection into lower early-career earnings

and unequal opportunity to change earnings ranks by race may have either stagnated or grown in the last 40 years.

Matching on human capital

Another mechanism that may underlie the relationship between early- and mid-career earnings is the matching of highly productive workers to high-paying jobs. Rooted in human capital theory, matching models of the labor market suggest that a high rank-rank correlation in earnings over the career may persist due to a selection effect where labor markets efficiently sort workers into jobs through a joint-optimization process where firms seek to hire workers with the highest expected productivity and workers maximize earnings. In pure matching models, skills and productivity are stable and mobility occurs when workers and employers learn new information about the quality of their current match (Jovanovic 1979b; Wilde 1979; Farber and Gibbons 1996; Altonji and Pierret 2001) or alternative prospects (Mortensen 1978; Jovanovic 1979a, 1984; Pissarides 1994). The matching model is also broadly consistent with sociological theories of status attainment where individual characteristics like family background, education, and social and cultural capital are converted into career paths (Blau and Duncan 1967; Sewell and Hauser 1975; Kalleberg and Mouw 2018b).

While productivity is difficult to observe, education is thought to increase workers' productivity and may also be interpreted as a signal of expected productivity by employers (Schultz 1961; Becker 1962; Spence 1973; Kerckhoff, Raudenbush, and Glennie 2001). Pure matching on education predicts that college-educated workers should have relatively high earnings at the beginning and the middle of their careers compared to non-college-educated workers because they are more productive. Under a matching model, the disproportionate sorting of college-educated workers into high earnings ranks early in the career creates a spurious association between early- and mid-career earnings due to differences in productivity between low- and high-earners early in the career. Controlling for education should therefore reduce rank-dependence and increase mobility opportunity.

Productivity may also moderate the relationship between early- and mid-career earnings. Because skills are assumed to be stable in pure matching models, resorting will occur when highly productive workers are under-placed at the beginning of their careers and less productive workers are over-placed. This re-sorting provides high-skill workers with greater opportunities for upward mobility. Thus, we should expect that holding a college degree increases mobility opportunity and decreases rank dependence, particularly for those at the bottom of the rank earnings distribution.

The effects of education on relative earnings mobility have likely grown over time. Skill-biased technological change complemented high-skill workers and substituted for routine labor that was characteristic of formerly well-paying blue-collar jobs in sectors like manufacturing (Autor et al. 2003; Acemoglu and Autor 2011), contributing to rising inequality in earnings and earnings growth by increasing the premium on education (Lemieux 2006b, 2008; Cheng 2021). Rising demand for labor in both technical and professional jobs and in service jobs and diminished demand in the middle of the occupational distribution (Autor et al. 2006, 2008; Autor and Dorn 2013) led to rising inequality in the occupational and earnings trajectories for workers with different levels of education (Altonji, Kahn, and Speer 2014; Cheng and Park 2020; Lin and Hung 2022). Growing inequalities in earnings and occupational trajectories between those with and without college degrees or highly desirable skills suggest that selection on education and

career processes that differentiate mobility patterns by education may have a stronger effect in recent cohorts.

Human capital investment

Career mobility patterns and their variation over time may also be driven by changes in how firms and workers invest in human capital over the career. A vast literature has shown that earnings increase substantially as workers accumulate skills and experience in the labor market, although there is some disagreement over the extent to which earnings growth is driven by the accumulation of generic, transferable skills or investment in human capital that is specific to jobs, firms, occupations, or industries (Mincer 1974, 1988, 1997; Hashimoto 1981; Altonji and Shakotko 1987; Neal 1995; Gibbons and Waldman 2004; Shaw and Lazear 2008; Sullivan 2010; Pavan 2011). Empirical evidence suggests that in general, investment in and returns to occupation-specific skill are especially high in primary-segment occupations such as managers, professionals, and craft workers and much lower among occupations in the secondary labor market like laborers and service workers (Shaw 1984, 1987; Gibbons and Waldman 2004; Kambourov and Manovskii 2009; Sullivan 2010). Because primary segment jobs tend to also have higher pay, it is possible that the relationship between early- and mid-career earnings ranks is mediated by the accumulation of general labor market experience or tenure within a given employer or occupation. Accumulating general or specific skills may also provide workers with greater opportunity for mobility from a given position in the earnings distribution.

The decline of long-term employment relations likely diminished the importance of firm-specific tenure and increased the importance of occupation-specific and general experience in shaping mobility. Through the 1970s, firms relied on internal labor markets (ILMs) that institutionalized pathways for upward intragenerational mobility through a combination of well-defined career ladders, wages that were tied to workers' job titles rather than their individual marginal product, investment in workers' skill development, and insulation from competition from workers outside the firm (Doeringer and Piore 1971; Kalleberg and Sorensen 1979; Kalleberg 1988; Althauser 1989; Osterman 1999). Long-term employment incentivized firms and workers to jointly invest in firm-specific skills, and firms ensured they could retain employees to capture returns on that investment by adopting deferred compensation schemes that paid employees below their marginal product early on and above their marginal product towards the end of their career (Kalleberg and Sørensen 1979; Lazear 1979; Medoff and Abraham 1980; Akerlof and Yellen 1986; Spilerman 1986; Baker, Gibbs, and Holmstrom 1994). But starting in the 1980s, models of production became less firm-specific and firms' demand for high-level general cognitive skills increased (DiPrete et al. 2002). At the same time, shareholders demanded that firms reduce labor costs (Fligstein 1993, 2001; Useem 1993; Uchitelle 2006; Fligstein and Shin 2007). Firms responded by moving away from ILMs in favor of external employment strategies, leading to a decline in firm-specific tenure and rise in nonstandard work arrangements (Kalleberg 2009; Farber 2010). As a result, returns to firm-specific tenure declined while returns to general experience grew, particularly for the highly educated (Marcotte 1998; Cappelli 2001; DiPrete et al. 2002; Altonji and Williams 2005). We may therefore expect that the positive effects on mobility opportunity and tempering effects on rank-dependence due to firm-specific tenure have declined while those effects from the accumulation of occupation-specific and general experience may have increased.

Job mobility

Changes in production and the organization of firms have also reshaped the occupational structure and how workers move between jobs. Skill-biased technological change has increased demand at the top and bottom of the occupational distribution while hollowing out the middle and also substantially increased wage inequality between occupations (Autor et al. 2006, 2008; Mouw and Kalleberg 2010b; Acemoglu and Autor 2011; Autor and Dorn 2013). In turn, patterns of occupational mobility have become increasingly rigid and access to career lines that promote earnings growth has become more restricted (Cheng and Park 2020; Lin and Hung 2022). Workers at the bottom of the occupational structure became increasingly mobile between occupations, but such mobility is largely to other low-skill occupations (Kim 2013; Jarvis and Song 2017; Cheng and Park 2020). As such, we may expect to see a growing divergence in the returns to job changes, where job changes in high-paying occupations increase mobility opportunity and decrease rank dependence while job changes in low-paying occupations constrain mobility and increase rank dependence.

Summary of hypotheses

Observed patterns of relative earnings mobility are expected to be explained partially through selection. Workers who are female, nonwhite, and do not have a college degree are expected to have relatively low earnings at any point in their career. Their disproportionate selection into the bottom of the rank earnings distribution early in the career likely creates a spurious association between early- and mid-career rank earnings that corresponds to high rank-dependence in the upper quantiles of their conditional earnings and low rank-dependence in the bottom quantiles. Race, gender, and education are also expected to moderate the relationship between early- and mid-career rank earnings. White, male, and college-educated workers are expected to experience greater upward mobility from the bottom of the rank earnings distribution and less downward mobility from the top. Gender is expected to have a greater effect on earnings mobility in older cohorts than in younger cohorts, although occupational integration by gender may offset this change. Race is not expected to change in its explanatory power. Education is expected to increase in its explanatory power.

I have also proposed some career processes through which relative earnings mobility unfolds. The accumulation of firm- and occupation-specific capital as well as general experience is expected to increase mobility opportunity and decrease rank dependence. The relative importance of firm-specific tenure is expected to decline with younger cohorts while the effect of occupation-specific and general work experience is expected to increase. Job changes in high-end occupations are expected to increase mobility opportunity and decrease rank dependence while the opposite is expected for job changes in low-end occupations. Job changes are expected to increase in importance in younger cohorts.

Data and Variables

Panel Study of Income Dynamics

Career earnings mobility is modeled using data from the Panel Study of Income Dynamics (PSID). The PSID is a longitudinal panel survey that began collecting data in 1968 from a sample of about 4,800 US households comprised of about 18,000 individuals. As household members aged and formed their own families, the total sample grew to about 80,000 individuals. PSID respondents were surveyed yearly from 1968 to 1997 and biennially since. The PSID collects information from surveys of a reference person (formerly “head of household”). The reference person is defined as the adult household member with the most financial responsibility

in the family unit. If this person is female and she has a male spouse or partner, he is designated as the reference person. The PSID collects detailed data from reference persons on their and their spouse's income and employment, as well as demographic, health, family, and other social and economic data.

Sample selection

This study models long-term relative earnings mobility between the beginning of respondents' career and their prime-earning years. The sample is restricted to reference persons and spouse/partners from the core PSID sample who are at least 45 years old by their most recent interview, have positive earnings for some years between ages 22 and 28 as well as between ages 42 and 48. Persons with missing data on analytic variables are dropped from the sample. The sample is also restricted to Black and white respondents due to small sample sizes among respondents of other races and ethnicities that result in prohibitively low statistical power to test differences between races or ethnicities. Longitudinal weights are used to account for attrition. The final analytical sample contains observations from 3,250 PSID respondents.

Variables

Respondents are divided into 10-year *birth cohorts* starting in 1940, 1950, 1960, and 1970. *Earnings* are measured yearly using respondents' total labor income including wages, bonuses, overtime, commissions, professional practice, and the labor part of business income. Earnings are adjusted for inflation to year-2000 dollars. To capture changes in long-term earnings and reduce noise from year-to-year fluctuations, *early-career* and *mid-career* earnings are measured using seven-year averages of earnings centered at age 25 and age 45, respectively. Early- and mid-career *earnings ranks* are determined by ranking individuals in a given year according to their earnings and then translating these ranks into percentiles. These earnings ranks represent individuals' position in the earnings distribution.

Respondents' *labor market experience* is the number of years a respondent has worked for pay. Experience is only recorded when the household's head or spouse changes. I impute labor market experience based on the number of years a respondent worked for pay between an interview year and the year in which their labor market experience was recorded. *Employer tenure* records the number of years a respondent has worked for their employer. When employer tenure is missing, I back-fill employer tenure using the most recent non-missing record minus the time between interviews if an individual's detailed industry code has not changed between the two records and the imputed value of tenure is positive.

Occupation is coded using a balanced panel of occupational codes developed by Autor and Dorn (2013). One-digit occupation codes describe the general category of respondents' occupations, and three-digit codes describe detailed occupations. *Occupational experience* reflects how many years through age 45 a respondent worked in a specific occupation. *Occupation change* reflects changes in occupation between interview rounds. Employers are not directly identified in the PSID. Following Brown and Light's (1992) recommendation, I infer an *employer change* when reported tenure is less than the time elapsed between interviews. In cases of missing tenure data, employer changes are inferred using industry changes between interviews.

Black is an indicator variable that takes on 0 if the respondent is white and 1 if the respondent is Black. *Female* is coded 0 for male and 1 for female. *College* indicates if the respondent has obtained a college degree. Fathers' occupations are coded using 1-digit

occupation codes based on the 1970 Census occupational coding scheme. Early-career exposure to a *recession* is coded 1 if a respondent worked between ages 22 and 28 during an economic recession.

Analytical Approach

Methodological limitations of prior research

Studies of relative earnings mobility typically rank individuals according to their earnings and then describe relative mobility either by analyzing transition matrices between earnings rank quantiles (e.g. 1st to 25th percentile) or by conducting a regression of destination rank on origin rank and interpreting the slope coefficient on origin rank as an estimate of rank mobility. In the transition matrix approach, analysts estimate the probability of attaining a destination position conditional on starting position and examine how the relative chances of attaining different earnings quantiles differ between starting positions. The main advantage to this approach is that it allows analysts to describe the full distribution of destinations conditional on starting rank. But the transition matrix approach has two key shortcomings. First, information is lost by collapsing continuous earnings ranks into categorical measures to define the rows and columns of the transition matrix. Second, the intragenerational relative earnings mobility literature typically uses this approach for descriptive analysis and does not quantitatively assess the factors that contribute to variation in mobility.

Researchers interested in analyzing the mechanisms that drive earnings mobility often opt to use OLS regressions to model the conditional mean of destination earnings rank, earnings quantile, or change in earnings rank, as a function of origin earnings position as well as demographic, life course, and labor market factors (Auten and Gee 2009; Bradbury 2018; Carr and Wiemers 2022). This approach is analogous to the rank-rank analysis of intergenerational mobility⁶ (e.g. Chetty, Hendren, Kline, and Saez 2014; Chetty, Hendren, Kline, Saez, et al. 2014). Analysts interpret the coefficient on origin rank as a measure of mobility, with larger coefficients indicating lower mobility. While the regression approach allows for the estimation of rank mobility net of control variables, it only allows researchers to model *mean* destination earnings ranks conditional on initial earnings and other factors, rather than describe the distribution of expected outcomes for individuals who start their career at a given earnings rank or describe how that distribution varies across early-career earnings ranks or population subgroups.

Modeling mobility using conditional quantile regression

I suggest that analyses of intragenerational relative earnings mobility should incorporate three desirable properties. First, they should quantitatively describe the strength of the association between origin and destination positions in the earnings distribution (rank-dependence). Second, they should capture the range of destination positions in the earnings distribution and the chances of attaining those positions given a starting rank (mobility opportunity). Third, analyses should allow for statistical inference that distinguishes between selection into early-career earnings ranks (due to education, demographics, etc.) and differences in mobility opportunities afforded to

⁶ Alternatively, many analyses of intergenerational mobility examine the intergenerational earnings elasticity (IGE) by regressing the log earnings of adults on the log earnings of their parents. While the IGE is affected by relative mobility, it is not a strict measure of relative mobility because it is influenced both by changes in the shape of the income distribution and mobility between positions in the income distribution (Goldthorpe 2013; Chetty, Hendren, Kline, and Saez 2014; Chetty, Hendren, Kline, Saez, et al. 2014; DiPrete 2020).

otherwise similar individuals who start their careers at different earnings ranks. The analysis of transition matrices as employed in the intragenerational relative earnings mobility literature meets the first and second criteria, and the rank-rank regression approach meets the first and third.

Conditional quantile regression (CQR) models of mobility can meet all three criteria. CQRs estimate the expected change in a given quantile of the outcome distribution associated with a one-unit change in a predictor variable for respondents with otherwise equal values for other covariates (Koenker and Bassett 1978; Koenker and Hallock 2001; Rios-Avila and Maroto 2022). For example, in this setting, CQRs can be used to answer the question: “what is the expected difference in men and women’s median mid-career earnings rank, conditional on starting their career in the 90th percentile of the early-career earnings rank distribution?”

The CQR models in this paper are specified as:

$$Q_{\tau}(\text{logit}(Y_{it=45}/100)|X, Y_{it=25}, V_i) = \beta_0(\tau) + \beta_1(\tau)Y_{it=25} + \beta_3(\tau)X_i + \beta_4(\tau)Y_{it=25} \times X_i + \gamma(\tau)V_i + \epsilon_i \quad (6)$$

Where $Y_{it=45}$ represents the respondent’s rank in earnings averaged over seven years at age 45 and $Y_{it=25}$ represents their rank at age 25. The logit transformation is used on rank earnings at age 45 to accurately model a dependent variable that is bounded between 0 and 100. X_i represents covariates used to test how mobility may vary according to traits such as gender or education. Interactions between $Y_{it=25}$ and X_i allow us to observe how these covariates differentially affect mobility from different ranks in the early-career earnings distribution. V_i represents additional controls that can be incorporated into the model. $Q_{\tau}(\text{logit}(Y_{it=45}/100)|X, V_i, Y_{it=25})$ is a quantile function representing the logit of mid-career earnings ranks above $\tau\%$ of all observations with the same early-career earnings rank and values on other covariates. The slope on $Y_{it=25}$ ($\beta_1(\tau)$) reflects the rank-dependence of a given quantile of the mid-career earnings rank distribution (e.g. how much median logit mid-career earnings rank changes with early-career earnings rank). The coefficients $\beta(\tau)$ vary between quantiles, allowing us to observe heterogeneous effects of predictor variables on different quantiles of the mid-career logit earnings rank distribution. Since the coefficients $\beta(\tau)$ describe effects on the logit scale, I estimate and report average marginal effects of each predictor variable on the original 0 to 100 rank earnings scale (Williams 2012).

I use predicted values from the CQRs to describe the full conditional distribution of mid-career earnings ranks conditional on early-career earnings and other covariates. This distribution is interpreted as the mobility opportunity for individuals with a given early-career earnings rank and set of values on additional covariates. I also characterize mobility opportunity using the interquartile range (75th percentile - 25th percentile; IQR) of predicted earnings ranks at age 45. I use OLS to model how the IQR of predicted earnings ranks at age 45 varies with earnings rank at age 25 and its square:

$$\hat{Q}_{75} - \hat{Q}_{25} = \beta_0 + \beta_1 Y_{it=25} + \beta_2 Y_{it=25}^2 + \epsilon_i \quad (7)$$

Examination of the IQRs of predicted mid-career earnings ranks suggests that the relationship between early-career earnings ranks and the IQRs is well approximated by a quadratic function. Together, the coefficients β_1 and β_2 describe how the predicted IQR may increase, level off, or decrease with early-career rank.

Testing hypotheses with regression adjustment and instrumental variables in CQRs

I use CQRs to test hypotheses about rank dependence and mobility opportunity in the relationship between early- and mid-career earnings ranks. First, I use a CQR with early-career earnings rank as the independent variable to examine unadjusted patterns of earnings rank mobility over the career. Then, I consider how much of the relationship between early- and mid-career earnings remains after adjusting for selection on education, race, and gender. I examine how the coefficient on early-career rank earnings is further attenuated by including mediating career processes represented by variables such as work experience and job mobility. I then use an instrumental variables (IV) approach to account for selection into early-career earnings ranks on both observable and unobservable characteristics such as skill, access to professional networks, or affability. I instrument early-career earnings with indicators for whether a recession occurred while a worker was employed from ages 22 to 28 and father's occupation. Appendix A discusses the validity of these instruments in greater detail.

Next, I test how race, gender, education, the accumulation of general work experience, firm-specific tenure, occupation-specific experience, and job mobility may moderate the relationship between early- and mid-career earnings ranks. I use CQRs where early-career earnings rank is interacted with each moderator to examine how the distribution of mobility outcomes varies between groups and how that variation changes depending on where they start their career in the earnings distribution.

Finally, I use a semiparametric decomposition method developed by DiNardo, Fortin, and Lemieux (DFL) (1996) to examine between-cohort differences in rank mobility. The DFL decomposition is a counterfactual weighting procedure that allows for the decomposition of the between-cohort difference in rank-dependence into components explained by cohort differences in the composition of the labor force upon entry into the labor market (composition effect) versus changes in how the labor market itself structures the association between early- and mid-career earnings (mobility structure effect⁷). Weights are constructed such that cohorts have the same distribution on observable covariates, conditional on early-career earnings rank, as the 1940-1949 cohort. Comparing these counterfactual cohorts to the 1940-1949 cohort reveals the mobility structure effect by answering the question “how much would mobility patterns have changed over time if we held the composition of the labor force constant?” and comparing the counterfactual cohorts to their unweighted, observed distribution reveals the composition effect by answering the question “how much would a cohort's mobility patterns change if its composition were the same as the 1940-1949 cohort?” Importantly, because we are interested in changes in mobility patterns conditional on starting positions, reweighting to achieve the 1940-1949 distribution of covariates *conditional on early-career earnings ranks* allows us to isolate the effects of changes to the mobility structure from changes in the allocation of workers across the earnings distribution at the beginning of their careers.

I construct the weights to generate the counterfactual distributions as follows:

$$\omega = (1 - C) + C * \frac{1 - P(C|X, r, X * r)}{P(C|X, r, X * r)} \quad (8)$$

where C is an indicator variable for belonging to the weighted cohort, X represents a set of covariates to balance on, and r represents early-career earnings rank. I use a probit model to

⁷ This effect is typically referred to as the “wage structure effect” in decompositions of wage inequality. I use the term “mobility structure effect” because this application of the DFL method decomposes inequality in earnings mobility rather than wages or earnings themselves.

estimate $P(C|X, r, X * r)$ for each individual worker. Conditioning on X , r , and their interaction ensures statistical independence between cohort membership and the distributions of the covariates X , early-career earnings ranks r , and the distribution of X over r . Doing so allows for the estimation of between-cohort differences in the effect of early-career earnings rank on mid-career earnings rank, net of between-cohort differences in worker characteristics and how workers sort on those characteristics into early-career earnings ranks. Before weighting, cohorts differ significantly in their distribution of covariates across early-career earnings ranks. After weighting, the cohorts are balanced on their covariate distributions across early-career earnings ranks (Appendix B).

I construct 8 models for each decomposition. Each model adds an additional covariate to construct weights that are applied to each respondent to realize a counterfactual where workers in each cohort follow the 1940 cohort's distribution on those variables conditional on early-career earnings rank. Variables are added roughly according to the temporal order which they occur. Demographic variables (gender and race) come first, followed by education, then general work experience, firm tenure, experience in service and managerial and professional occupations, total employer changes, and job changes in managerial and professional occupations. Through this decomposition, I demonstrate the extent to which cohort differences in distributions of each variable and economic returns to each variable contribute to between-cohort inequality in relative earnings mobility.

Results

Descriptive statistics

The analytic sample contains data from 3,250 PSID respondents from four birth cohorts spanning 10 years each beginning in 1940, 1950, 1960, and 1970 respectively (Table 3.1). Just under 20 percent of the sample is from the 1940 cohort, 37 percent is from the 1950 cohort, 31 percent from the 1960 cohort, and 12 percent from the 1970 cohort. The sample skews slightly female, is about two-thirds white, and about a third hold college degrees. On average, workers in the sample have worked for about 24 years by age 45 and their longest spell with a single employer is 12 years. Workers in the sample have accumulated the most work experience in managerial, professional, technical, and laborer occupations. The average worker has had six employers and job changes are most common within managerial and professional occupations. On average, workers enter the labor market slightly below the median of the earnings distribution and by age 45 are slightly above the median. High standard deviations indicate that workers vary considerably in earnings ranks at age 25 and 45. On average, workers move up 4 percentiles in the earnings distribution between age 25 and 45, and the high standard deviation indicates that substantial rank mobility is common.

Table 3.1. Descriptive statistics

Variable	% or mean	SD
Birth cohort		
1940-1949	19.72	
1950-1959	37.38	
1960-1960	30.62	
1970-1979	12.28	
Gender		
Male	45.85	
Female	54.15	
Race		
White	65.57	
Black	34.43	
College degree	35.05	
Work experience	23.68	5.04
Longest employer tenure	12.02	7.1
Total years experience within occupation group		
Managerial and professional specialty	5.82	7.58
Technical, sales, administrative support	3.22	5.52
Service	1.79	4.32
Farming, forestry, fishing	0.34	1.83
Precision production, craft, and repair	1.19	3.51
Operators, fabricators, laborers	2.43	5.31
Total employer changes	6.06	3.26
Total occupation changes within occupation group		
Managerial and professional specialty	2.19	2.5
Technical, sales, administrative support	1.82	2.53
Service	0.84	1.46
Farming, forestry, fishing	0.23	0.68
Precision production, craft, and repair	0.69	1.59
Operators, fabricators, laborers	1.08	1.97
Weekly earnings rank age 25	51.49	27.74
Weekly earnings rank age 45	47.44	28.02
Change in weekly earnings rank	4.04	25.52
N	3250	

Relative earnings mobility in the pooled sample

A transition matrix describing mobility between earnings quintiles between ages 25 and 45 is presented in Table 3.2. Immobility from respondents' earnings quintile at age 25 is greatest in the bottom and top quintiles, where 38 and 62 percent of respondents remain in the same quintile at age 45, respectively. Persistence is around 30 percent in the middle quintiles. In general,

mobility more than one quintile away from one's origin quintile is rare. This results in compression in mobility from bottom of the earnings distribution, where 70 percent of workers remain in their origin quintile or move up one quintile. The same mobility pattern holds for 80 percent of workers who begin their careers at the top of the earnings distribution. For those who begin their career in the middle quintiles, a similar percentage remain in their origin quintile or move one quintile up or down. There is therefore greater variation in mobility outcomes experienced by those who begin their careers in the middle of the earnings distribution than those who begin in the tails.

Table 3.2. Transition matrix between earnings quintiles for the pooled sample

Weekly Earnings Quintile Age 25	Weekly Earnings Quintile Age 45				
	0-20	20-40	40-60	60-80	80-100
0-20	38.4	30.4	18.9	9.4	3.0
20-40	19.5	27.7	27.6	16.2	9.0
40-60	9.7	21.5	28.3	23.9	16.6
60-80	7.3	9.1	22.0	30.4	31.3
80-100	3.2	4.1	11.4	19.6	61.6

Results from unadjusted quantile regressions of age 45 earnings rank on age 25 earnings rank from the pooled PSID sample are presented in the first column of Table 3.3 and Figure 3.3. These findings are generally consistent with descriptive findings from the transition matrix. Figure 3.3 plots the predicted earnings rank distribution of workers at age 45 conditional on early-career rank and shows compression in mobility opportunity at the bottom and top of the age 25 earnings distribution. Most workers who enter the labor market at the bottom of the earnings distribution tend to remain near the bottom and a relatively small proportion tend to move into the middle and upper ranks. The opposite is true for workers beginning their careers at the top, who tend to remain towards the top of the distribution and rarely fall very far. The IQR of age 45 ranks is about 15 percentile points larger for workers who begin their careers at the middle of the earnings distribution than for those who begin at the tails.

Figure 3.3. Overall predicted rank earnings and mobility opportunity

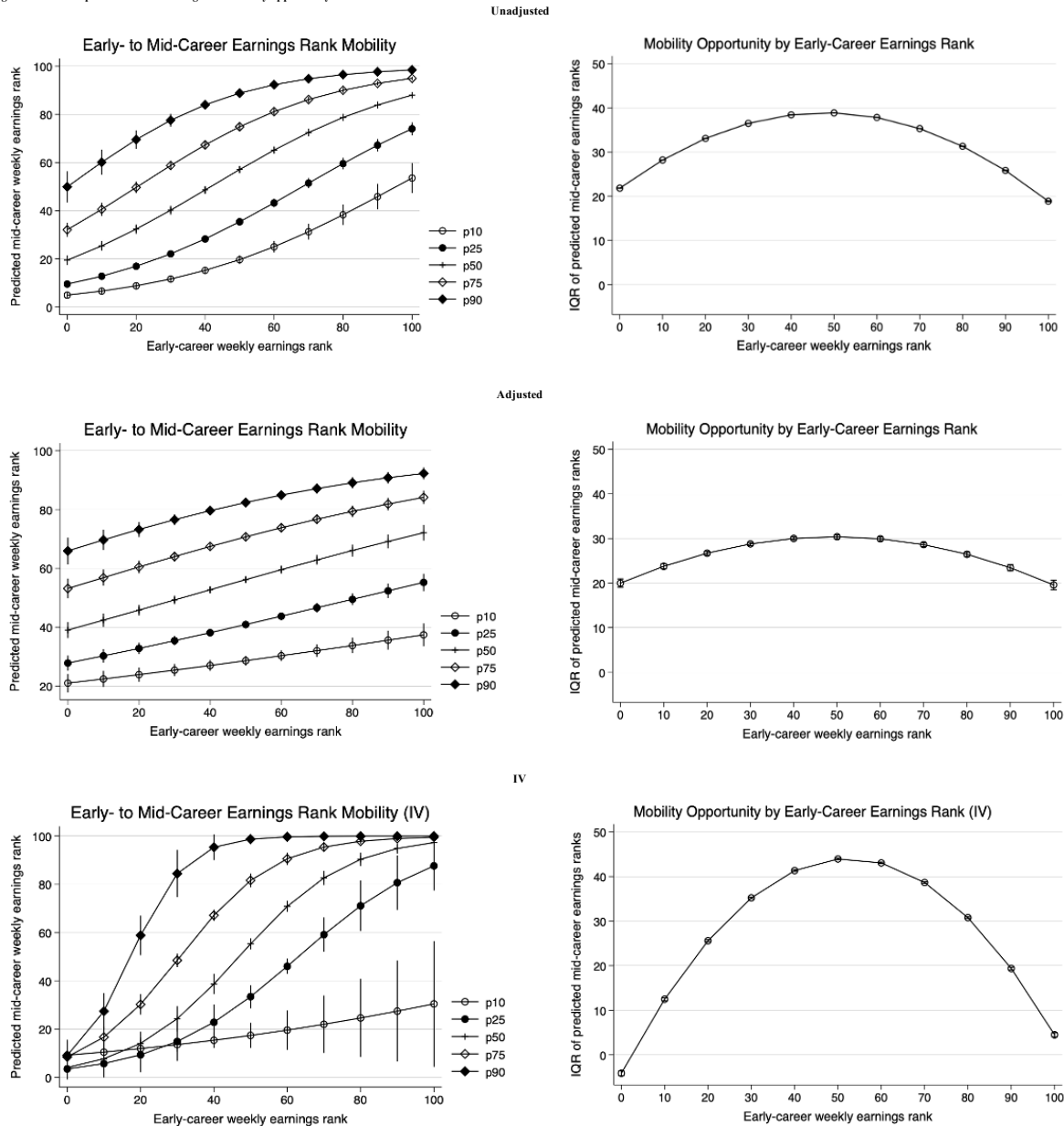


Table 3.3 contains average marginal effects on the conditional 10th, 25th, 50th, 75th, and 90th percentile age-45 earnings rank for a one-percentage increase in earnings rank at age 25. These marginal effects describe rank-dependence, or how quantiles of the distribution of ranks that respondents attain in the earnings by age 45 changes shape depending on where they fall in the earnings rank distribution at age 25. All quantiles of the conditional earnings rank distribution at age 45 are significantly associated with earnings rank at age 25. The association between age-25 and age-45 earnings rank is strongest at the middle of the distribution, where the median earnings rank at age 45 increases by 0.685 for each one-percentage increase in age-25 earnings rank. This association is weaker but still substantial at the tails of the distribution – 10th and 90th percentile age-45 earnings ranks increase by 0.500 and 0.463 with a one-unit increase in earnings rank at age 25.

Table 3.3. Estimated average marginal effects from CQRs of mid-career earnings on early-career earnings

Conditional mid-career earnings quantile	10th Percentile					25th Percentile					50th Percentile				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Early-career rank	0.500***	0.366***	0.344***	0.201***	0.161***	0.657***	0.542***	0.462***	0.277***	0.269***	0.685***	0.624***	0.489***	0.296***	0.308***
Black		0.332	0.911	-1.080	0.00492		-3.107	-4.160*	0.962	0.174		-3.982*	-2.540	-1.854	-0.933
Female		-15.63***	-18.29***	-12.64***	-12.20***		-12.38***	-15.58***	-12.06***	-12.31***		-6.447***	-11.51***	-14.38***	-12.53***
College			8.274***	5.332*	4.398**			13.95***	4.619**	3.827**		17.93***	6.543***	6.216***	6.216***
Work experience				1.426***	1.307***				0.979***	0.942***			0.687***	0.648***	0.648***
Employer tenure				0.621***	0.595***				0.616***	0.611***			0.490***	0.518***	0.518***
Occupation-specific experience															
Manager/professional				0.909***	0.841***				1.189***	1.114***			1.297***	0.983***	0.983***
Technical, sales, and admin				0.468***	0.332*				0.548***	0.596***			0.635***	0.532***	0.532***
Service				-0.559***	-0.590***				-0.412**	-0.188			-0.247	-0.103	-0.103
Farming, forestry, and fishing				-0.445	-0.550				0.0974	-0.165			0.237	-0.194	-0.194
Precision production				0.236*	0.267				0.176	0.336**			-0.0182	-0.0502	-0.0502
Total employer changes				-0.788**						-0.154				0.0664	0.0664
Total occupation changes															
Manager/professional				0.591						0.860**				1.357***	1.357***
Technical, sales, and admin				0.469						0.287				0.287	0.287
Service				0.0870						-1.003				-0.888*	-0.888*
Farming, forestry, and fishing				2.008*						1.932*				0.737	0.737
Precision production				-0.187						-0.483				0.303	0.303
Conditional mid-career earnings quantile															
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Early-career rank	0.616***	0.526***	0.414***	0.302***	0.292***	0.463***	0.411***	0.321***	0.246***	0.269***	0.685***	0.624***	0.489***	0.296***	0.308***
Black		-4.536**	-2.210	-0.541	-0.0804		-3.885	-2.936*	-1.158	-0.952		-3.982*	-2.540	-1.854	-0.933
Female		-9.577***	-10.54***	-12.03***	-11.92***		-8.231***	-9.622***	-9.415***	-9.608***		-6.447***	-11.51***	-14.38***	-12.53***
College			15.15***	8.948**	7.762***			14.40***	8.242***	6.396***		17.93***	6.543***	6.216***	6.216***
Work experience				0.348*	0.321**				0.191	0.169			0.687***	0.648***	0.648***
Employer tenure				0.405***	0.321***				0.121	0.0679			0.490***	0.518***	0.518***
Occupation-specific experience															
Manager/professional				1.057***	0.951***				1.045***	1.009***			1.297***	0.983***	0.983***
Technical, sales, and admin				0.414***	0.491***				0.226	0.208			0.635***	0.532***	0.532***
Service				-0.323*	-0.0245				-0.139	-0.0798			-0.247	-0.103	-0.103
Farming, forestry, and fishing				-0.229*	-0.162				-0.358*	-0.327			0.237	-0.194	-0.194
Precision production				-0.233	-0.334***				-0.000792	0.0475			-0.0182	-0.0502	-0.0502
Total employer changes															
Total occupation changes															
Manager/professional															
Technical, sales, and admin															
Service															
Farming, forestry, and fishing															
Precision production															

Note: *p<0.10 **p<0.05 ***p<0.001; N=3250

Table 3.3 also reports average marginal effects from CQRs that sequentially add sets of variables that correspond to four mechanisms of mobility in the labor market. Model 2 controls for race and gender, resulting in large reductions in rank-dependence across quantiles of the mid-career rank earnings distribution. This suggests selection into early-career earnings ranks by race and gender accounts for some of the observed immobility between earnings ranks over the career. Controlling for holding a college degree also reduces estimates of rank-dependence across the rank-earnings distribution at age 45 (Model 3). Accounting for differences in the accumulation of general, firm-specific, and occupation-specific experience over the career further attenuates estimates of rank-dependence (Model 4). The inclusion of controls for employer changes and occupation changes within various occupational groups has a smaller effect on estimates of rank-dependence. After adjusting for these controls, mobility from the tails of the earnings distribution is still more constrained than mobility from the middle of the distribution. But the IQR of earnings ranks at age 45 is about 10 percentile points smaller for workers who begin their careers at the median of the distribution than in the unadjusted model, while mobility opportunity does not change much for workers at the tails of the distribution.

Estimates of rank-dependence from IV models tell a slightly different story. While Models 1-3 examine how estimates of rank-dependence are affected by the inclusion of controls for observable pre-market differences between workers who begin their careers in different positions in the earnings distribution, IV models also account for selection on unobservables. The IV estimates of rank-dependence are much higher than the unadjusted and covariate-adjusted estimates at and above the 25th percentile of earnings ranks at age 45. The estimated average marginal effects just under 1 suggest a highly rigid mobility regime where a one-rank increase in early-career earnings is associated with roughly a one-rank increase in rank earnings in the middle of workers' careers. Examining the predicted distribution of earnings ranks at age 45 in Figure 3, we see that the IV models predict much more constrained mobility among workers who begin their careers at the bottom and top of the rank earnings distribution, with IQRs between 0 and 20 percentile points at the tails of the distribution and over 40 in the middle. These results suggest that a substantial amount of upward mobility from the bottom of the earnings distribution and downward mobility from the top is driven by selection and that earnings determination processes within the labor market produce highly rigid patterns of rank immobility for low- and high-earners.

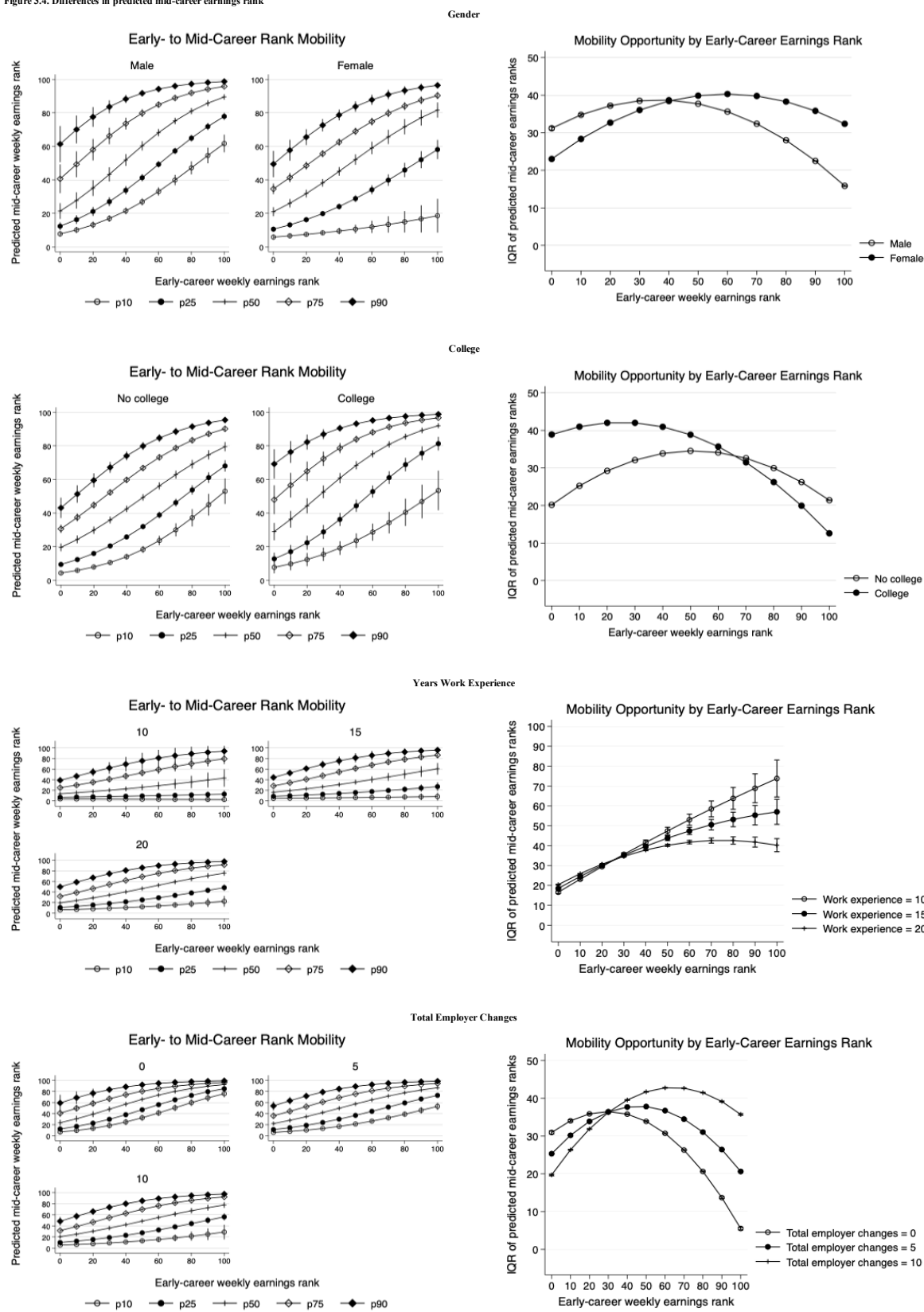
Next, I consider how mobility patterns differ between groups. Results from CQRs where early-career earnings rank is interacted with each covariate are presented in Table 3.4 and select predicted mid-career earnings ranks and IQRs are presented in Figure 3.4. There is little meaningful difference in how the distributions of mid-career rank earnings for Black and white workers change with early-career rank earnings. Rank-dependence is much lower for women while their mobility opportunity is more constrained at the bottom of the earnings distribution and much greater at the top. Compared to men, women who begin their careers at the top of the earnings distribution attain median mid-career earnings ranks that are about 10 percentile points lower, 25th percentile ranks that are 20 percentile points lower, and 10th percentile ranks that are 40 percentile points lower. Consistent with human capital theory, holding a college degree affects rank-dependence primarily at the top of the mid-career rank earnings distribution by reducing the effect of early-career earnings rank on the upper tail of the distribution, thereby increasing the opportunity for upward mobility among workers who start their careers towards the bottom of the distribution.

Table 3.4. Group differences in estimated marginal effects of early-career earnings on mid-career earnings

Conditional mid-career earnings quantile	10th		25th		50th		75th		90th	
	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted
Overall	0.500***	0.161***	0.657***	0.260***	0.685***	0.308***	0.616***	0.292***	0.463***	0.260***
Race										
White	0.505	0.161	0.671	0.267	0.679	0.319	0.609	0.302	0.435	0.263
Black	0.414	0.172	0.565+	0.178**	0.679	0.212*	0.565	0.19	0.457	0.197
Gender										
Male	0.552	0.281	0.664	0.36	0.68	0.404	0.537	0.364	0.354	0.276
Female	0.130***	-0.0269***	0.484***	0.154***	0.609	0.215***	0.55	0.230***	0.455	0.219
Education										
Non-college	0.502	0.186	0.598	0.24	0.603	0.244	0.59	0.259	0.509	0.249
College	0.468	0.146	0.694*	0.278	0.623	0.374***	0.471*	0.367**	0.280***	0.271
Work experience										
15 years	-0.0100	-0.0586	0.0594	0.0438	0.301	0.194	0.546	0.185	0.537	0.232
25 years	0.0346*	-0.0240**	0.186***	0.114***	0.447***	0.245***	0.579	0.228+	0.502	0.244
30 years	0.167***	0.0553***	0.380***	0.192***	0.564***	0.292***	0.587	0.266+	0.459	0.253
Employer tenure										
5 years	0.319	0.0801	0.547	0.202	0.654	0.293	0.644	0.266	0.532	0.264
10 years	0.387**	0.132***	0.576*	0.237**	0.638	0.316+	0.604***	0.283+	0.477**	0.261
20 years	0.513*	0.244***	0.602	0.301**	0.585+	0.355+	0.518***	0.311+	0.367*	0.257
Occupation experience: manager/professional										
5 years	0.331	0.151	0.526	0.247	0.608	0.314	0.604	0.318	0.539	0.268
10 years	0.385**	0.165	0.545	0.269+	0.585+	0.33	0.540***	0.32	0.423***	0.251
20 years	0.426*	0.177	0.542	0.285	0.537**	0.339	0.461***	0.315	0.306***	0.227
Occupation experience: service										
0 years	0.511	0.165	0.629	0.27	0.652	0.313	0.586	0.291	0.405	0.246
5 years	0.297	0.176	0.536**	0.220*	0.613	0.286	0.627**	0.306	0.491***	0.276*
10 years	0.133	0.186	0.426**	0.169*	0.537	0.257	0.659*	0.322	0.575***	0.306*
Total employer changes										
0	0.705	0.281	0.732	0.328	0.682	0.418	0.537	0.365	0.376	0.274
5	0.482***	0.183*	0.626***	0.264*	0.645	0.331***	0.571	0.305**	0.424	0.255
10	0.241**	0.0870*	0.469***	0.196*	0.573+	0.228***	0.597	0.235**	0.47	0.235
Occupation changes: manager/professional										
0	0.439	0.161	0.596	0.253	0.666	0.328	0.649	0.315	0.587	0.264
3	0.479	0.164	0.612	0.269	0.624*	0.317	0.536***	0.294	0.395***	0.253
6	0.49	0.167	0.593	0.283	0.536***	0.302	0.400***	0.272	0.224***	0.242
Occupation changes: service										
0	0.523	0.207	0.659	0.287	0.651	0.352	0.571	0.311	0.406	0.267
3	0.0233***	0.0422*	0.359***	0.115**	0.451***	0.114***	0.509	0.136*	0.389	0.202
6	-0.0319***	-0.0973**	0.0898***	-0.0570***	0.134***	-0.166***	0.264*	-0.108*	0.127	0.110

Note: +p<0.10 *p<0.05 **p<0.01 ***p<0.001; N=3250. Each set of rows represents marginal effects obtained from separate regressions where the variable in bold is interacted with early-career weekly earnings rank. Stars indicate statistical significance of difference in average marginal effects between group and reference category.

Figure 3.4. Differences in predicted mid-career earnings rank



Accumulating general work experience, firm tenure, and experience in managerial and professional occupations increases rank-dependence at the bottom of the earnings distribution, benefitting high-earners by decreasing their chance of downward mobility. Accumulating experience in service occupations has the opposite effect, depressing workers' opportunity for upward mobility and increasing their chances of downward mobility. The effects of general experience, firm tenure, and service sector experience persist after including controls. Changing employers also tends to inhibit mobility by diminishing workers' chances of upward mobility from low earnings ranks and increasing their chances of substantial downward mobility from high earnings ranks. This effect is particularly pronounced for job changes within the service sector even after including controls.

All told, in the pooled sample, workers' earnings rank at age 45 is highly dependent on their rank at age 25. Selection on race, gender, and education explain some of this association. Inequality in the accumulation of human capital over the career also explains some of this association, but inequality in job change patterns explain less. Early-career rank earnings affect mid-career rank earnings differently between groups. Bottom-tail outcomes for women are much less dependent on early-career earnings than for men. Holding a college degree tends to equalize upper-tail outcomes for low- and high-earners. Accumulating work experience, firm tenure, and experience in managerial and professional occupations tends to equalize upper-tail outcomes and exacerbate inequality in lower-tail outcomes, while experience and job changes in service occupations do the opposite.

Cohort trends in relative earnings mobility

Next, I examine between-cohort differences in relative earnings mobility. Transition matrices for each cohort show that mobility patterns are similar between cohorts, but with stronger persistence at the top and bottom of the earnings distribution in the 1940 and 1970 cohorts (Table 3.5). Figure 3.5 shows predicted distributions of mid-career rank earnings by early-career rank earnings for each cohort and produces similar results.

Table 3.5. Transition matrices between earnings quintiles by cohort

Table 5.3. Transition matrices between earnings quintiles by cohort

Birth cohort	1940-1949					Birth cohort	1950-1959				
	Weekly Earnings Quintile Age 45						Weekly Earnings Quintile Age 45				
	Weekly Earnings Quintile Age 25	0-20	20-40	40-60	60-80		80-100	Weekly Earnings Quintile Age 25	0-20	20-40	40-60
0-20	39.5	29.8	16.4	12.9	1.4	0-20	35.1	33.9	19.5	9.9	1.5
20-40	19.5	33.4	27.1	14.0	6.0	20-40	17.9	23.7	29.9	15.7	12.8
40-60	8.7	23.3	28.4	25.8	13.7	40-60	10.0	22.6	33.4	20.0	14.0
60-80	5.5	11.1	20.8	30.7	32.0	60-80	4.9	10.6	21.1	30.4	33.1
80-100	1.9	3.1	6.8	22.3	65.8	80-100	2.1	4.2	15.3	18.4	60.0
Birth cohort	1960-1969					Birth cohort	1970-1979				
	Weekly Earnings Quintile Age 45						Weekly Earnings Quintile Age 45				
	Weekly Earnings Quintile Age 25	0-20	20-40	40-60	60-80		80-100	Weekly Earnings Quintile Age 25	0-20	20-40	40-60
0-20	39.7	28.4	20.4	7.6	3.9	0-20	42.4	26.6	17.5	6.7	6.9
20-40	22.4	21.9	25.9	21.3	8.6	20-40	17.8	40.9	26.5	10.5	4.2
40-60	10.5	20.1	20.3	28.0	21.1	40-60	8.3	19.9	34.3	22.0	15.4
60-80	8.8	7.1	22.5	30.6	30.9	60-80	13.7	6.0	25.2	29.2	25.9
80-100	3.9	5.9	12.5	19.3	58.5	80-100	6.9	0.2	3.6	19.4	69.9

Figure 3.5. Predicted mid-career earnings rank by cohort

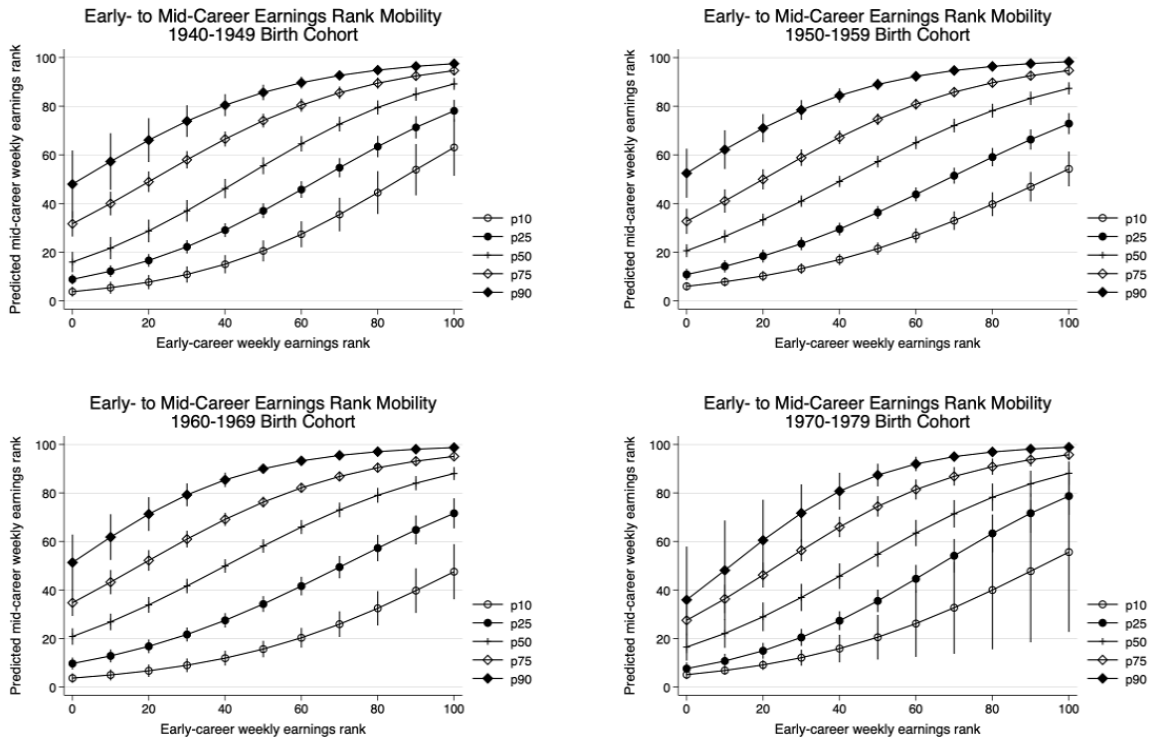
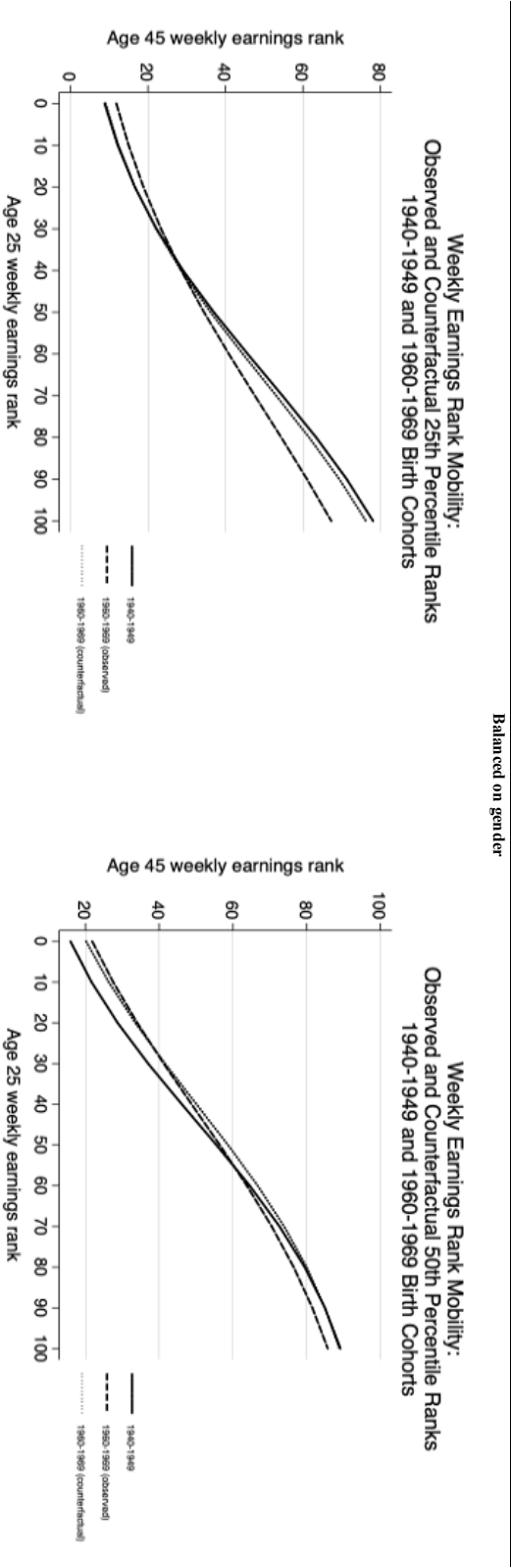


Table 3.6 contains results from the decomposition of between-cohort differences in rank-dependence into mobility structure and composition effects. Rows labeled “observed” contain unadjusted coefficients. Each subsequent row contains results from a separate decomposition where the 1950, 1960, and 1970 cohorts are weighted to match the 1940 cohort’s distribution of the listed trait and the traits before it across the early-career earnings rank distribution. For example, the row labeled “Black” describes a decomposition where each cohort is weighted to have the same distribution of Black and female workers at any given point in the age-25 earnings distribution as the 1940 cohort. The composition effect describes the extent to which between-cohort differences in rank-dependence are explained by changes in workers’ observed characteristics and how they sort into positions in the early-career earnings distribution, while the mobility structure effect describes between-cohort differences in the determinants of rank mobility, or how rank mobility is structured for otherwise similar individuals. Figures 3.6 and 3.7 present plots of selected observed and counterfactual mobility patterns.

Table 3.6. Decomposition of between-cohort inequality in rank-dependence

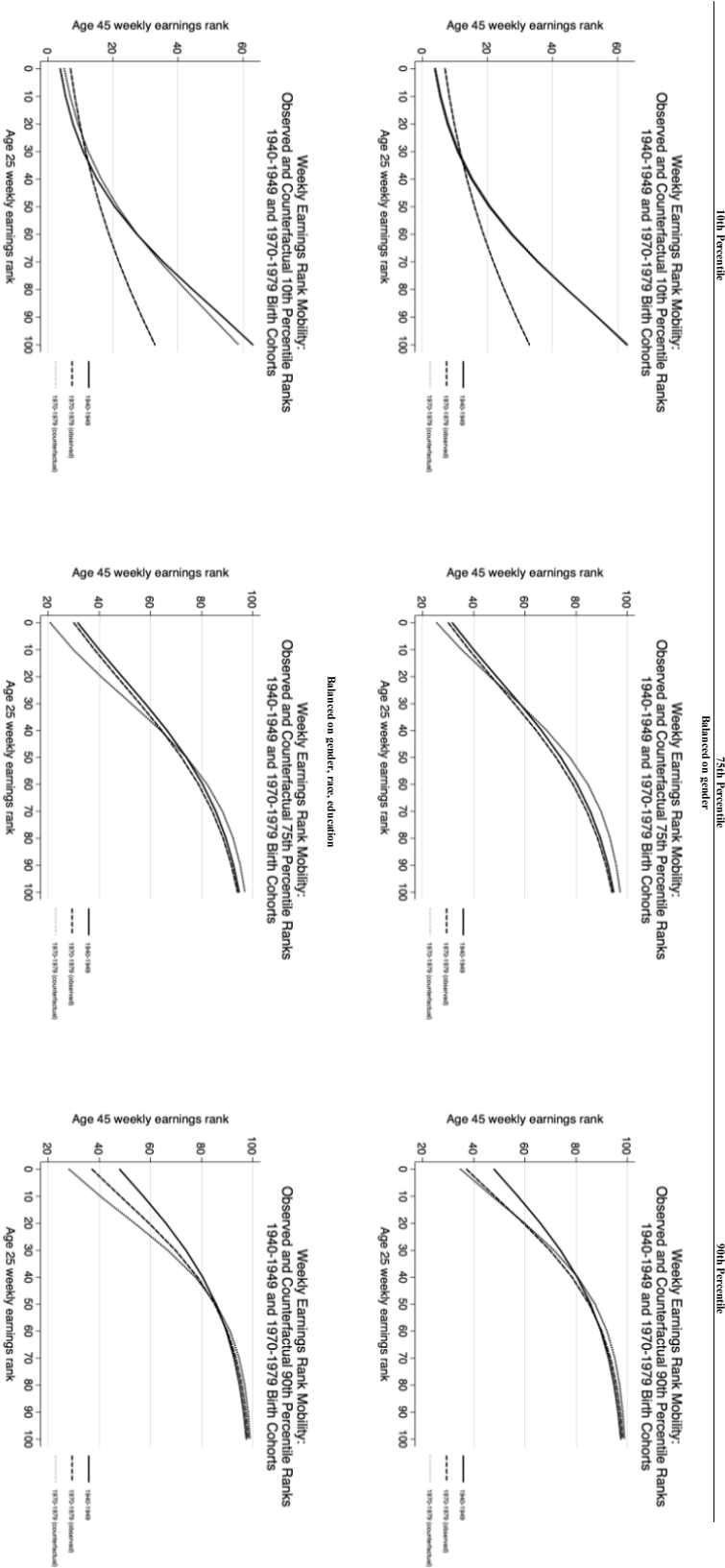
Conditional mid-career earnings quantile										
Birth cohort	1940-1949		1950-1959		1960-1969		1970-1979		10th Percentile	
	Coefficient	Coefficient	Mobility Structure Effect	Composition Effect	Coefficient	Mobility Structure Effect	Composition Effect	Coefficient	Mobility Structure Effect	Composition Effect
Observed	.6144069	.4986244			.4766304			.2673275*		
Female		.5146649	-.099742	.0160404	.5370731	-.0760886	.0604428	.6088796	-.0060902	.3415521*
Black		.5290636	-.0855691	.0303444	.5391471	-.0741839	.0625713	.5798554	-.035692	.3123754*
College degree		.5354564	-.0786506	.0369557	.5549351	-.0581376	.0781582	.5561283	-.0608763	.2881947+
Work experience		.5535177	-.061337	.0545909	.5619579	-.0512886	.0848787	.5944898	-.0227686	.3264769+
Firm tenure		.5501456	-.0647849	.0511914	.5566095	-.0563012	.0798076	.5736073	-.0422577	.3059112*
Experience: manager/professional		.5619315	-.0529306	.0630234	.5825966	-.0298716	.1062519	.5870758	-.0279872	.31961*
Experience: service		.5635876	-.0511701	.0647264	.5933796	-.0191842	.1168428	.6816009	.0662649	.4139569**
Total employer changes		.5847891	-.0297852	.0861309	.5727362	-.0406287	.0956863	.6609182	.0464861	.3935467**
Occupation changes: manager/professional		.5736623	-.0409752	.0749485	.5756093	-.0378949	.0983562	.6601115	.0466308	.3930032**
Occupation changes: service		.5746168	-.0399742	.0759325	.5946322	-.0191449	.1171749	.6606582	.0466899	.3934203**
Conditional mid-career earnings quantile										
Birth cohort	1940-1949		1950-1959		1960-1969		1970-1979		25th Percentile	
	Coefficient	Coefficient	Mobility Structure Effect	Composition Effect	Coefficient	Mobility Structure Effect	Composition Effect	Coefficient	Mobility Structure Effect	Composition Effect
Observed	.7045054	.6368634+			.5611232**			.6839706		
Female		.6370844	-.067421	.000221	.6785081	-.0203183	.1173849*	.7274275	.025908	.043457
Black		.6386855	-.0664252	.0140885	.6854199	-.0142257	.1239565*	.7280946	.0259633	.0435345
College degree		.6727528	-.0299286	.037136	.6997536	.0018414	.1389753**	.7333351	.0315852	.0489455
Work experience		.6858577	-.016702	.0502619	.7125853	.0156849	.1522012***	.7325918	.0315845	.0488113
Firm tenure		.6864052	-.0164134	.0506322	.7080532	.011348	.1478264**	.7357533	.0359112	.0531307
Experience: manager/professional		.6832108	-.019568	.0474737	.7205967	.0236458	.1603874***	.7600371	.0601367	.077461
Experience: service		.6754231	-.0271428	.0398319	.7199002	.0235314	.1599009***	.7588514	.0598538	.0770186
Total employer changes		.7082683	.0053494	.0724884+	.720371	.023152	.1598738***	.7579747	.0589987	.0762641
Occupation changes: manager/professional		.690761	-.0121024	.0550088	.7203785	.02352	.159983***	.7566615	.0579067	.0752486
Occupation changes: service		.7025938	-.000366	.0667798+	.7233734	.0261367	.1627415***	.752946	.0536472	.0710106
Conditional mid-career earnings quantile										
Birth cohort	1940-1949		1950-1959		1960-1969		1970-1979		50th Percentile	
	Coefficient	Coefficient	Mobility Structure Effect	Composition Effect	Coefficient	Mobility Structure Effect	Composition Effect	Coefficient	Mobility Structure Effect	Composition Effect
Observed	.7291794	.67519			.6311057*			.672909		
Female		.6732547	-.0559247	-.0019353	.675533	-.0461454	.0444273	.7445746	.0198925	.0716656
Black		.6623331	-.06751+	-.0133514	.6763233	-.0464129	.0445602	.7375439	.0124489	.0643242
College degree		.702343	-.0242334	.0291024	.6887179	-.0317248	.058363	.737159	.014777	.0659573
Work experience		.707525	-.0179342	.0351033	.6955428	-.0230384	.0663549+	.7506865	.0299559	.0806968
Firm tenure		.7083844	-.0173919	.0357216	.6938854	-.0247083	.0646546+	.7927904	.0724829	.123169+
Experience: manager/professional		.7113761	-.0144	.0387136	.6941748	-.0251674	.0644427+	.7722257	.051144	.1020816+
Experience: service		.7111593	-.0144296	.038639	.6905373	-.0278027	.0614333+	.7697793	.0505022	.1009791+
Total employer changes		.7182048	-.008028	.0451936	.6929607	-.0258987	.0636002+	.7696583	.0495158	.1002408+
Occupation changes: manager/professional		.7044438	-.021639	.0315485	.6843182	-.0338874	.0553768	.7707476	.0498663	.1008148+
Occupation changes: service		.7059083	-.0203981	.0328476	.6884291	-.0301948	.0592523+	.7593478	.0380591	.0890979
Conditional mid-career earnings quantile										
Birth cohort	1940-1949		1950-1959		1960-1969		1970-1979		75th Percentile	
	Coefficient	Coefficient	Mobility Structure Effect	Composition Effect	Coefficient	Mobility Structure Effect	Composition Effect	Coefficient	Mobility Structure Effect	Composition Effect
Observed	.6130908	.623622			.5884744			.6206873		
Female		.6064406	-.0066502	-.0171814	.6116651	.0017637	.0231907	.689111	.0788375	.0684237
Black		.6034923	-.0097555	-.0203376	.5868378	-.0235506	-.0020673	.6883804	.0783328+	.0678511
College degree		.631766	.0199047	.0095184	.608085	-.0012754	.0200958	.7274621	.1206027**	.1100958*
Work experience		.630528	.0197929	.0094146	.6127249	.0045988	.0258232	.7322211	.1265458**	.1160973*
Firm tenure		.6305718	.0197072	.00931	.6118362	.0034307	.0246633	.7326679	.1263158**	.1159778*
Experience: manager/professional		.6293985	.0184928	.0080998	.5857587	-.0233736	-.0020884	.6972684	.0902146+	.0798707
Experience: service		.6295415	.0186513	.0082745	.5814634	-.0270352	-.0058192	.6950879	.0893158+	.0790317
Total employer changes		.6300055	.0186642	.0082697	.5815942	-.0265725	-.0053526	.6827753	.0759279	.0656636
Occupation changes: manager/professional		.6269324	.015731	.005338	.5840089	-.0236979	-.0025193	.6926442	.0846822+	.0744501
Occupation changes: service		.6271077	.0157489	.0053478	.580721	-.0270593	-.0058448	.6867378	.0788625	.0685783
Conditional mid-career earnings quantile										
Birth cohort	1940-1949		1950-1959		1960-1969		1970-1979		90th Percentile	
	Coefficient	Coefficient	Mobility Structure Effect	Composition Effect	Coefficient	Mobility Structure Effect	Composition Effect	Coefficient	Mobility Structure Effect	Composition Effect
Observed	.4742402	.4795408			.4975974			.5809913		
Female		.4334341	-.0408061	-.0461067	.4541258	-.0209463	-.0434716	.6065978	.1339546	.0256065
Black		.4190447	-.0549983	-.0602375	.4156312	-.0594074	-.0818515	.5998627	.1278634	.0196516
College degree		.4638545	-.0106017	-.0160561	.4240969	-.0509952	-.0736415	.6639475	.1937951*	.0874911
Work experience		.466576	-.0073101	-.0127585	.4444983	-.030312	-.0530123	.6621509	.1922184*	.0865394
Firm tenure		.4664612	-.0073881	-.0128164	.445014	-.0302079	-.05298	.6640766	.1929262*	.0869338
Experience: manager/professional		.4690212	-.0048887	-.0103229	.4150254	-.0607396	-.0835512	.6545451	.1828577+	.0767706
Experience: service		.4385104	-.0354751	-.0409267	.4151418	-.0604612	-.0833093	.6513459	.1800356	.0744894
Total employer changes		.4553464	-.0189034	-.0243439	.4143821	-.0603891	-.083037	.6462136	.1740488	.0680602
Occupation changes: manager/professional		.4580741	-.0160932	-.0215337	.413957	-.0606055	-.0832602	.666837	.1937696*	.0872608
Occupation changes: service		.4580576	-.0161447	-.0215767	.4048428	-.0694198	-.0920075	.6631668	.1905653*	.0840576

Figure 3.6. Decomposition of 1940 vs 1960 cohort differences in rank-dependence in 10th and 90th percentile earnings



There is no statistically significant difference in rank-dependence between the 1940 and 1950 birth cohorts at any point of the mid-career rank earnings distribution. The 1960 birth cohort has significantly lower rank-dependence at the 25th and 50th percentiles of the mid-career rank earnings distribution. At the 25th percentile, this difference is entirely explained by between-cohort differences in labor force composition. Cohort differences in the distribution of female workers across early-career ranks explain nearly 80 percent of the difference in rank-dependence (Figure 3.6). Differences in the distributions of subsequent balancing variables across early-career ranks explain almost all the remaining difference in rank-dependence. At the 50th percentile, equalizing the 1960 and 1940 cohorts' distributions of female workers explains just under half of the difference in rank-dependence. The composition effect at the 50th percentile is significant at $p < 0.10$ after also balancing on race, education, and work experience. The nonsignificant mobility structure effect indicates that the determinants of rank mobility within the labor market have not changed significantly between cohorts.

Figure 3.7. Decomposition of 1940 vs 1970 cohort differences in rank-dependence in 10th and 90th percentile earnings



Differences in rank-dependence between the 1940 and 1970 cohorts are driven by a combination of changes in the labor force and structural changes in mobility opportunity. Compared to the 1940 cohort, the 10th percentile of mid-career earnings ranks increases much less with early-career earnings in the 1970 cohort because high earners are more likely to experience substantial downward mobility. Weighting the 1970 cohort to match the 1940 cohort in its distribution of women across early-career ranks explains the entire between-cohort gap in rank-dependence at the 10th percentile (Figure 7). The 1970 cohort has more women with high early-career earnings than the 1940 cohort, and women are disproportionately likely to move into low mid-career earnings ranks, resulting in lower observed rank-dependence in 10th percentile rank earnings for the 1970 cohort. At the 50th percentile, balancing on gender also explains the entire between-cohort difference in rank-dependence. However, the composition effect is not significant until the cohorts are also balanced on race, education, work experience, and firm tenure.

The 75th and 90th percentiles of the mid-career earnings rank distribution change with early-career earnings at rates that are not significantly different in the 1940 and 1970 cohorts. This apparent stability in rank-dependence is maintained by a combination of changes in the composition of the labor force and in the structure of mobility. If the distribution of workers by education across early-career earnings ranks had not changed between 1940 and 1970, rank-dependence at the 75th and 90th percentile would be much higher in 1970 than as observed in 1940 because the effect of holding a college degree on workers' opportunity to attain higher earnings ranks is much greater in the 1970 cohort than in the 1940 cohort. At the same time, the large composition effect suggests that if the educational attainment of low earners had not improved since 1940, mobility at the 75th and 90th percentile would be more rank-dependent. This effect is only statistically significant at the 75th percentile.

Conclusion

Workers vary considerably in how their earnings change over their career. One important and under-studied dimension of stratification related to career earnings mobility is how workers' point of entry into the labor market constrains their opportunity to change positions in the earnings distribution over their career. Studies of mobility in absolute earnings over the career have revealed patterns of inequality in earnings trajectories over the career (e.g. Fuller 2008; Cheng 2014, 2021; Maume and Wilson 2015; Doren and Lin 2019). Analyses of relative mobility offer a complementary perspective by considering how variation in earnings trajectories may result in mobility between positions in the earnings distribution. Relative mobility describes the rigidity of earnings stratification by describing how workers' opportunity to move up or down relative to others in the earnings distribution is constrained by the position where they enter the labor market. By focusing on rank mobility rather than absolute mobility, these analyses allow for a comparison of mobility rates net of how the earnings distribution may change shapes over time or between contexts.

In line with previous research (e.g. Carr and Wiemers 2022), I find that workers' position in the earnings distribution when they enter the labor market is a strong determinant of their position in the earnings distribution later in their career. This is especially true for workers who begin their careers at the tails of the earnings distribution. I extend prior research on relative earnings mobility by examining how the entire distribution of mid-career earnings ranks varies with early-career earnings using a novel application of conditional quantile regressions. Using CQRs, I show that the lower and upper limits of the earnings ranks that workers attain are less

sensitive to where they begin their career than are their typical outcomes. While I find that some of the observed inequality in mobility by workers' early-career earnings can be attributed to selection on race, gender, and education, IV analyses suggest that the opportunity for relative earnings mobility is tightly constrained for workers who enter the labor market at the tails of the earning distribution.

I find evidence that a substantial proportion of the relationship between early- and mid-career earnings ranks is driven by women's disproportionate risk of substantial downward relative mobility from the top of the earnings distribution. This is consistent with prior research showing especially large motherhood penalties for high-earning women (e.g. England et al. 2016), as nearly all women in the sample become mothers before age 45. I also find that gender plays an important role in explaining changes in rank mobility over time: the bottom of the mid-career rank earnings distribution for high-earners has become increasingly similar to that of low-earners largely because more women are entering the labor market with relatively high earnings and these women often experience significant downward mobility.

I also find evidence that both premarket human capital and human capital acquired within the labor market are important determinants of rank mobility. Education shapes mobility primarily through its effect on the upper half of the rank earnings distribution. Mobility into higher earnings ranks for workers with college degrees is much less constrained by their early-career earnings than for workers without college degrees. The mobility returns to education have also become much more important over time. Rank mobility at the top of the earnings distribution was stable across cohorts almost entirely due to rising educational attainment among workers who begin their careers towards the bottom of the earnings distribution. If educational attainment had not changed since the 1940 cohort, upward mobility from the bottom of the earnings distribution would have been much more limited because workers without college degrees have much more dismal prospects of upward mobility from low earnings ranks in more recent cohorts. Human capital acquired within the labor market tends to both improve upper-tail outcomes for low-earners and limit lower-tail outcomes for high-earners.

Altogether, I find that the weakened association between early-career earnings and the bottom of the mid-career earnings distribution is driven by changes in the demographic composition of workers who start their careers at the top of the earnings rank distribution and by changes in how labor market experiences differ between workers who begin their careers at the top and bottom of the earnings distribution. Observed stability in the association between early-career earnings and the top of the mid-career earnings distribution was maintained by the offsetting effects of rising returns to education and rising educational attainment among low-earners.

In addition to these substantive findings, this work embraces the notion that the variability of social outcomes, rather than the average, is of considerable importance to social scientists (Duncan 1984), and offers a new method to characterize variation in mobility outcomes using CQRs. I present two metrics that allow researchers to describe the range of outcomes that workers experience and how that range changes depending on where workers begin their careers. This approach provides parsimonious parametric descriptions of mobility and allows researchers to estimate metrics of mobility net of confounding variables. While I focus these analyses on rank mobility, the same approach could be used to study absolute earnings mobility.

While this paper offers a step towards a fuller understanding of relative earnings mobility, it is not without its limitations. First, because I focus on the relationship between earnings at age 25 and 45, the youngest respondents I can observe were born in the late 1970s

and entered the labor market during the 1990s. Although more recent cohorts have entered the labor market since, their longer-term career dynamics cannot yet be examined. Limited sample sizes also preclude the analysis of the careers of Hispanic workers, who comprise a large and growing portion of the labor force. Finally, selection on unobservables appears to be an important determinant of rank-dependent earnings mobility, suggesting that the labor market itself may do far less to promote positional mobility than previously believed. Further research is warranted to uncover mechanisms that may facilitate positional mobility in the earnings distribution after accounting for the nonrandom allocation of workers into starting positions at the beginning of their careers.

Chapter 4: Black-White Inequality in Job Tasks and Earnings Mobility After Job Displacement, 1984-2020

Introduction

Job displacement – involuntary job loss resulting from economic conditions beyond the control of the worker – is an important dimension of economic precarity that negatively affects workers' short- and long-term economic wellbeing. Displaced workers experience negative health and psychological outcomes, lost earnings due to unemployment, and downward earnings and occupational mobility upon reemployment (Farber 1993; Stevens 1997; Kletzer 1998; Hall 2005; Burgard, Brand, and House 2007; Davis and von Wachter 2011; Brand 2015). In the long-run, job displacement can have negative scarring effects on workers' earnings that persist for up to two decades (Ruhm 1991; Jacobson, LaLonde, and Sullivan 1993; Couch and Placzek 2010; Davis and von Wachter 2011; Schmieder, von Wachter, and Heining 2023). What is more, as the US economy has become increasingly characterized by instability, precarity, and inequality, job displacement has become more disruptive for workers' careers: rates of re-employment, workers' chances of finding full-time work, and earnings recovery after job loss have decreased substantially since the 1980s (Farber 2017).

Perhaps surprisingly, even though social scientists have devoted substantial attention to documenting racial stratification in labor market outcomes such as earnings and employment, racial inequalities in job loss and recovery have received much less attention. Just a few studies have systematically studied racial gaps in job displacement. Fairlie and Kletzer (1996, 1998) show that Black men experience job displacement at a rate 30 percent higher than White men and have reemployment rates 30 percent lower. Wrigley-Field and Seltzer (2020) extend this analysis to 2017 and document sharply rising racial gaps in job displacement. Even less work has systematically documented historical changes in the racial patterning of recovery after displacement. Previous research has either analyzed a single survey year of the Displaced Workers Supplement (DWS) to the Current Population Survey (CPS) or pooled observations across survey years to examine racial gaps in the length of unemployment spells, re-employment, and earnings post-displacement (Fairlie and Kletzer 1998; Spalter-Roth and Deitch 1999; Farber 2017). While these studies offer important insights into racial inequalities related to job displacement, they do not describe how these inequalities change over time. No research since Fairlie and Kletzer (1996) has systematically documented historical patterns of racial inequality in recovery after job displacement.

There is ample reason to expect racial inequalities in post-displacement outcomes and to expect that these patterns change over time. A large body of research documents persistent racial gaps in hiring (e.g. Bertrand and Mullainathan 2004; Pager, Western, and Bonikowski 2009; Quillian et al. 2017) and in earnings (Cancio, Evans, and Maume 1996; Neal and Johnson 1996b; Huffman and Cohen 2004; Carneiro et al. 2005; Fryer et al. 2013; Bloome 2014; Mandel and Semyonov 2016; Bayer and Charles 2018). Because job displacement exposes workers to re-sorting in a labor market where Black jobseekers are disadvantaged relative to White jobseekers, I expect that Black workers experience longer periods of unemployment and lower quality employment upon finding new work, leading to greater earnings losses for Black workers following displacement.

Moreover, since Fairlie and Kletzer's analysis in the early 1990s, the US experienced significant economic restructuring that may have reshaped racial inequalities in the consequences of job displacement. Since 1990, employment decreased in middle-paying jobs characterized by

easily automated routine tasks (e.g. clerical work and repetitive manufacturing production), and grew in both high-paying jobs characterized by abstract tasks (e.g. managers and professionals engaged in creative work and problem-solving) and low-paying jobs characterized by manual non-routine tasks (e.g. retail workers providing customer service) (Autor et al. 2006; Acemoglu and Autor 2011; Autor and Dorn 2013; Acemoglu and Restrepo 2022). Employment in declining middle-skill jobs provided particularly important economic opportunities for Black workers to earn decent wages (Wilson 1996). During this period of economic polarization, the costs of job displacement from routine jobs increased as displaced workers experienced substantial earnings losses and largely were reemployed in low-paying low-skill nonroutine occupations (Autor and Dorn 2009; Blien, Dauth, and Roth 2021). The combination of persistent racial economic inequality in hiring and earnings with economic restructuring that particularly disadvantages Black workers creates a set of economic conditions that may significantly amplify racial inequalities in the economic costs of job displacement.

I argue that changing demand for different types of tasks due to economic polarization is a key driver of post-displacement racial inequalities. Due to historical patterns of occupational segregation and labor market discrimination, I suggest that Black workers will be more likely to sort into jobs characterized by manual tasks while White workers will be more likely to sort into jobs characterized by abstract tasks. Further, I expect that the marked decline in middle-paying routine-task-intensive jobs amplifies racial inequalities in recovery from job loss. As the demand for routine labor declines, racial inequalities in the types of jobs that workers sort into after displacement, and consequently racial earnings inequalities, should increase.

This paper updates and refines our understanding of racial inequalities in the economic consequences job displacement. I offer the first historical accounting of racial gaps in post-displacement earnings and employment outcomes since the 1990s. I also estimate racial gaps net of differences in individual traits and local labor market characteristics, and account for differential selection into reemployment. After examining how the levels and determinants racial inequalities in economic recovery after job displacement have evolved from the 1980s to present day, I turn to an analysis of how these inequalities are generated. I argue that the effect of job displacement on earnings can be decomposed into components specific to workers' lost jobs and workers' new jobs. Drawing on matching and queueing models of the labor market, I argue that White workers' labor market advantages should leave them with more to losses from job displacement but also better prospects for reemployment after being displaced. I test this model empirically by examining how the task composition of Black and White workers' jobs changes after job displacement, and in turn how re-sorting into jobs with different tasks shapes racial inequalities in the effect of displacement on earnings.

Using data from the 1984 to 2020 waves of the DWS, I update estimates of racial inequalities in economic recovery after job displacement and their trends over time, document changes in the determinants of these inequalities, and examine how changes to the structure of labor demand over time and across the US shape racial economic inequality after job loss. I demonstrate that in general, racial inequalities in job search length and change in weekly earnings follow a U-shaped pattern over time, declining between the 1980s and early 2000s before increasing again in the 2010s. Across periods, differences in pre-displacement job characteristics significantly disadvantage White workers in earnings losses following job displacement. However, this effect is significantly outweighed by Black workers' disadvantage in labor market matching, which leads to lower quality post-displacement employment. Further, I show that the task composition of workers' new jobs plays an outsized role in explaining Black

workers' disadvantage in earnings recovery after job loss. Finally, I show that as the state-level employment share of jobs specializing in routine tasks decreases, Black workers increasingly sort into jobs with high levels of specialization in manual tasks and low specialization in abstract tasks while White workers sort into jobs with similar task compositions as their lost job. As a result, racial inequalities in post-displacement earnings recovering increases significantly as the demand for routine labor decreases.

Background

Black-White inequality in job displacement and its consequences

The economic costs of job displacement

Job displacement refers to job loss that can be attributed to economic conditions beyond workers' control and are not tied to workers' individual performance, including mass layoffs, plant closures, or employers going out of business (Brand 2015). Displacement does not include job separations due to firing or quits. Job displacement has attracted particular attention from social scientists because it reflects how employers' business decisions, rather than employee performance or individual choices, affect workers' employment insecurity. Job displacement is therefore important to study because it reflects a form of economic precarity that is both largely out of employees' control and has substantial negative effects on workers' future employment and earnings.

Job displacement has significant negative effects on displaced workers' economic wellbeing. Displaced workers typically experience a period of unemployment after losing their job (Howland and Peterson 1988; Ruhm 1991; Gardner 1995; Farber 2017). On average, displaced workers in the DWS take about 10 to 15 weeks to find a new job after being displaced and only about two-thirds of workers are reemployed by the survey date, which can be up to three years after displacement (Farber 2017). Reemployed displaced workers typically earn less at their new job than at their previous job. Estimates of earnings loss vary between studies, but prior work generally suggest that short-run earnings losses amount to 25 to 33 percent and long-run earnings decrease by 10 to 15 percent (Jacobson et al. 1993; Gardner 1995; Fallick 1996; Kletzer 1998; Cha and Morgan 2010; Couch and Placzek 2010; Davis and von Wachter 2011; Farber 2017). However, earnings changes after job displacement vary considerably (Carrington and Fallick 2017). Schoeni and Dardia (1997) show that between 1989 and 1994, the bottom quartile of displaced workers in California experienced a roughly 50 percent reduction in earnings while the top quartile actually increased their earnings by about 20 percent. Similarly, Lachowska, Mas, and Woodbury (2020) estimate that the bottom quintile of Washington's displaced workers from 2008 to 2010 lost about 30 percent of their earnings while the top quintile experienced no change. Estimates of long-term earnings losses vary, but most evidence suggests that job displacement negatively affects workers' earnings for years after workers find new employment, and some studies suggest that scarring effects last up to two decades (Ruhm 1991; Jacobson et al. 1993; Couch and Placzek 2010; Davis and von Wachter 2011).

Job displacement and racial inequality from 1980 to 1990

Job displacement plays an important role in shaping economic stratification over workers' careers. Every year, millions of workers are displaced. These displaced workers experience substantial short- and long-run earnings losses. There is reason to expect that the consequences of job displacement are generally worse for Black workers than White workers. Cross-sectional analyses show that both the incidence and costs of job displacement are greater for Black

workers than White workers. On average, Black workers experience longer spells of unemployment, lower rates of reemployment, and larger earnings losses following job displacement (Moore 1990; Fairlie and Kletzer 1998; Spalter-Roth and Deitch 1999; Hu and Taber 2005; Farber 2017).

By most prominent accounts, job displacement is highly countercyclical, reflecting broader patterns of macroeconomic and industrial restructuring (Kletzer 1998; Kalleberg 2009; Brand 2015; Farber 2017). In the 1980s and early 1990s, racial inequalities in job displacement and post-displacement outcomes were largely tied to how Black and White workers were distributed across jobs that were downsized due to economic restructuring. During the recession of the early 1980s, firms sought to reduce labor costs and improve efficiency by adopting new automation technologies, laying off production workers, and reducing their commitment to stable, long-term employment relations. Layoffs disproportionately affected blue-collar workers without college degrees (Gardner 1995; Farber 1996). Black workers experienced especially high rates of displacement in this era due to their relatively low education and concentration in production jobs (Fairlie and Kletzer 1996, 1998). The early-1990s recession spurred firms to “trim the fat” through downsizing initiatives that affected predominantly White, white-collar middle management positions (Cappelli 1992; Gardner 1995). As firms focused on leaning out, Black workers’ disadvantage in reemployment rates narrowed and White workers experienced greater earnings losses than Black workers (Gardner 1995; Fairlie and Kletzer 1996).

Economic restructuring since 1990 and its effect on post-displacement racial inequalities

To the author’s knowledge, no research has examined how trends in racial inequality in post-displacement outcomes have changed since the early-1990s. Yet, the United States has since undergone significant economic restructuring and cyclical fluctuations that may well have reshaped how job displacement affects racial economic inequality. While employment growth between 1980 and 1990 was monotonically increasing with occupation average wages, employment growth after 1990 became highly polarized – employment increased somewhat in low-paying jobs such as retail and food service, decreased in middle-paying jobs characterized by routine tasks like manufacturing production and clerical work, and grew substantially in high-paying managerial, professional, and technical occupations (Autor et al. 2006). From 2000 onward, employment at the bottom and top of the labor market grew significantly while employment in the middle continued to decline (Autor and Dorn 2013). At the same time, union power further diminished and nonstandard, contingent, and precarious employment relations became more common, all contributing to polarization between the growing top and bottom of the labor market and a hollowing out of the middle (Kalleberg 2009; Western and Rosenfeld 2011). Declining employment in the middle of the occupational distribution had an outsized effect on Black workers, for whom employment in routine jobs such as manufacturing production or clerical work provided important economic opportunities that were challenging to find elsewhere (Wilson 1996; Acemoglu and Restrepo 2022).

Many of these inequalities resulting from economic polarization came to a head during the Great Recession beginning in December 2007. Rates of job displacement, unemployment among displaced workers, re-employment in part-time work, and earnings losses all rose to their highest levels since the 1980s (Song and Von Wachter 2014; Farber 2015). Displacement rates increased across the board, but were particularly high among younger, low-tenure, and less-educated workers, as well as in industries like manufacturing and construction that tend to provide relatively high quality employment to non-college-educated men, and Black men in

particular (Farber 2017; Rothstein 2017). While aggregate employment in routine jobs typically recovered after recessions before 1990, the Great Recession led to permanent reductions in aggregate employment in routine jobs and an uptick in the creation of lower-quality jobs (Kahn and McEntarfer 2014; Kalleberg and Von Wachter 2017; Jaimovich and Siu 2020), potentially amplifying downward mobility among displaced workers. The Great Recession's combined effect of high rates of job displacement among workers in routine manual jobs where Black workers are concentrated and the funneling of displaced workers into lower-paying service jobs suggests that racial inequalities in the economic consequences of job displacement may have grown since the 1990s.

Hypothesis 1: Black workers' disadvantage relative to White workers in re-employment, job search, and earnings loss after displacement grew during recessions after 1990.

Why earnings fall after job displacement and implications for racial inequality

Labor market matching and racialized labor queues

Understanding racial inequalities in the effect of job displacement on earnings requires considering how workers' earnings are determined at both their lost job and their new job. A displaced worker's earnings may decrease when they move to a new job because their earnings were especially high at the lost job, because the worker re-sorted into a lower-paying new job, or a combination of both. In what follows, I leverage matching and queuing models of the labor market to theorize why Black and White workers may experience different patterns of earnings mobility after job displacement and how those inequalities may change over time.

Matching models of the labor market can provide a helpful framework to understand why workers' earnings might decrease after job loss. Workers are matched to jobs in a sorting process where workers leverage their personal resources to compete for their most desired jobs and firms offer wages and benefits to attract their most desired workers. Workers competing for jobs leverage a broad set of personal resources including their general skills, skills specific to an occupation or industry, educational credentials, work history, social capital, cultural capital, parental status, race, or gender. At the same time, firms evaluate job candidates based on their expected productivity at the job, but they also consider candidates' cultural fit within an organization, referrals and other social connections to the firm, educational credentials and prestige, and other factors that might affect match quality. Thus, workers' chances depend on their broadly defined personal resources, the resources of fellow jobseekers, and the set of available job openings (Sørensen 1977; Jovanovic 1979b; Sørensen and Kalleberg 1981; Coleman 1991).

While workers and firms consider a broad set of factors in the matching process, one key characteristic of jobs that workers and firms consider is the bundle of tasks performed at the job. Tasks are specific work activities that produce some output. Examples of tasks include operating machinery, analyzing data, or preparing food. In task-based models of the labor market, worker-job matches are determined by the compatibility between jobs' task demands and workers' skills (Acemoglu and Autor 2011). Changes to the task-structure of the US labor market played an outsized role in shaping trends in employment and inequality over the last half century, explaining over half of the increase in overall inequality and driving patterns of how workers are distributed across jobs (Autor et al. 2008; Autor and Dorn 2009; Acemoglu and Restrepo 2022). Tasks therefore provide a useful lens to understand the structure of job opportunities in the labor market, how workers' personal resources may match up with open jobs, and how jobs' economic

rewards may vary. Later, I will elaborate how changes to the task structure of the US economy may affect racial inequalities in post-displacement outcomes.

Queueing theory is a useful framework for understanding Black workers' disadvantage in labor market matching processes (Thurow 1969; Hodge 1973; Weiss 1980; Reskin and Roos 1990). Queueing theory describes labor market matching processes where firms hoping to fill a job opening rank jobseekers from their most to least preferred (the labor queue) and jobseekers rank jobs in a similar fashion (the jobs queue). Firms attempt to fill a vacancy by making offers down the labor queue until the vacancy is filled. When applied to racial or gender inequality, queueing theory has been used to argue that nonwhite and female workers' relatively poor economic outcomes are explained by firms ranking them relatively low in the labor queue (Hodge 1973; Reskin and Roos 1990; Spalter-Roth and Deitch 1999; Campero and Fernandez 2019). In what follows, I consider how Black workers' relatively low position in the labor queue might affect racial inequalities in how job displacement affects earnings.

Inequalities due to devalued human capital investments and rents

Job displacement is likely to lead to earnings loss for several reasons. First, assuming efficient matching in workers' initial job search, workers are matched to their best possible job, given available alternatives and other job seekers. Even relaxing assumptions of optimal matching, it still makes intuitive sense that most workers are likely to choose the best jobs available to them. Second, once worker-job matches are achieved, workers may invest in skills that enhance their productivity at their job. These skills can be specific to their productivity at their current firm, their productivity in a specific occupation, or generally applicable across occupations and industries. Firm-, occupation-, and industry-specific skills that enhance workers' productivity and wages in their initial job may not fully transfer to a new job.

White workers are advantaged over Black workers in both job matching and human capital accumulation. Employers prefer to hire White workers over otherwise similar Black workers (Kirschenman and Neckerman 1991; Fernandez and Fernandez-Mateo 2006; Pager et al. 2009; Quillian et al. 2017; Pedulla 2020). Moreover, White workers accrue more human capital by accumulating more general experience and firm tenure than Black workers, and White workers also receive greater returns to labor market experience than Black workers (Duncan and Hoffman 1979; Tienda and Stier 1996; Bratsberg and Terrell 1998; Tomaskovic-Devey et al. 2005; Castilla 2008).

White workers' relative advantage in matching into high quality jobs and firms, as well as their advantage in accumulating investments in firm-specific human capital, could disadvantage White workers with respect to how their earnings change due to job displacement. In a sense, because White workers accumulate advantages from their positions at the top of the labor queue in both internal and external labor markets, they have more to lose when they are displaced. Consistent with this line of thought, some evidence suggests that White workers experience greater earnings loss after displacement due to lost firm-specific investments in human capital (Addison and Portugal 1989). Therefore, I expect that White workers' advantages in accumulated general (labor market experience) and specific (firm tenure) human capital, as well as characteristics of their lost job such as occupation, industry, and job tasks, *disadvantage* White workers, relative to Black workers, in earnings recovery after job displacement.

Hypothesis 2: Differences in Black and White workers' levels of pre-displacement labor market experience, firm tenure, and job characteristics are associated with

larger earnings losses for White workers than Black workers after they are reemployed.

Inequalities due to re-sorting in the labor market

Inequality in how workers' earnings change after job displacement also depends on the type of job they can obtain after being displaced. Little of the negative effect of job displacement on earnings is explained by workers moving into lower quality firms (i.e. firms with lower pay rates). Rather, far and away the most important factor that explains this effect is workers moving into lower quality matches (Lachowska et al. 2020). That is to say, displaced workers' earnings losses are largely explained by moving into jobs that are a worse fit between worker and job. This is consistent with matching models of the labor market because job displacements sever high quality matches and workers are then left to re-sort into their next-best alternative. Generally, matching and queueing models would predict that workers at the top of the labor queue would achieve the highest quality matches when re-sorting. If White workers disproportionately occupy the top of the labor queue, we would expect displaced White workers to be reemployed at better quality jobs than displaced Black workers.

Diminished match quality after job displacement can be explained by several factors. One source of lost earnings is the imperfect transferability of human capital investments made at workers' lost jobs. Some earnings loss can be explained by firm-specific human capital that was valuable at workers' initial jobs and is less valuable or not at all valuable at their new job (Becker 1962; Mincer 1962). In a similar vein, human capital investments specific to workers' initial occupation or industry diminish in value when workers move to dissimilar new jobs (Shaw 1984; Neal 1995). Moving into new firms, job types, or industries results in lower returns to the skills that workers acquired at their previous job.

Beyond lost investments in human capital, job displacement exposes Black workers to potential discrimination in hiring and wage offers. Prior research has shown that employers tend to rank White workers higher in labor queues than Black workers, giving rise to inequality in the jobs that White and Black workers can access (Hodge 1973; Lieberman 1980; Reskin and Roos 1990; Eliason 1995; Huffman and Cohen 2004; Fernandez and Mors 2008; Kornrich 2009; McTague, Stainback, and Tomaskovic-Devey 2009; Campero and Fernandez 2019). However, there is substantial between-firm variation in discrimination (Kline, Rose, and Walters 2022). Some evidence suggests that Black workers tend to sort into relatively non-discriminatory firms, and that job displacement causes Black workers to then re-sort into more discrimination-prone firms (Hu and Taber 2005). All told, if employers rank Black workers lower in the labor queue than otherwise similar White workers, and Black workers are displaced from relatively non-discriminatory firms, Black workers will experience disproportionate losses in earnings and job quality due to job displacement.

Hypothesis 3: Differences in the characteristics of the jobs that Black and White workers sort into after being displaced disadvantage Black workers relative to White workers in the effect of job displacement on earnings.

Changing job tasks and earnings loss

To gain a firmer grasp on how job displacement might cause Black workers to re-sort into disproportionately lower quality jobs and lead to racial inequalities in earnings loss, I consider how the task composition of workers' jobs changes after job loss. Jobs can be characterized by their bundle of tasks, or the activities that workers perform to produce an output. Viewing jobs

through this task model, Autor, Levy, and Murnane (ALM) develop a typology of job tasks along two dimensions (Autor et al. 2003). The first dimension distinguishes between routine and nonroutine tasks. Simply put, routine tasks are those that can be carried out by machines following programmable rules. These tasks might include cutting sheet metal or processing forms. Nonroutine tasks might include strategic planning or providing customer service. The second dimension of ALM's task model is manual versus cognitive (or abstract) tasks. Manual tasks are carried out physically (e.g. cleaning) while cognitive tasks involve processing information and reasoning (e.g. managing employees).

The task-based approach offers substantial explanatory power when examining changes in employment and inequality over the last 40 years. Unlike occupation-based analyses that have trouble capturing trends in income inequality (Kim and Sakamoto 2008b; Sakamoto and Wang 2020), analyses of the tasks that workers perform and changes to the task composition of jobs and occupations explain at least half of the changes in US wages and wage inequality over the last few decades (Autor et al. 2003; Acemoglu and Autor 2011; Firpo, Fortin, and Lemieux 2011; Acemoglu and Restrepo 2022). Job tasks offer a conceptually grounded and empirically validated link between occupations and wages.

Automation and changing demand for routine job tasks have played a central role in rising economic polarization since 1980. Technological advances over the last few decades have allowed employers to automate routine tasks, leading to a decline in demand for labor in middle-skill, middle-paying jobs like clerical work, manufacturing production, and monitoring jobs. At the same time, demand rose both for lower-paying non-routine manual tasks such as those that involve interpersonal interaction, driving, or cooking, and for higher-paying abstract tasks that involve creativity, quantitative reasoning, or problem solving (Acemoglu and Autor 2011; Autor and Dorn 2013). Acemoglu and Restrepo (2022) demonstrate that the wages of a given demographic group are strongly tied to the extent to which they experience task displacement, or the share of tasks that a demographic group loses due to automation. When workers are displaced from routine jobs, some move into higher-paying abstract-task-intensive jobs, but most typically move into lower-paying jobs that are more manual-task-intensive (Autor and Dorn 2009). Net of any other differences between Black and White workers, one might expect that Black workers are more likely to sort into jobs characterized by manual tasks due to their relatively low position in the labor queue. As a result, I expect that Black workers experience disproportionate earnings loss following job displacement largely due to racial differences in the task composition of workers' new jobs.

Hypothesis 4a: After job displacement, Black workers sort into more nonroutine-manual-task-intensive jobs than otherwise similar White workers.

Hypothesis 4b: After job displacement, Black workers sort into less nonroutine-abstract-task-intensive jobs than otherwise similar White workers.

Hypothesis 4c: The relationship between race and change in earnings after job displacement is mediated by the task composition of workers' new jobs.

Changing demand for routine labor

Displaced workers' economic recovery is significantly influenced by labor market conditions. Earnings losses among displaced workers are highly countercyclical, ranging from about 5 percent during periods with strong labor markets to almost 40 percent during the Great Recession (Gardner 1995; Davis and von Wachter 2011; Farber 2015, 2017). These effects are felt strongly at the local labor market level. Previous work has shown that local economic downturns

exacerbate earnings losses among displaced workers (Howland and Peterson 1988; Carrington 1993; Jacobson et al. 1993). There is also some evidence that the economic downturn has disproportionately negative effects on Black displaced workers (Couch and Fairlie 2010; Chattopadhyay and Bianchi 2021), suggesting that Black displaced workers may be especially vulnerable to changes in the structure of labor demand.

Historically, Black employment in routine-intensive jobs in sectors like manufacturing and public administration was an important factor in promoting the formation of Black working and middle classes (Landry 1987; Wilson 1996; Wilson et al. 2013). The decline of US manufacturing played a significant role in amplifying racial inequality in earnings and employment (Wilson 1987; Wilson, Tienda, and Wu 1995; Western and Pettit 2005). Because Black workers have limited access to high-paying jobs (Anderson and Shapiro 1996; Grodsky and Pager 2001; Huffman and Cohen 2004) and are at greater risk of downward occupational mobility (McBrier and Wilson 2004; Wilson and Roscigno 2010; Wilson et al. 2013), I expect that declining demand for routine labor within workers' local labor markets exacerbates Black-White inequalities in both the types of jobs (job tasks) and earnings that workers attain after job displacement:

Hypothesis 5: Black-White inequality in the effect of job displacement on post-displacement job tasks and earnings is exacerbated by declining local demand for routine labor.

Data and Methods

The Displaced Workers Supplement

This study uses data from the 1984 to 2020⁸ waves of the Displaced Workers Supplement (DWS) to the Current Population Survey (CPS) obtained from IPUMS (Flood et al. 2023). The DWS records information from individuals who lost their job in the previous several years about their earnings and employment at their lost job and current job. CPS respondents 20 years and older who meet the criteria of a “displaced worker” are included in the sample. The definition of “displaced worker” varies between survey years. In order to make consistent comparisons across survey years, I limit the sample to the most restrictive definition, which defines displaced workers as respondents who lost or left a job due to layoffs or shutdowns within the past three years, were not self-employed, and did not expect to be recalled to work within the next six months. This definition has been in place since 1998 and can be applied back to previous survey years. I limit the sample to Black and White individuals in civilian occupations between the ages of 25 and 54 who lost a full-time job. In line with previous research on displaced workers, I focus on workers displaced from full-time jobs to exclude individuals who are only marginally attached to the labor force (e.g. Fairlie and Kletzer 1996, 1998; Farber 2017). I also drop respondents who are missing data on the analytic variables. All analyses use weights specific to the DWS.

Key Variables

Dependent variables

This study examines three outcomes: reemployment, change in earnings, and change in job tasks. Respondents are coded as *reemployed* if they obtained any type of employment after

⁸ The DWS is fielded biennially in either January or February. The job displacements recorded in the 2020 DWS were not driven by the COVID-19 pandemic, which had a massive effect on job loss beginning in March 2020 (Ansell and Mullins 2021).

displacement. *Weekly earnings* are standardized to year-2000 US dollars. Top-coded values are multiplied by 1.4, as is a standard practice in labor economics (e.g. Lemieux 2006). The difference in the logarithm of weekly earnings at respondents current and lost job is used as the outcome variable in earnings analyses. *Change in job task intensity* is the difference in (abstract, routine, or manual) task intensity at respondents' current and lost job. The coding of occupational tasks and task intensity is described below.

Occupations and tasks

The CPS records respondents' occupations using US Census occupational coding schemes. Between 1984 and 2020, the US Census updated their occupation codes five times. With each change in coding schemes, some occupations disappear, some new occupations appear, some occupations are merged, and others are broken apart. These coding changes make it difficult to examine changes within occupations over time. Because this study matches job tasks to detailed occupation codes, I use a standardized occupational coding scheme developed by David Dorn (Dorn 2009; Autor and Dorn 2013) and subsequently used in numerous economic studies of occupations and inequality. The Dorn occupation codes provide a balanced panel of occupations that are consistently defined across US Census occupation coding schemes, allowing analysts to make consistent comparisons within and between occupations over time. These codes result primarily from aggregating detailed occupation codes. These analyses use both detailed occupation codes at the 3-digit level and aggregate 1-digit occupation codes.

Job tasks are measured using task scores from the Dictionary of Occupational Titles and matched to Dorn occupations (Autor and Dorn 2013). Each occupation is scored on a scale of 0 to 10 in its use of *abstract*, *routine*, and *manual* tasks (Autor et al. 2003; Dorn 2009; Autor and Dorn 2013). Following Autor and Dorn (2013), *task intensity* is defined as the difference between the logarithm of a detailed occupation's score on the focal job task and the logarithm of the occupation's score on other job tasks. For example, routine task intensity is the logarithm of an occupation's routine task score minus the logarithm of its abstract task score minus the logarithm of its manual task score. A state's *routine employment share* is defined at the state-year level and refers to the proportion of employees within a state who are employed in jobs with a routine task intensity above the 66th percentile.

Control variables

Race is coded using an indicator variable for if a respondent is *Black*. *Female* is coded 1 for female respondents. *Married* is coded 1 for all married respondents, regardless of if the spouse is present in the household. *Education* is coded as "less than high school", "high school degree", or "more than high school". Analyses also control for the *number of children* in the respondent's household, years of *tenure* at the respondent's lost job, *potential experience* (age – years of education – 6), *years since job displacement*, and whether the respondent *moved* since displacement. Cox proportional hazards models define analysis time as *weeks unemployed* after displacement. Heckman-corrected models use two selection variables: an indicator for whether the respondent *received unemployment benefits* and the respondent's *dependency ratio*, which is defined as the ratio of number of children in the household to total household size.

Analytic approach

Time periods

For most analyses, respondents are divided into five-year time periods (1984-1989, 1990-1994, and so on) to examine how racial inequalities in post-displacement outcomes vary over time.

Job search

I first examine how Black and White displaced workers differ in their length of job search from 1984 to 2020. Racial inequalities in job search are modeled using Cox proportional hazards models specified as follows:

$$h(t; z) = h_0(t) \exp(\delta \text{Black} + \eta_t + X\beta) \quad (9)$$

where time is defined in weeks of unemployment after job displacement and failure is defined as obtaining any new job. δ describes the Black-White difference in the expected logarithm of the hazard of becoming reemployed. Exponentiated coefficients are reported and describe the ratio of Black and White hazards of reemployment. η_t are year fixed effects. X represents a vector of control variables including individual characteristics, lost job characteristics, and state-year economic characteristics.

Earnings and task change regressions

Next, I examine how re-employed Black and White displaced workers earnings and job tasks change relative to their earnings and tasks at their previous jobs using OLS. The outcome of interest in the earnings regressions is the difference in the logarithm of respondents' weekly earnings at their current job and the logarithm of weekly earnings at their previous job. Task change regressions model the difference in the abstract, routine, and manual task intensity at workers' current and lost jobs. The models are specified as:

$$y_1 - y_0 = \beta_0 + \beta_1 \text{Black} + \beta_2 y_0 + \eta_t + X\gamma \quad (10)$$

$$A/R/MTI_1 - A/R/MTI_0 = \beta_0 + \beta_1 \text{Black} + \beta_2 A/R/MTI_0 + \eta_t + X\gamma \quad (11)$$

where y represents the logarithm of weekly earnings and its subscripts 0 and 1 refer to respondents' lost and current jobs, respectively. A/R/MTI refer to three outcomes: abstract task intensity, routine task intensity, and manual task intensity. The coefficient of interest β_1 describes Black-White inequality in respondents' average difference in log earnings (task intensity) upon reemployment after job displacement. Its value can be interpreted approximately as a percent change in earnings (change in task intensity). Similar to a lagged dependent variable approach, these models control for earnings (task intensity) at respondents' lost jobs. This approach addresses the potential spurious correlation between race and change in outcomes due to racial differences in earnings and job tasks. η_t are year fixed effects and X represents a vector of controls including years since job displacement, year fixed effects, individual characteristics, lost job characteristics, and state-year economic characteristics.

I also estimate models that use a Heckman correction (Heckman 1979) to address selection bias stemming from missing data for respondents who are unemployed at the time of the survey. This approach requires modeling selection into employment using at least one variable that predicts employment but does not directly affect earnings or job tasks. Selection is modeled using an indicator for receipt of unemployment benefits and respondents' dependency ratio, which is defined as the ratio of children in respondents' household to the total household size. Both receipt of unemployment benefits and number of children are expected to affect respondents' labor supply (Katz and Meyer 1990; Angrist and Evans 1998) but not directly affect earnings or job tasks. Heckman models are estimated via maximum likelihood.

Decomposition of racial inequality in change in earnings

To test how the characteristics of workers' pre-displacement and post-displacement jobs contribute to racial inequalities in the effect of displacement on earnings, I conduct a Kitagawa-Oaxaca-Blinder decomposition (Kitagawa 1955; Blinder 1973; Oaxaca 1973) of the Black-White gap in earnings change. Following Neumark (1988), I estimate the decomposition as follows:

$$\Delta y^W - \Delta y^B = [\bar{X}^W - \bar{X}^B]\beta^* + [\bar{X}^W(\beta^W - \beta^*) + \bar{X}^B(\beta^* - \beta^B)] \quad (12)$$

where y represents the logarithm of weekly earnings and its superscripts W and B refer to White and Black. $\bar{X}^W$ and $\bar{X}^B$ refer to race-specific average characteristics. β^W and β^B refer to race-specific coefficients and β^* refers to coefficients from a pooled model. I use coefficients from a pooled model as the reference coefficient because discrimination can affect how both White and Black workers are treated in the labor market. The decompositions are estimated net of the logarithm of weekly earnings at workers' lost jobs, years since displacement, and year fixed effects.

The first component of the decomposition is the "explained" component. It allows us to observe how racial differences in average characteristics such as education, occupation, or job tasks affect racial inequality in how earnings change after job displacement. The second component describes how racial differences in coefficients contribute to differences in outcomes. This second component is the "unexplained" component and is often interpreted as evidence of discrimination.

Mediation by new job task composition

Next, I estimate how much of the Black-White gap in change in log earnings following job displacement can be explained by differences in the task composition of Black and White workers' new jobs. I use the Karlson, Holm, and Breen (Karlson, Holm, and Breen 2012) (KHB) method to decompose the covariate-adjusted Black-White gap into direct effects of race and indirect effects of racial sorting into different job tasks. These analyses test if the coefficient on *Black* changes between Model (2) and the following model that controls for the task composition at respondents' new jobs:

$$y_1 - y_0 = \beta_0 + \beta_1 \text{Black} + \beta_2 y_0 + \beta_3 \text{abstract}_1 + \beta_4 \text{routine}_1 + \beta_5 \text{manual}_1 + \eta_t + X\gamma \quad (13)$$

where *abstract*, *routine*, and *manual* refer to the DOT derived task ratings for respondents' new occupation. Significant differences between the β_1 coefficients in Equations (2) and (5) indicate mediation by task sorting. Mediation analyses are implemented using the user-written *-khb-*command in Stata (Kohler, Karlson, and Holm 2011). Because the outcomes are continuous and modeled using linear regression, this approach is essentially the same as the standard Baron and Kenny (1986) approach to mediation analysis. The KHB procedure has the benefit of easily accommodating multiple mediators and determining their individual contribution to the overall level of mediation.

Local labor market task structure

Last, I examine how the task composition of respondents' local labor markets affects racial inequalities in patterns of task sorting and earnings changes by estimating the following models:

$$\Delta y = \beta_0 + \beta_1 \text{Black} + \beta_2 \text{RSH}_t + \beta_3 \text{Black} \times \text{RSH}_t + \beta_4 y_0 + \alpha_i + \eta_t + X\gamma \quad (14)$$

$$\Delta(A/R/M)TI = \beta_0 + \beta_1 \text{Black} + \beta_2 \text{RSH}_t + \beta_3 \text{Black} \times \text{RSH}_t + \beta_4 (A/R/M)TI_0 + \alpha_i + \eta_t + X\gamma \quad (15)$$

where *RSH* refers to the respondent's state's routine employment share in year t and $(A/R/M)TI$ refers to the abstract, routine, or manual task intensity of their job. The coefficient β_3 describes how the Black-White gap in economic outcomes after job displacement change with local

demand for routine labor. By including state (α_i) and year (η_t) fixed effects, these models estimate how within-state racial inequalities change as states' demand for labor changes, net of time-invariant differences between states and national trends in economic recovery after job displacement.

Results

Descriptive statistics

The demographic composition of the DWS sample does not change substantially over time (Table 4.1a). Just over 10 percent of the sample is Black and around 40 percent is female. Marriage rates decline from just under 65 percent in 1984-1989 to about 53 percent in 2015-2020 and the percent of respondents with children in the household declines from 57 to 52 percent. Educational attainment increases significantly over time. While only 36 percent of displaced workers from 1984 to 1989 had an education beyond a high school degree, over 70 percent were educated past high school in 2015 to 2020. Potential experience and tenure at respondents' lost job are fairly steady over time. Reemployment rates are highly cyclical, sitting in the low 60s during the mid-late 1980s, early 1990s, and early 2010s, and in the mid 70s during the remaining periods.

Table 4.1a. Descriptive statistics of analytic sample

	1984-1989	1990-1994	1995-1999	2000-2004	2005-2009	2010-2014	2015-2020
Black	11.64	10.79	10.1	11.11	12.43	13.37	13.25
Female	35.54	40.58	43.49	41.94	43.26	38.56	41.1
Married	64.68	61.45	61.16	58.44	57.44	53.48	53.49
Has kids	57.18	55.06	55.5	54.25	54.14	52.47	52.2
Education							
Less than HS	17.78	10.87	7.57	5.68	5.54	5.28	3.54
High school	46.15	41.74	35.33	33.24	33.54	31.79	25.55
More than HS	36.07	47.4	57.1	61.07	60.92	62.94	70.91
Potential experience	17.27	18.07	19.1	19.78	20.56	20.18	19.37
Tenure (lost job)	4.56	4.74	5.15	4.85	5.23	4.87	4.71
Currently employed	62.62	65.85	77.54	72.08	74.63	60.67	75.93
Moved since displacement	17.12	15.66	17.34	13.78	14.19	12.75	13.64
Years since displacement	1.85	1.82	1.84	1.79	1.86	1.85	1.81
N	6401	6220	3357	5806	2728	5342	2090

Table 4.1b. Lost and current job characteristics

Occupation	1984-1989		1990-1994		1995-1999		2000-2004		2005-2009		2010-2014		2015-2020	
	Lost job	Current job	Lost job	Current job	Lost job	Current job	Lost job	Current job	Lost job	Current job	Lost job	Current job	Lost job	Current job
Manager professional technical	2461	25.33	29.47	31.42	35.42	37.88	38.7	40.14	36.47	40.18	37.35	40.45	45.93	46.5
Admin support and retail sales	16.15	21.29	21.01	23.34	22.28	22.74	20.67	21.65	22.84	21.46	19	20.18	16.27	17.77
Service	6.59	10.56	6.5	9.11	7.63	8.61	6.05	9.1	7.37	9.23	8.69	12.28	9.52	10.21
Precision production and craft	5.17	4.54	4.15	3.39	2.74	2.61	3.58	2.05	2.64	2.41	2.92	2.01	1.72	1.7
Operators assemblers inspectors	19.09	10.36	14.31	9.2	9.5	7.41	10.33	5.9	9.49	6.04	7.81	4.5	5.69	3.84
Transportation construction mechanics														
mining agriculture	28.39	27.93	24.57	23.54	22.43	20.75	20.67	21.15	21.19	20.68	24.24	20.58	20.86	19.97
Task intensity														
Abstract	-0.32	-0.06	0.08	0.24	0.3	0.39	0.39	0.44	0.43	0.5	0.33	0.42	0.55	0.49
Routine	1.13	1.21	1.21	1.23	1.15	1.14	1.05	0.99	1.14	1.05	1	0.93	0.83	0.76
Manual	-2.46	-2.62	-2.82	-2.86	-2.91	-2.94	-2.96	-2.9	-3	-2.96	-2.86	-2.8	-2.92	-2.81
Industry														
Agriculture forestry and fisheries	1.77	1.47	1.11	1.15	1.37	1.15	0.93	1.31	0.92	1.13	1.29	1.45	1.48	1.51
Mining	4.97	1.92	2.07	1.34	1.1	0.69	1.21	0.69	0.62	0.79	1.42	1.3	3.4	1.76
Construction	11.28	11.63	13.36	10.38	11.62	9.72	10.44	9.61	11.4	10.56	14.51	10.61	11.44	10.21
Manufacturing	39.24	24.83	30.63	22.27	24.64	19.13	26.16	16.08	23.68	15.96	18.68	12.28	15.84	12.48
Transportation and other public utilities	7.84	8.08	6.37	7.2	7.36	7.15	9.06	7.57	8.98	8.69	7.47	7.87	7.32	8.19
Wholesale trade	5.78	5.39	5.68	5.05	4.8	4.73	4.98	4.9	3.67	4.17	3.2	3.09	3.3	2.77
Retail trade	9.95	14.77	13.3	15.36	14.18	13.95	12.3	14.19	13.53	12.97	13.72	15.12	13.06	13.74
Finance insurance and real estate	3.47	5.89	7.11	7.35	7.57	7.11	6.44	8.12	9.13	9.72	7.94	7.93	7.13	7.69
Business and repair services	5.19	5.94	6.05	7.67	7.33	10.3	11.28	12	9.53	9.87	9.92	10.68	11.53	11.66
Personal services	1.56	2.67	2.06	2.69	1.7	2.31	1.71	2.08	1.43	2.46	1.72	2.01	1.67	2.27
Entertainment and recreation services	0.92	0.8	1.16	1.07	1.58	1.96	1.27	1.79	1.39	1.77	1.68	2.31	1.96	1.45
Professional and related services	6.73	13.62	9.84	15.6	14.3	19.17	13.02	19.5	14.63	19.65	16.94	22.34	20	23.13
Public administration	1.3	2.99	1.29	2.88	2.47	2.65	1.21	2.15	1.1	2.26	1.5	3.02	1.87	3.15
Weekly earnings (2000 \$)	544.51	515.05	587.77	546.14	633.73	600.35	739.31	670.48	708.29	679.52	714.82	648.54	796.64	770.65
N	6401	4008	6220	4096	3357	2603	5806	4185	2728	2036	5342	3241	2090	1587

Differences between workers' lost and current jobs are surprisingly consistent across time periods (Table 4.1b). A few clear trends emerge. First, workers consistently sort out of production and operator occupations and into either service or managerial, professional, and technical occupations. This corresponds to higher abstract task ratings at respondents' current jobs and lower routine task ratings. Similarly, reemployment rates are low in declining industries like manufacturing and high in industries like retail trade and professional services. These trends reflect broader patterns of economic polarization in the late 20th and early 21st century: displaced workers leave middle-paying routine-intensive jobs for either lower-paying manual or service work or higher-paying abstract work. Across all periods, job displacement is associated with substantial earnings losses.

Reemployment

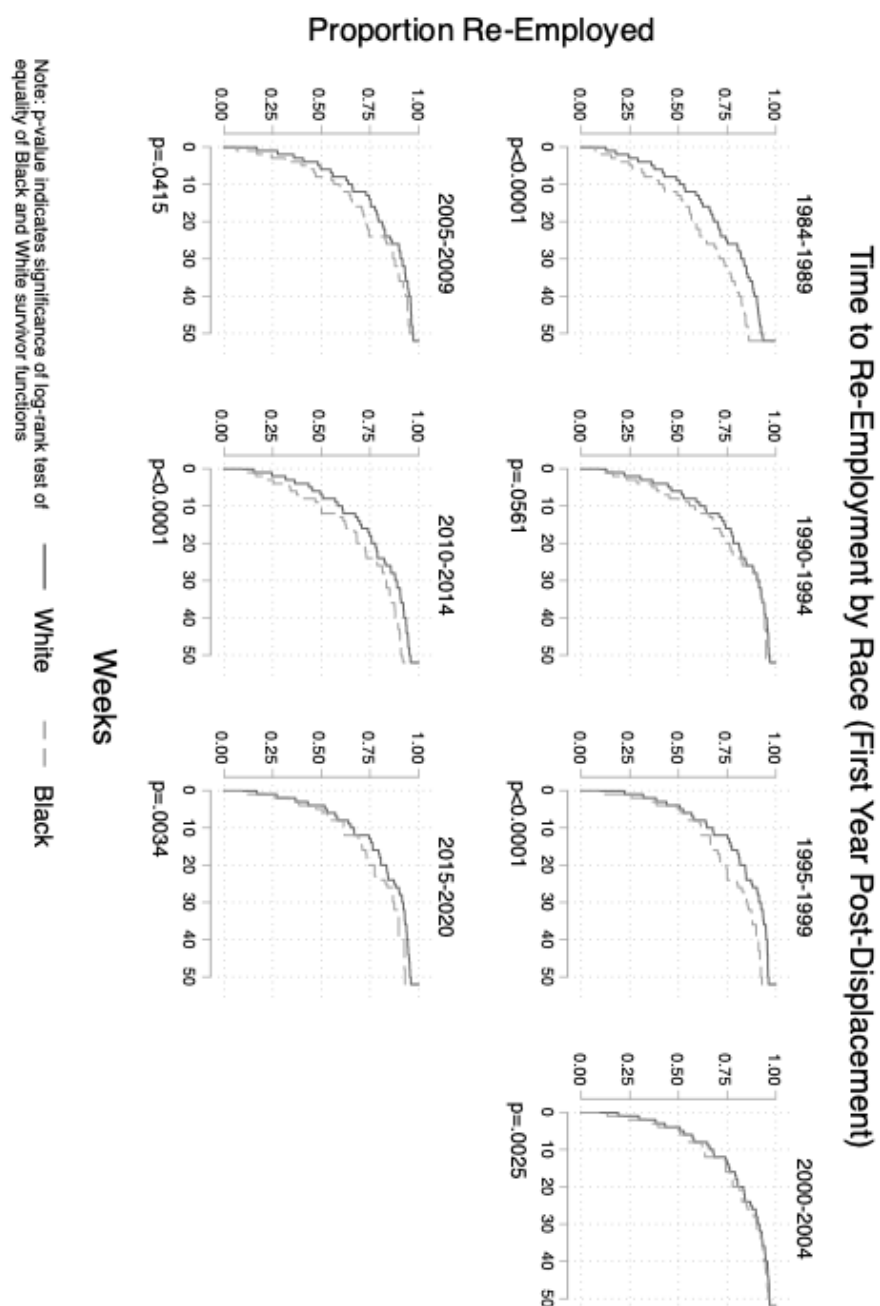
First, I examine racial inequalities in time to reemployment after job displacement. Table 4.2 presents coefficients from Cox proportional hazards models that describe Black displaced workers' hazard of becoming reemployed relative to that of White workers. Column (1) adjusts for survey year fixed effects. Column (2) includes individual-level controls such as demographics, education, experience, and lost job characteristics. Column (3) adds state-year level controls including the state's industrial composition, unemployment rate, and routine employment share. Across all time periods, Black workers' hazard of becoming reemployed after job displacement is significantly lower than that of White workers (Table 4.2; Figure 4.1). Racial inequality in the rate of becoming reemployed is especially high between 1984 and 1989, where the hazard of finding a new job is about 30 percent lower for Black workers than White workers. Consistent with Hypothesis 1, the next highest rates of racial inequality in reemployment since 1990 are in the two other time periods that immediately follow large recessions. Black workers' hazard of becoming reemployed is about 23 percent lower from 1995 to 1999 and 20 percent lower from 2010 to 2014. During periods of rising unemployment (1990-1994 ($p < 0.10$), 2000-2004, 2005-2009), we observe smaller but still significant racial inequalities in rates of reemployment. Estimates of Black-White inequality in reemployment are not particularly sensitive to the inclusion of control variables.

Table 4.2. Cox proportional hazard models of time to re-employment

	(1)	(2)	(3)	N
Black-White gap in hazard ratios				
1984-1989	0.705***	0.729***	0.709***	5663
1990-1994	0.915+	0.899+	0.876*	3441
1995-1999	0.801***	0.797***	0.772***	4033
2000-2004	0.916*	0.922*	0.916*	6105
2005-2009	0.900*	0.866*	0.845**	3006
2010-2014	0.821***	0.827***	0.811***	5198
2015-2020	0.880*	0.869**	0.872*	2886
Controls				
Year fixed effects	Yes	Yes	Yes	
Individual	No	Yes	Yes	
State-year	No	No	Yes	

Note: +p<0.10 *p<0.05 **p<0.01 ***p<0.001; robust standard errors. Exponentiated coefficients on indicator variable for race (reference=white) obtained from Cox proportional hazards models. Individual controls include gender, marital status, number of children, educational attainment, potential experience, potential experience squared, years tenure (lost job), occupation (lost job), industry (lost job), task composition of lost job, and moved since job displacement. State-year controls include year-specific industry composition, unemployment rate, and routine employment share.

Figure 4.1. Time to re-employment by race

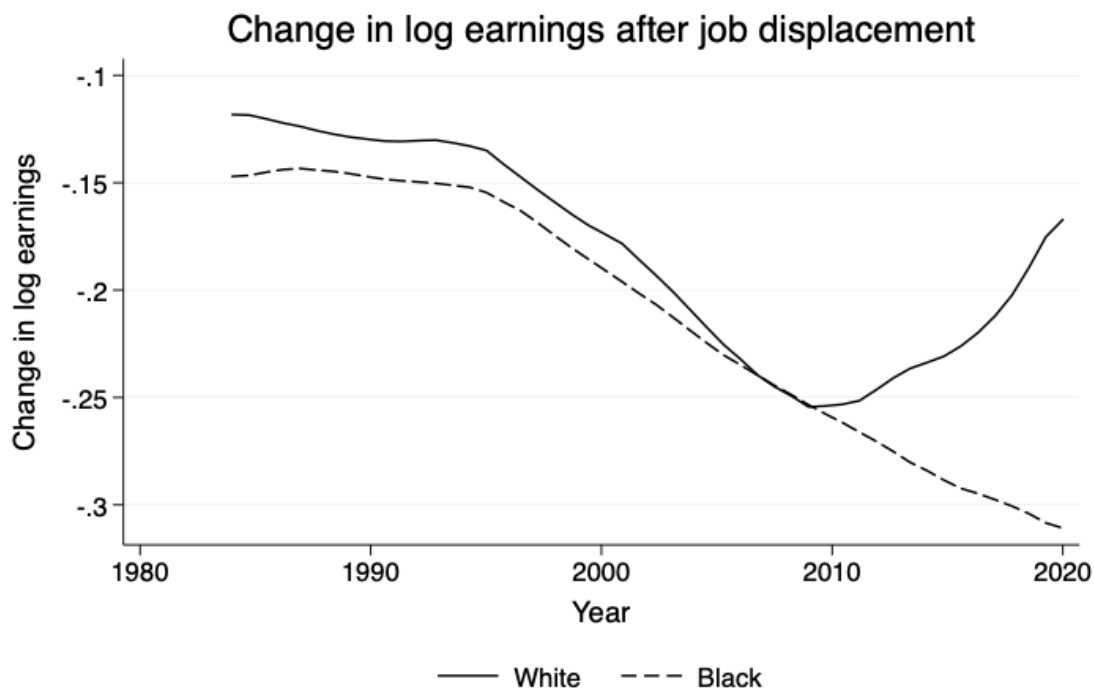


Change in earnings

Next, I examine racial inequality in the difference in earnings at respondents' lost and current jobs. Figure 4.2 plots observed changes in log weekly earnings for Black and White DWS respondents. In almost every year, Black displaced workers experience greater earnings losses than White displaced workers. Consistent with prior literature, the Black-White gap in earnings losses narrows between the mid-1980s and the mid-1990s. This gap continues to narrow and

eventually disappear altogether by the mid-2000s. However, consistent with Hypothesis 1, the Black-White gap in earnings loss rapidly expands following the Great Recession in 2008, far surpassing inequality observed in the 1980s.

Figure 4.2. Change in log earnings after job displacement by race



Regression analyses presented in Table 4.3 and Figure 4.3 show a similar pattern. Coefficients reported in Table 4.3 describe the difference in expected changes in log earnings for Black and White workers. Separate models are run for each five-year period and each row reports results from period-specific models. The first column reports coefficients from models that adjust for survey year fixed effects, years since job displacement, and the respondent's log earnings at their lost job. The second column also adjusts for individual- and state-year-level controls. From Column 1, we see that from 1984 to 1989, Black workers' earnings losses are about 12 percent [$\exp(-0.133)-1$] greater than White workers' losses. This gap narrows and becomes statistically insignificant by the 2005 to 2009 period. The Black-White gap in earnings losses after displacement then expands to 16 percent [$\exp(-0.177)-1$] in 2010 to 2014 and 19 percent [$\exp(-0.205)-1$] in 2015 to 2020.

Coefficients in Column 2 indicate that controlling for individual characteristics, lost job characteristics, and state-year economic characteristics somewhat attenuates estimates of racial inequalities in earnings loss in most periods. This is especially notable between 2015 and 2020, where including controls reduces the point estimate on the Black coefficient by over 50 percent and renders the coefficient not statistically significant. In this model, Black-White inequalities in earnings loss are highest in the periods immediately following economic recessions (1984-1989, 1995-1999, and 2010-2014).

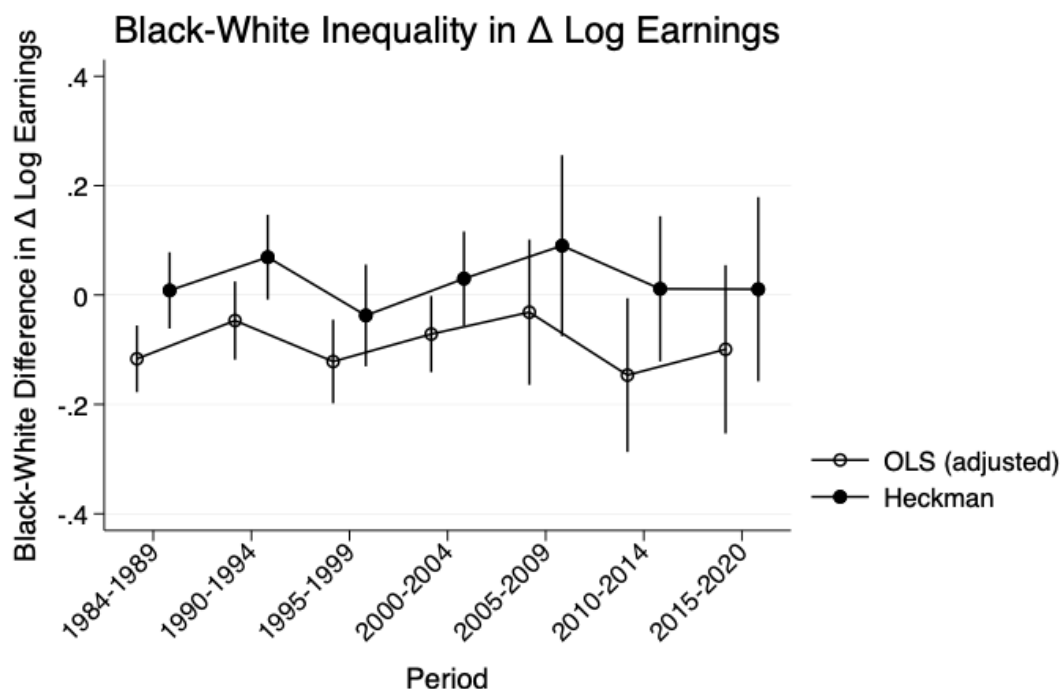
Table 4.3. Racial inequality in change in log earnings after job displacement

	OLS (1)	OLS (2)	Heckman
Black-White inequality in change in log earnings			
1984-1989	-0.133***	-0.117***	0.00839
1990-1994	-0.0723*	-0.0467	0.0692+
1995-1999	-0.113**	-0.122**	-0.0374
2000-2004	-0.112**	-0.0714*	0.0300
2005-2009	-0.0501	-0.0314	0.0902
2010-2014	-0.177**	-0.146*	0.0113
2015-2020	-0.205*	-0.0993	0.0106
Controls			
Log weekly earnings (lost job)	Yes	Yes	Yes
Years since job displacement	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Individual	No	Yes	Yes
State-year	No	Yes	Yes

Note: + $p < 0.10$ * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$; robust standard errors. Coefficients on indicator variable for race (reference=white) obtained from OLS and Heckman-corrected models. Heckman selection variables include dependency ratio and receipt of unemployment benefits. Individual controls include gender, marital status, number of children, educational attainment, potential experience, potential experience squared, years tenure (lost job), occupation (lost job), industry (lost job), task composition of lost job, and moved since job displacement. State-year controls include year-specific industry composition, unemployment rate, and routine employment share.

It is possible that we observe Black-White inequalities in earnings losses following job displacement because Black and White workers differentially select into reemployment. I showed earlier that White workers become reemployed more quickly than Black workers. Estimates from the Heckman-corrected models allow us to examine what racial inequality in earnings loss after job displacement might look like if all displaced workers became reemployed (Table 4.3, Column 3). Across all periods, the Black-White gap in post-displacement changes in earnings is not significant at conventional thresholds. This suggests that racial inequalities in earnings loss after job displacement are largely driven by racial differences in who becomes reemployed and who remains not working.

Figure 4.3. Predicted black-white inequality in change in log earnings after job displacement



Decomposition analysis: the role of pre- and post-displacement job characteristics

Hypotheses 2 and 3 propose that pre- and post-displacement job characteristics play different roles in shaping Black-White inequality in how job displacement affects workers' earnings. Specifically, racial differences in pre-displacement jobs should *reduce* racial inequality in the effect of displacement on earnings while post-displacement jobs should *increase* racial inequality.

I test these hypotheses through a decomposition analysis of Black-White inequality in the change in log earnings among reemployed displaced workers. Results from the decomposition are reported in Table 4.4. Each column in Table 4.4 corresponds to a separate decomposition analysis for DWS respondents in the survey years corresponding to the column label. The top section of the table reports average Black and White changes in log earnings, adjusted for log earnings at their lost job. The row labeled "Difference" reports the difference between White and Black workers' average change in log earnings. The row labeled "Explained" describes the component of that difference that is attributable to differences in Black and White workers' values on covariates used in the decomposition. It can be interpreted as how much the gap would change if Black workers had the same characteristics as White workers. The "Unexplained" component reflects how much the gap would change if Black and White workers had the same coefficients, i.e. if they received the same returns to education, experience, etc. The explained and unexplained components are then further decomposed in the second and third sections of the table. In the "Explained" section of the table, individual cells describe how much the Black-White gap in how displacement affects log earnings would change in the counterfactual where Black workers had the same average value on that covariate as White workers (e.g. if Black workers had the same average educational attainment as White workers). Cells in the "Unexplained" section of the table describe how the gap in change in log earnings would change in the counterfactual where Black and White workers have the same coefficient on a covariate

(e.g. if an additional year of experience had the same effect on earnings for Black and White workers).

Consistent with Hypothesis 2, the “Lost job characteristics” row of the Explained section of Table 4 indicates that differences in lost-job characteristics – occupation, industry, and task composition – reduce racial inequality in post-displacement earnings changes (Table 4.4). The negative and significant values reported in this row indicate that if Black workers’ lost jobs followed the same occupational, industrial, and task distribution as those of White workers, racial inequality in earnings losses would have been even greater. Point estimates for the lost-job component of the decomposition are negative in every time period and statistically significant between 1984 and 1999. Racial inequalities in labor market experience follow a similar pattern. If Black workers had the same amount of experience as White workers, they would have experienced even greater earnings losses. Trends regarding job tenure are more ambiguous. From 1984 to 1994, if Black workers lost jobs with the same level of tenure as White workers, they would have experienced smaller earnings losses. However, from 1995 onward, equalizing Black and White workers’ average tenure would exacerbate Black workers’ earnings losses following displacement.

Table 4.4. Decomposition of Black-White inequality in change in log earnings

	1984-1989	1990-1994	1995-1999	2000-2004	2005-2009	2010-2014	2015-2020
White Δ log earnings	-0.113***	-0.139***	-0.117***	-0.197***	-0.206***	-0.281***	-0.141***
Black Δ log earnings	-0.169***	-0.127***	-0.130***	-0.186***	-0.143**	-0.372***	-0.261***
Difference (Δ White- Δ Black)	0.0560+	-0.0114	0.0135	-0.0101	-0.0624	0.0910	0.120+
Explained	0.0508***	0.0127	0.0148	0.00239	0.00930	-0.0213	0.106**
Unexplained	0.00520	-0.0241	-0.00129	-0.0125	-0.0717	0.112+	0.0136
Explained							
Female	0.00439+	0.00433	0.00639	0.00569*	-0.00138	-0.00522	-0.00252
Family structure	0.00480	0.000728	0.00132	0.00399	-0.00301	0.00751	0.0306**
Education	0.00169	-0.00363	-0.000470	-0.00630+	-0.00312	-0.00102	-0.00734
Potential experience	-0.00154	-0.00287	-0.00310	-0.00154	-0.00606	-0.0108**	0.000800
Years tenure (lost job)	0.00440	0.00746*	-0.0107*	-0.000844	-0.00635	-0.00344	-0.00351
Lost job characteristics	-0.0196**	-0.0247**	-0.0305*	-0.0133	-0.0319	-0.0113	-0.0277
Current job characteristics	0.0819***	0.0434***	0.0646***	0.0249*	0.0416+	0.00258	0.0755***
Moved since displacement	-0.00238	-0.000477	-0.00158	-0.000367	-0.000638	0.00439+	0.000267
State economic characteristics	-0.0229***	-0.0115*	-0.0111	-0.00985	0.0201	-0.00403	0.0402*
Unexplained							
Female	-0.0322	-0.0429	0.0100	0.0213	-0.110+	-0.173*	-0.0717
Family structure	-0.0162	-0.0196	0.0556	-0.00994	-0.0316	0.143	0.121
Education	0.0212	0.112+	-0.0388	0.136	-0.0825	0.186	-0.485
Potential experience	-0.0433	0.0954	-0.0828	-0.162*	0.00627	0.225	-0.0684
Years tenure (lost job)	-0.0192	-0.0524+	0.0323	-0.00708	-0.00520	-0.0746	0.130
Lost job characteristics	0.191	-0.348	-0.515	0.968*	0.270	-0.600	-0.0187
Current job characteristics	0.101	0.698*	0.0628	0.331	1.433*	1.719+	-1.270
Moved since displacement	-0.0143	0.00371	-0.0254+	0.00556	-0.0513*	-0.0192	0.0801*
State economic characteristics	-0.466	-0.494	4.724+	-4.353	7.923+	4.198	-12.32*
Constant	0.0715	-1.354	-4.024	3.304	-9.450+	-4.833	14.33*
N	4007	4096	2603	4185	2036	3241	1587

Note: +p<0.10 *p<0.05 **p<0.01 ***p<0.001; robust standard errors; all models adjusted for log weekly earnings at lost job and survey year fixed effects. Family structure includes marital status and number of children. Lost and current job characteristics include occupation group, industry group, and task composition. State economic characteristics include industrial composition, unemployment rate, and routine employment share.

In line with Hypothesis 3, the explained component of the decomposition corresponding to workers’ current jobs is positive in every period and statistically significant in all periods except 2010-2014. These values indicate that if Black workers sorted into jobs with the same

occupational, industrial, and task composition as White workers, the Black-White gap in change in log earnings after job displacement would shrink. Instead, because Black displaced workers become reemployed in different types of jobs than White displaced workers, they experience greater losses in log earnings upon reemployment. Altogether, these results strongly support the expectation that White workers have more to lose at their pre-displacement jobs, but Black workers lose more because they find relatively low-quality employment post-displacement.

Earnings and task sorting

In most periods, controlling for workers' pre-displacement characteristics explains relatively little of the Black-White gap in earnings losses after job displacement. Because much of racial inequality in earnings is due to the allocation of Black and White workers to different segments of the labor market, it seems likely that racial inequality in post-displacement earnings changes might be explained by racial differences in the types of work that displaced workers sort into when reentering the labor market.

Change in job tasks

Table 4.5 presents results from regressions modeling racial inequalities in how the task composition of workers' jobs changes after displacement. Headings in Table 4.5 correspond to three outcome variables: change in abstract task intensity, change in routine task intensity, and change in manual task intensity. Each column under the heading corresponds to different model specifications: OLS with controls for survey year, years since displacement, and task intensity at the lost job, OLS with additional individual and state-year controls, and Heckman-corrected models. Each row reports coefficients from separate models for each five-year period. Coefficients describe the difference in how the task intensity of Black displaced workers' new jobs changes upon reemployment relative to White workers.

Hypothesis 4a predicts that Black workers will disproportionately sort into manual-task-intensive work after displacement. Consistent with this hypothesis, the manual task intensity of Black workers' jobs increases significantly and substantially more than for White workers after displacement. This trend holds after controlling for differences in observables and accounting for selection into employment in all periods except for 1990-1994 and 2010-2014. This trend is strongest from 1984 to 1989, where OLS and Heckman models indicate that Black workers experience an additional 0.5-point increase in manual task intensity (0.25 SDs) relative to White workers. This difference in change in manual task intensity diminishes to about 0.25 points (0.12 SDs) from 2000 to 2004 before increasing to about 0.4 points (0.2 SDs) in the period of 2015 to 2020.

Hypothesis 4b predicts that White workers disproportionately sort into abstract-task-intensive work after displacement. I find evidence consistent with this hypothesis in the periods 1984-1989, 1995-1999, and 2015-2020. Negative estimates of the Black coefficient (OLS (2)) indicate that, relative to White workers, Black workers experience a reduction in abstract task intensity after displacement of 0.25 points (0.13 SDs) from 1984 to 1989, 0.3 points (0.16 SDs) from 1995 to 1999, and 0.44 points (0.23 SDs) from 2015 to 2020. While point estimates on the Black coefficient are also negative in other periods, they are not statistically significant.

Table 4.5. Racial inequality in change in job tasks after job displacement

Dependent Variable	Change in abstract task intensity			Change in routine task intensity			Change in manual task intensity		
	OLS (1)	OLS (2)	Heckman	OLS (1)	OLS (2)	Heckman	OLS (1)	OLS (2)	Heckman
Black-White inequality in change in log earnings									
1984-1989	-0.224*	-0.250**	-0.231*	-0.218*	-0.171+	-0.131	0.522***	0.538***	0.498***
1990-1994	-0.0224	-0.0872	-0.0683	0.0792	0.0761	-0.304*	0.0223	0.0755	0.109
1995-1999	-0.176	-0.292*	-0.240+	0.0970	0.103	-0.215	0.300*	0.373*	0.365
2000-2004	-0.0899	-0.0905	-0.0619	0.00651	0.00660	0.0190	0.242*	0.232*	0.190+
2005-2009	-0.208	-0.216	-0.177	0.0216	-0.0308	-0.0240	0.271+	0.327*	0.313+
2010-2014	0.0533	-0.0849	-0.281*	0.0177	0.0364	0.0237	-0.0256	0.0426	0.0654
2015-2020	-0.320*	-0.438**	-0.450**	-0.105	-0.205	-0.410**	0.294+	0.420**	0.412**
Controls									
Task intensity (lost job)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Years since job displacement	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
State-year	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes

Note: +p<0.10 *p<0.05 **p<0.01 ***p<0.001; robust standard errors. Coefficients on indicator variable for race (reference=white) obtained from OLS and Heckman-corrected models. Heckman selection variables include dependency ratio and receipt of unemployment benefits. Individual controls include gender, marital status, number of children, educational attainment, potential experience, potential experience squared, years tenure (lost job), occupation (lost job), industry (lost job), and moved since job displacement. State-year controls include year-specific industry composition, unemployment rate, and routine employment share.

Does task sorting explain racial differences in how job displacement affects earnings?

The previous analyses show that after job displacement, net of other observable differences, Black workers sort into jobs with relatively high manual task intensity and relatively low abstract task intensity. Hypothesis 4c predicts that these racial patterns to task sorting explain a significant amount of racial inequality in how job displacement affects earnings. Table 4.6 presents results from mediation analyses that estimate how much of the Black-White gap in earnings losses, net of pre-displacement controls, is explained by the task composition of the jobs that workers sort into after being displaced. The total effect describes the Black-White gap in earnings losses net of differences on observables in pre-displacement characteristics. The indirect effect describes how much of this difference is explained by the task composition of workers' new jobs. The direct effect describes the remaining difference. The right-hand column describes the proportion of the total effect that can be explained by differences in each type of task by race.

Table 4.6. Mediation of racial inequality in change in log earnings by task sorting

	Total effect	Direct effect	Indirect effect	% of total effect explained
Black-White inequality in change in log earnings				
1984-1989	-0.117***	-0.0735*	-0.0433***	Manual tasks: -0.9% Routine tasks: 20.7% Abstract tasks: 17.3%
	100%	63%	37%	
1990-1994	-0.0467	-0.0354	-0.0113	Manual tasks: -0.4% Routine tasks: -0.3% Abstract tasks: 24.9%
	100%	76%	24%	
1995-1999	-0.122**	-0.0766+	-0.0450***	Manual tasks: -1.2% Routine tasks: 3.2% Abstract tasks: 35.0%
	100%	63%	37%	
2000-2004	-0.0714*	-0.0525	-0.0189**	Manual tasks: -0.1% Routine tasks: 7.8% Abstract tasks: 18.8%
	100%	74%	26%	
2005-2009	-0.0314	-0.00141	-0.0300*	Manual tasks: -2.0% Routine tasks: 22.8% Abstract tasks: 74.8%
	100%	4%	96%	
2010-2014	-0.146*	-0.142*	-0.00431	Manual tasks: -0.2% Routine tasks: -0.2% Abstract tasks: 3.3%
	100%	97%	3%	
2015-2020	-0.0993	-0.0761	-0.0232	Manual tasks: -2.9% Routine tasks: -2.3% Abstract tasks: 28.6%
	100%	77%	23%	

Note: +p<0.10 *p<0.05 **p<0.01 ***p<0.001; robust standard errors. All models control for gender, marital status, number of children, educational attainment, potential experience, potential experience squared, years tenure (lost job), occupation (lost job), industry (lost job), task composition of lost job, and moved since job displacement, year fixed effects, and state-year-specific industry composition, unemployment rate, and routine employment share.

From 1984 to 2004 and 2015 to 2020, the task composition of workers' new jobs explains between a quarter and a third of the adjusted Black-White gap in earnings. Between 2005 and 2009, the Black-White gap is very small, and new job task composition explains 96 percent of the gap. But its effect on the coefficient in log points, rather than percent change, is comparable to other periods. New jobs' abstract task score explains a significant proportion of racial inequality in post-displacement earnings. In most periods, abstract task scores explain between one-fifth and one-third of the total Black-White gap. The explanatory power of new jobs' routine task score declines over time. The routine task score is the strongest mediator from 1984 to 1989, explaining about 20 percent of the adjusted Black-White gap in earnings change. From 2000 to 2009, the routine task score of workers' new job plays a smaller but meaningful role in explaining racial inequalities in how earnings change after displacement. All told, racial differences in task sorting explain a substantial proportion of racial inequalities in earnings changes after job displacement.

Local demand for routine labor

Hypothesis 5 predicts that declining demand for routine labor will exacerbate racial inequalities in task sorting and earnings changes after job displacement. I test these hypotheses by examining how racial differences in job tasks and earnings change within states as their demand for routine labor changes. Table 7 reports results from regression analyses where changes in task intensity and log earnings are predicted by race, state-year-level routine task share, and their interaction. The coefficient on the interaction is of interest, and it describes differences in the effect of state-level demand for routine labor on outcomes for Black and White workers.

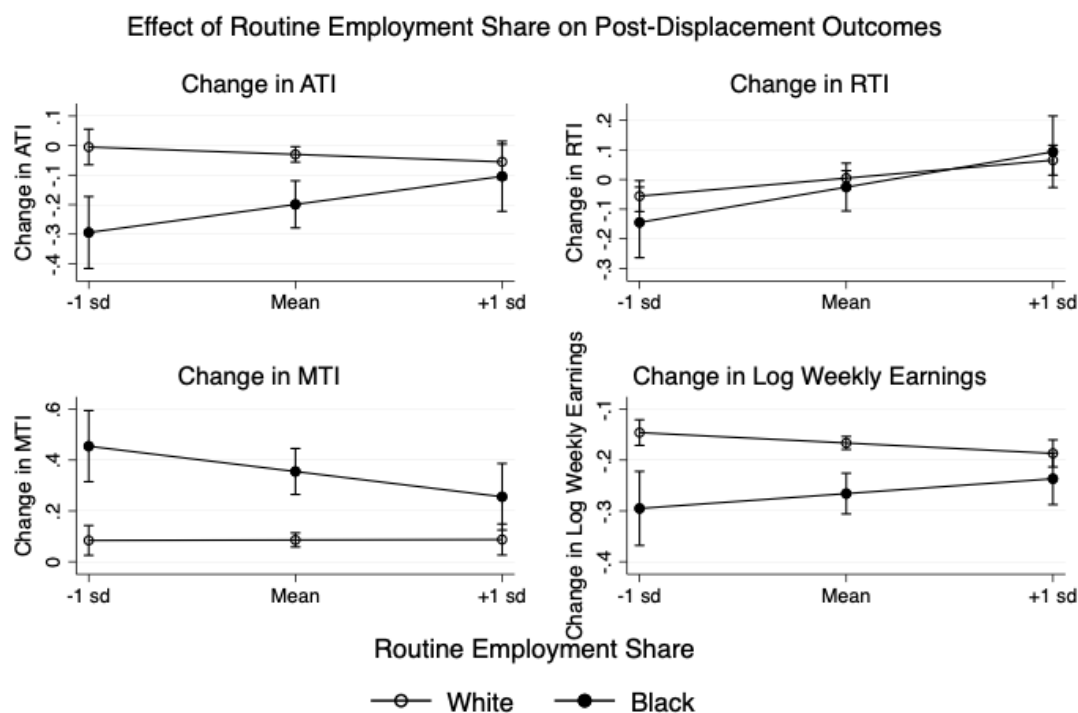
Regression results presented in Table 4.7 and Figure 4.4 provide strong evidence in favor of Hypothesis 5. First, as a state's routine employment share declines, both Black and White workers see similar declines in the routine task intensity of their new jobs. Major inequalities emerge when we consider the other tasks that characterize workers' new jobs. Black-White gaps in the abstract task intensity of workers' new jobs grow substantially as the demand for routine labor declines. While White workers' abstract task intensity is not sensitive to their state's routine task share, Black workers' average new job abstract task intensity declines significantly compared to their old job. At the same time, Black workers' new job manual task intensity grows substantially as the demand for routine labor declines, while White workers' manual task intensity does not change. Taken together, these trends suggest that while White workers are able to find reemployment in jobs with relatively similar manual and abstract task structures after losing their jobs, Black workers sort away from jobs with higher-paying abstract tasks and into jobs characterized by lower-paying manual tasks.

Table 4.7. Effect of local routine employment share on inequality in post-displacement outcomes

Dependent Variable	Change in abstract task intensity			Change in routine task intensity			Change in manual task intensity			Change in log earnings		
	OLS (1)	OLS (2)	Heckman	OLS (1)	OLS (2)	Heckman	OLS (1)	OLS (2)	Heckman	OLS (1)	OLS (2)	Heckman
Black	-1.350**	-1.605**	-1.630**	-0.715	-0.730	-0.337	1.235*	1.472*	1.485*	-0.631*	-0.694*	-0.807*
Routine task share (state-year)	-0.408	-0.966	-0.949	2.056*	2.380**	2.103*	-0.481	0.121	0.112	-0.531	-0.803+	-0.739
Black X routine task share (state-year)	4.059*	4.710**	4.885**	2.339	2.300	-0.210	-3.340+	-4.006*	-4.097*	1.707+	1.954*	2.796**
<i>Controls</i>												
Log weekly earnings (lost job)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Years since job displacement	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
State-year	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes

Note: +p<0.10 *p<0.05 **p<0.01 ***p<0.001; cluster robust (state-year) standard errors (OLS) or robust standard errors (Heckman). Coefficients on indicator variable for race (reference=white) obtained from OLS and Heckman-corrected models. Heckman selection variables include dependency ratio and receipt of unemployment benefits. All models control for log earnings at lost job, years since job displacement, state fixed effects, and year fixed effects. Individual controls include gender, marital status, number of children, educational attainment, potential experience, potential experience squared, years tenure (lost job), occupation (lost job), industry (lost job), and moved since job displacement. State-year controls include year-specific industry composition and unemployment rate. Task intensity models control for the corresponding measure of task intensity at lost job. Log earnings model controls for task scores of the lost job.

Figure 4.4. Effect of local routine employment share on inequality in post-displacement outcomes



These trends are consistent with how racial differences in earnings are affected by changes in local demand for routine labor. As states' routine task share declines, Black workers experience greater earnings losses while White workers remain unaffected. Altogether, these results suggest that among displaced workers, the costs of declining demand for routine labor are borne disproportionately by Black workers.

Conclusions

Job displacement is a highly disruptive event that has significant negative consequences for workers' short- and long-run economic wellbeing. While social scientists have devoted considerable attention to understanding racial inequalities in other economic outcomes, surprisingly little work has examined racial inequalities in job displacement. This paper makes two contributions towards that end. First, I examine trends in Black-White inequality in the effect of displacement on job search and earnings for the first time since Fairlie and Kletzer's analyses of job displacement in the 1980s and 1990s (Fairlie and Kletzer 1996, 1998). I show that while racial inequalities in post-displacement outcomes narrowed through the mid-2000s, they widened considerably after the Great Recession.

Second, this paper's main contribution is a theoretical and empirical elaboration of the mechanisms that explain why Black and White workers' earnings are differently affected by job displacement. I draw on matching and queueing models of the labor market to suggest that we can better understand the consequences of job displacement by considering what workers lose by being displaced from their old job and what workers gain through reemployment at their new job. I argue that due to their advantages in labor market matching processes and firm internal labor markets, White workers have more to lose from being displaced. Conversely, due to Black workers' relative disadvantage in the labor queues, I argue that Black job seekers have less to gain after being displaced. In line with this argument, I show that White workers experience significant and

disproportionate earnings losses relative to Black workers because they are displaced from higher quality jobs on average. I also show that net of differences in pre-displacement individual and job characteristics, Black workers consistently sort into lower quality jobs after being displaced and experience significant earnings losses as a result. All told, White workers' disproportionate earnings losses attributable to their pre-displacement jobs are outweighed by Black workers' disadvantage in re-sorting after displacement, leading Black workers to experience greater earnings losses after job displacement.

These analyses also highlight the importance of job tasks for explaining patterns of economic stratification. Over the last half century, economic restructuring and automation combined to dramatically change the structure of labor demand in the United States. A major consequence of these changes was reduced demand for routine labor and increased demand for nonroutine manual (typically low paying) and abstract labor (typically high paying). While previous work has shown that declining demand for routine labor led to significant earnings losses for Black workers because of their disproportionate representation in routine-intensive jobs, I also show that reduced demand for routine labor disproportionately funnels Black workers into lower paying nonroutine manual jobs compared to otherwise similar White workers. I demonstrate that job displacement triggers this racial pattern of task sorting, thereby exacerbating racial economic inequality by reallocating Black and White workers to different segments of the labor market.

More broadly, these analyses highlight Black workers' precarious position in the labor market and the real challenges that Black workers face in finding high quality employment. I have demonstrated that Black workers' lower position in the labor queue poses a significant disadvantage in finding high quality employment after being displaced. These findings are consistent with prior work suggesting that job loss may be particularly harmful for Black workers because they are likely to initially be employed at (and displaced from) relatively nondiscriminatory firms, and will have to search for a new job among firms with heterogeneous tastes for discrimination that are likely to be more discriminatory than their former employer (Hu and Taber 2005). In the face of a discriminatory labor market, maintaining durable employment relations may be especially important for Black workers' career trajectories and long-run economic wellbeing.

While this paper only examines racial inequalities in the short-run consequences of job displacement, future work should investigate how racial inequalities after job displacement change in the long-run. It may be the case that scarring effects are particularly strong for Black workers. This seems likely if Black workers sort into jobs where the returns to experience are relatively low (as is the case with much nonroutine manual work) or if Black workers cannot effectively switch jobs further down the road to find employment in less-discriminatory firms. In addition, future work may be interested in examining racial inequalities in the psychological and health effects of job displacement (see Burgard et al. 2007; Brand, Levy, and Gallo 2008; Black, Devereux, and Salvanes 2015; Brand 2015). If Black workers indeed experience a more difficult and less fruitful search for high quality employment after displacement, they may experience worse psychological and health outcomes as a result.

Chapter 5: Conclusion

One of sociology's central interests over the last century has been understanding how people are allocated to positions in the socioeconomic structure. As the United States and Western European capitalist countries experienced massive economic growth, restructuring, and rising inequality in the latter half of the 20th century, sociologists became increasingly interested in examining inequalities in economic opportunity. For many of these scholars, the normative concerns surrounding economic growth and rising inequality were centered around questions regarding how access to the gains from economic growth was distributed. Much of stratification research was concerned with how individuals' economic attainment was constrained by the circumstances of their birth. Analyses of intergenerational mobility examined how children's adult outcomes were shaped by their parents' occupations, education, and income, as well as their position in other social institutions such as neighborhoods and schools. Inequalities in economic attainment attributable to individuals' socioeconomic backgrounds were interpreted as limitations on social fluidity, economic opportunity, and class mobility, and comparisons in mobility rates between countries and over time revealed how the structure of economic opportunity varied over time and between places (Breen and Jonsson 2005).

While the intergenerational mobility literature undoubtedly describes social dynamics that are key to understanding inequalities in socioeconomic attainment, it does not capture the processes where individuals' personal resources are converted into economic capital. These processes occur within the labor market over workers' careers, and they are the focus of research on intragenerational mobility. Intragenerational mobility describes how individuals experience changes in earnings, jobs, occupations, firms, employment, and other markers of socioeconomic status over the course of their careers. Beginning with Blau and Duncan's (1967) analysis of occupational mobility, research in the status attainment tradition recognized how individuals' economic attainment later in their career was influenced both by intergenerational factors such as parental socioeconomic status and by intragenerational labor market processes such as how individuals' first occupation affects their future occupational attainment. Subsequent research bridged the status attainment perspective with structural analyses of the labor market to examine how changes in individuals' socioeconomic status over the career were shaped not only by their own personal traits, but also by structural features of the labor market such as the occupational structure, internal labor markets, or career lines (Sørensen 1975). Motivated by similar concerns as those held in the intergenerational mobility literature around the equality of opportunity, the intragenerational mobility literature focused on how labor market processes may sustain, ameliorate, or amplify economic inequality.

While research on the topic of intragenerational was highly active through the 1990s, such analyses largely fell by the wayside by the turn of the century. In the meantime, the United States experienced dramatic and widespread economic restructuring. The economy became more polarized, with significant growth in high-skill managerial, professional, and technical occupations and in low-skill personal service occupations. Technology substituted for much routine, middle-skill work and complemented low- and high-skill labor. Educational attainment rose, as did the returns to education. Immigration continued to increase. Earnings inequality rose substantially. Worker power diminished as unions continued to decline. Firms increasingly abandoned internal labor markets in favor of external hiring. Firms outsourced non-core jobs and increasingly relied on nonstandard, part-time, and otherwise precarious forms of labor. Moreover, all these changes occurred unevenly across the country. Both economic growth and

economic polarization were concentrated in large, mainly coastal cities, while much of the middle of the country experienced economic stagnation or decline due to changes in the US economic structure and the concentration of high-skill workers and high-paying jobs in wealthy cities.

All this is to say, since the time that sociologists moved away from studying intragenerational mobility, the US economy experienced significant changes to both its labor supply and its demand for labor. These massive changes have likely fundamentally altered the role that labor markets play in shaping economic inequality. And to the credit of contemporary sociologists, there has been a recent resurgence in intragenerational mobility research since the mid-2010s, including research by Jarvis and Song (2017) on trends in intragenerational occupational mobility, recent advances in understanding linkages between occupations that facilitate mobility (Cheng and Park 2020; Lin and Hung 2022), and Cheng's innovative work on life-course earnings mobility (Cheng 2014, 2021). This dissertation aims to contribute to the resurgence of intragenerational mobility research.

This dissertation advances research on intragenerational mobility on several fronts. First, I take seriously Sørensen's critique that status attainment research fails to account for how structural features of the labor market shape how individuals convert their personal resources into economic outcomes. I contend that this shortcoming persists in many contemporary studies of intragenerational mobility. By leveraging sociological and economic theories of labor market matching, I consider how structural features of local labor markets create opportunity structures for mobility that shape how patterns of inequality emerge through mobility over workers' careers.

Moreover, while some previous work examines how nationwide changes to structural features of the labor market such as occupational polarization or shifting industry shares contribute to inequality, I note that structural change has occurred unevenly across the US. Growth in high-paying sectors such as technology or finance largely occurred in just a few major cities, while declining manufacturing hit the Rust Belt hardest. At the same time, while some workers do move between cities over their career, the vast majority of job changes occur within workers' local labor market. As such, I argue that *local labor markets* provide workers' primary opportunity structure for intragenerational mobility. In my analyses of workers' career earnings trajectories and economic recovery after job displacement, I demonstrate that patterns of intragenerational mobility vary substantially by local labor market characteristics.

Chapter 2 examines how the level of occupational polarization in workers' local labor markets shapes patterns of inequality in workers' career earnings trajectories. First, I show that occupational polarization at the local level facilitates lifecycle earnings inequality through sorting at the beginning of the career. On average, workers who begin their careers in more polarized labor markets have higher earnings upon entering the labor market than similar workers who begin their careers in less polarized labor markets. Average rates of earnings growth are similar across labor markets. But, *variation* in earnings growth rates differs between more and less polarized labor markets. In the least polarized labor markets, workers who begin their careers with relatively low earnings experience faster earnings growth than workers who begin with relatively high earnings, leading earnings to converge as workers age. In more polarized labor markets, this association weakens substantially, and inequality persists throughout workers' careers. Although I do not directly test this claim, I suspect that polarization entrenches inequality in career earnings mobility because a large and robust top of the labor market provides opportunity for high-skill workers to make real economic gains over their

careers and because the expansion of low-wage, low-skill jobs at the bottom of the labor market may trap more low-earners in “dead-end jobs”. Further investigation is warranted to examine these claims. Recent work by Mouw and colleagues is consistent with the possibility that some low-paying occupations may impede upward mobility for low-earners (Mouw, Kalleberg, and Schultz 2024).

The importance of local labor market structure for how workers move within the labor market is also apparent in my analysis of racial disparities in economic recovery after job displacement in Chapter 4. After accounting for pre-displacement differences between Black and White workers, I show that Black workers still experience significantly larger earnings losses than White workers. Up to a third of this gap can be explained by Black and White workers sorting into new jobs with different task compositions: Black workers tend to sort into jobs characterized by more manual tasks (typically low-paying) and fewer abstract tasks (typically high-paying). However, this pattern is highly sensitive to the task structure of workers’ state-level labor market. I examine how racial inequalities in post-displacement earnings loss change within states based on state-level demand for routine tasks – tasks that are repetitive in nature and easily programmable, are most likely to be displaced by automation, and characterize middle-paying jobs that once provided important economic opportunities for Black workers. I show that as states’ demand for routine labor declines, Black displaced workers increasingly and disproportionately sort into manual labor and out of abstract labor, leading the Black-White gap in post-displacement earnings loss to grow substantially.

My analyses of the relationship between changes to the structure of local labor markets and patterns of intragenerational mobility also reflect my belief that the analysis of social life ought to focus on variation, heterogeneity, and social differentiation. The social structure itself is defined by differentiation – the categorization of people into groups, the division of labor across occupations, firms, and industries, the segregation of people between places, etc., and by individuals’ membership in multiple, cross-cutting social positions (Blau 1977). I argue that the most interesting findings from these chapters are not the average associations between polarization and earnings growth or average racial inequalities in earnings losses after job displacement, but rather how inequalities in earnings trajectories or recovery from job loss vary within and between labor markets, between groups, and over time. While analyses of average differences in outcomes offer an important first cut to understanding economic inequality, further interrogating inequality through analyses of variances in outcomes, changes in population level measures of inequality, and variation in inequalities between places and their historical evolution get us a step closer to understanding the processes underlying social stratification.

Chapter 3 most strongly embodies this perspective. Previous analyses of intragenerational mobility typically examine how workers’ position when they enter the labor market affects their average mid-career outcomes. In contrast, I develop a new framework for thinking about intragenerational mobility between income ranks that considers the entire distribution of ranks that individuals may attain, conditional on where they enter the labor market. This perspective echoes Otis Dudley Duncan’s population-focused perspective on how to conceptualize the social world (Xie 2007). He argues that “Whereas statistics was once known as the ‘science of averages,’ it is better (though incompletely) described as the ‘science of variation’” (Duncan 1984:224). My analysis of earnings rank mobility using quantile regressions describes variation in individuals’ career earnings mobility that goes beyond demonstrating a strong association between early-career earnings and average mid-career earnings. I show that workers’ early-career earnings have different effects on their upper- and lower-tail outcomes. Moreover, I show

that factors like gender and education affect average outcomes through their effects on different parts of the earnings distribution. The association between early- and mid-career earnings ranks is weaker among women than men because women experience much more dramatic downward mobility from high-earning positions. Patterns of upward mobility from low-earning positions do not vary significantly by gender. Education works in the opposite fashion. There is a weaker association between early- and mid-career earnings for college-educated workers because college-educated workers experience greater upward mobility from the bottom of the earnings distribution. While gender affects mobility from the top of the earnings distribution, education affects mobility from the bottom. These analyses not only reveal important information about how the entire distribution of economic mobility and opportunity varies by workers' point of entry into the labor market and other stratifying characteristics, but also highlights how apparently similar average associations can be driven by very different social dynamics that affect different parts of the outcome distribution.

My analysis of how local labor market polarization shapes variation in workers' career earnings trajectories also shifts our focus away from average outcomes towards variation in outcomes. Multilevel growth curve models provide a statistical framework to describe inequality in early-career earnings, earnings growth rates, and the relationship between early-career earnings and earnings growth through an analysis of the model's variance components. While a standard regression framework allows us to characterize inequality by describe average differences between groups (e.g. how average rates of earnings growth change between levels of polarization), this empirical approach allows me to generate new insights about variation within groups (e.g. how much earnings growth rates vary within similarly polarized commuting zones).

To recapitulate, I have argued that understanding socioeconomic inequality requires examining intragenerational mobility in order to understand the labor market processes by which individuals attain positions in the stratification system. I have also argued that characterizing the labor market processes that underlie social stratification requires theorizing and modeling how patterns of mobility and attainment are shaped by the interaction between individuals and the economic structure in which they are embedded. Finally, I have advocated for devoting greater attention to, and developing statistical methods for, the analysis of variation in outcomes. The three empirical chapters of this dissertation embody this perspective, and they demonstrate its utility for understanding how inequality is produced through labor market matching processes that are both geographically and historically contingent, unfold over workers' careers, and result in the allocation of individuals to positions in the system of stratification.

I hope that future research will build on both this theoretical perspective and on some of the empirical results that I have reported. Broadly, I believe much more work is needed to develop models of the labor market at the population level. Demographic and ecological perspectives, as well as sociological and economic models of labor market matching, provide powerful tools that can be used to characterize populations of firms, populations of workers, their interaction, their variation, and their change over time. This approach is crucial when considering how labor markets produce inequality because firms' hiring choices and workers' employment decisions depend on their available alternatives. In particular, I hope that this perspective will be utilized to understand changes to the structure of firm and worker power in labor markets. For example, this perspective could be mobilized to consider how rising labor market concentration, vertical disintegration, and segmentation have changed the sets of jobs available to workers and their access to pathways for upward mobility.

In light of recent research on precarious work arrangements such as nonstandard, contract, and part-time work, as well as the proliferation of low-paying jobs with highly unstable and unpredictable work schedules, I also hope that this perspective will be mobilized to examine how workers move between precarious work arrangements and tradeoff between wages and non-wage dimensions of job quality. In addition, future research may be interested in how these tradeoffs depend on the structural features of local labor markets that I have previously discussed.

Finally, building on traditional status attainment research, I hope that future work will continue to examine how intragenerational mobility relates to the intergenerational transmission of socioeconomic status. As Sørensen (1975) argued, intergenerational mobility inherently depends on intragenerational mobility. Recent work by Siwei Cheng and Xi Song builds on this observation by examining how the strength of intergenerational transmission varies over the life course (Cheng and Song 2019). Future work should build on this perspective and examine how structural features of the labor market shape intragenerational mobility in ways that may either strengthen or weaken the association between individuals' origins and their eventual economic attainment.

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Appendix 1. Chapter 2: Robustness Checks

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.

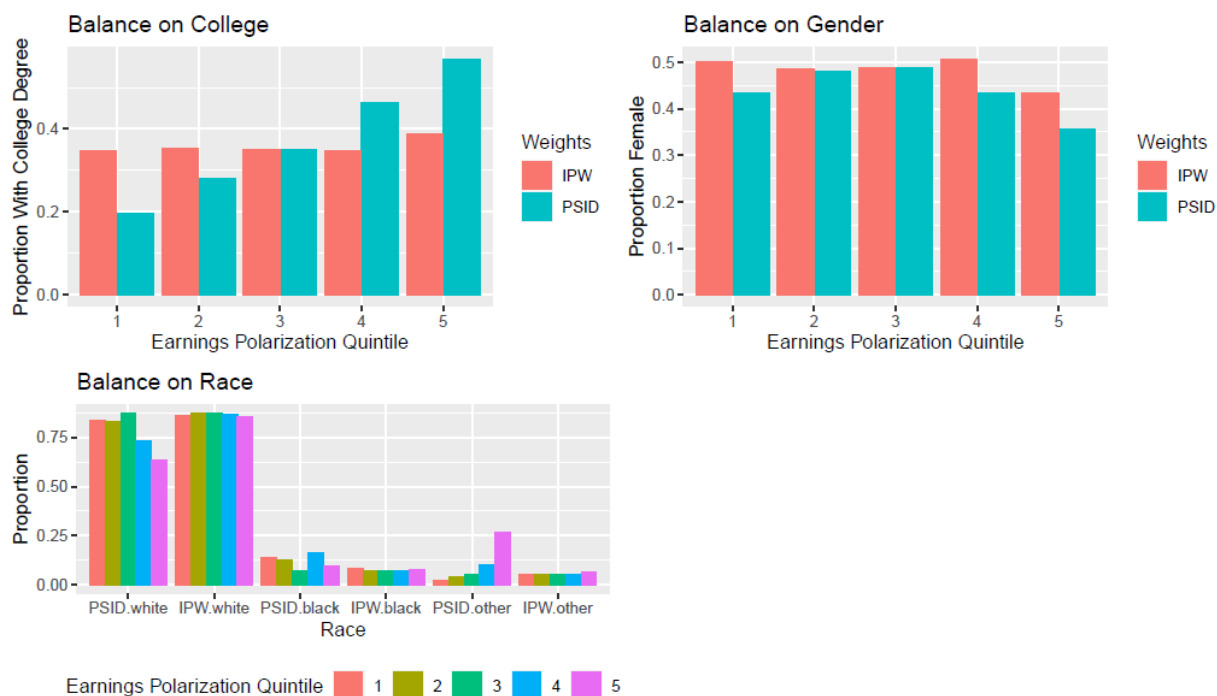
Figure A1.1 Balance tables for earnings polarization analyses
Balance Tables 1960 Cohort



Balance Tables 1965 Cohort



Balance Tables 1970 Cohort



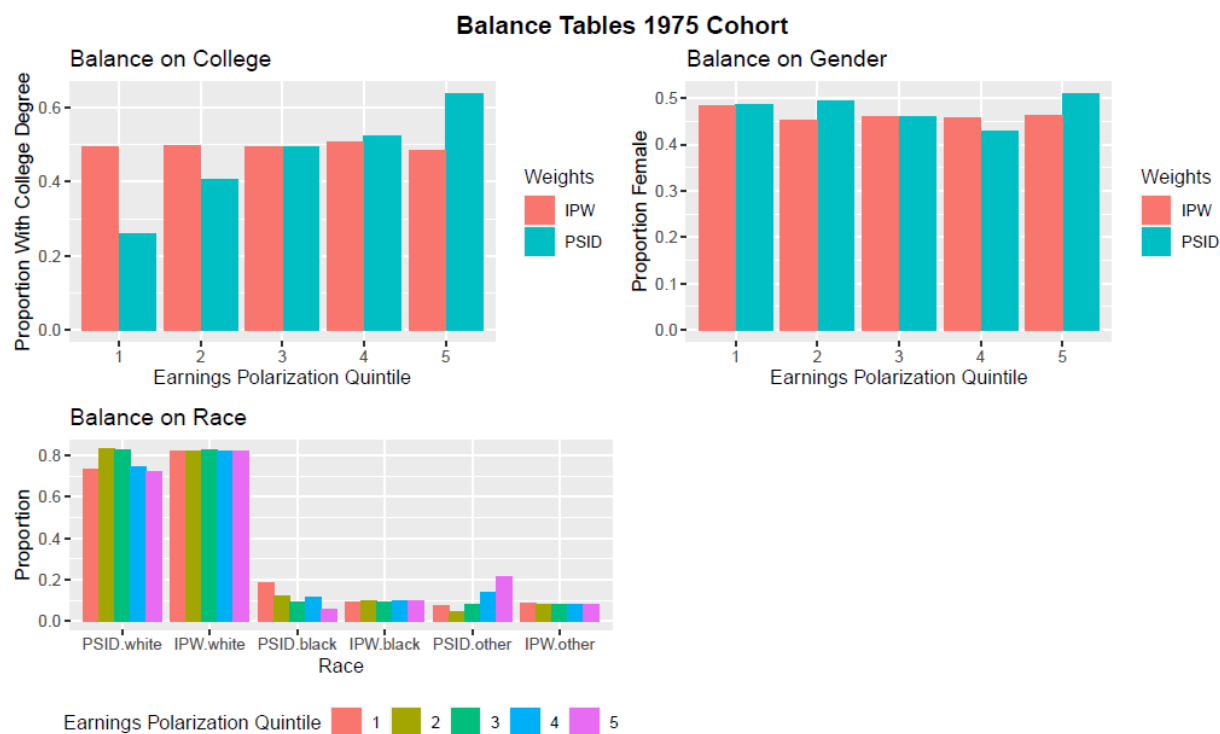


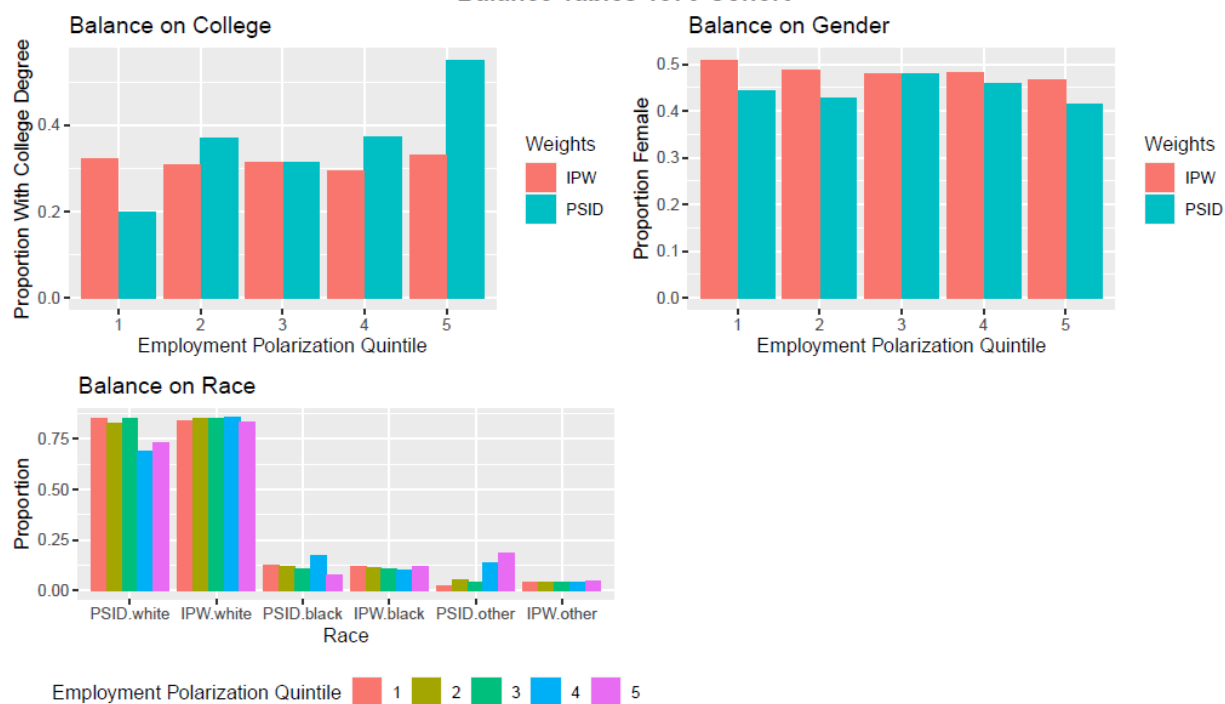
Figure A1.2 Balance tables for employment polarization analyses
Balance Tables 1960 Cohort



Balance Tables 1965 Cohort



Balance Tables 1970 Cohort



Balance Tables 1975 Cohort



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

Fixed effects	Earnings polarization					Employment polarization		
	1960-1964	1965-1969	1970-1974	1975-1980	1960-1964	1965-1969	1970-1974	1975-1980
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	0.142	0.111	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	0.146+	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	-0.364
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.

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Appendix 2. Chapter 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:

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

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

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

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

Appendix 3. Chapter 3: Instrumental Variables Analysis

Instrumental variables (IV) analysis estimates a local average treatment effect (LATE) that describes the causal effect of the treatment on the outcome among individuals for whom the instrument affects their treatment status (Imbens and Angrist 1994). Three assumptions are required for IV estimation: 1) the IV is a strong predictor of treatment (relevance), 2) the IV only affects the outcome through the treatment (exclusion restriction), and 3) there is no confounder causing both the instrument and the outcome (exchangeability). Satisfying all three assumptions allows for an unbiased estimate of the causal effect of a treatment on an outcome. I instrument early-career earnings rank using an indicator for whether a recession occurred while a worker was employed from ages 22 to 28 and father's occupation. I use the `-ivreg2-` command in Stata (Baum, Schaffer, and Stillman 2007) to conduct statistical tests to assess the extent to which these instruments satisfy the assumptions of IV analysis and present the results of those tests in Table A3.1. IV quantile regressions are conducted using the Stata program `-sivqr-` developed by Kaplan (2022).

1. Relevance

Workers who enter the labor market during a recession experience a considerable reduction in early-career earnings (Oreopoulos, von Wachter, and Heisz 2012; Altonji, Kahn, and Speer 2016; Schwandt and von Wachter 2019; Rothstein 2021). There is substantial variation within the sample in whether respondents experienced a recession while working between ages 22 and 28 and exposure to a recession early in the career is a significant predictor of early-career rank earnings.

Parent socioeconomic status (SES) is a strong predictor of workers' labor market outcomes. In the mobility and status attainment literatures, parent SES is typically operationalized using measures of parents' occupations, education, and income (e.g. Blau and Duncan 1967; Sewell and Hauser 1975). I operationalize parent SES using father's occupation. Father's education was not used because statistical tests indicated that the instrument was redundant. Mother's education was not used because statistical tests suggest the instrument is not orthogonal. Parent income and mother's occupation were not used because these data are not available for many PSID respondents. Father's occupation varies considerably within the sample and is a strong predictor of early-career rank earnings.

When used simultaneously as instruments for early-career rank earnings, the two instruments satisfy the relevance assumption. I conduct a few statistical tests to assess underidentification, weak identification, overidentification, and instrument redundancy. Underidentification is assessed using the Kleibergen-Paap LM statistic. The test statistic is statistically significant, rejecting the null hypothesis that the model is underidentified. Weak identification is assessed using the Cragg-Donald Wald F statistic. The F statistic is greater than 10, which satisfies the rule-of-thumb cutoff of $F > 10$ for relevance. The F statistic is also greater than the Stock-Yogo critical value of 6.61 for 20% maximal IV size and just less than the critical value for 10%, meaning that the bias of these IV estimates is limited to 20% of the bias in OLS. The Hansen J statistic of 11.241 and corresponding p-value of 0.2595 indicates that the model is not overidentified. The redundancy test produces acceptably low p-values indicating that father's occupation and the recession indicator are not redundant.

2. Exclusion and Exchangeability

The exclusion restriction and exchangeability cannot be directly tested. But, it seems unlikely that exposure to a recession early in a worker's career would affect the worker's rank earnings 20 years later through any pathway other than its effect on their early-career economic status. It also seems unlikely that an early-career economic recession could be caused by some variable that also affects a worker's rank earnings 20 years later. It is less certain that parent SES satisfies the exclusion restriction and assumption of exchangeability. Well known econometric models of labor force participation (e.g. Heckman 1981) and status attainment models (e.g. Blau and Duncan 1967) suggest that parent SES affects entry into the labor market but has little or no effect on post-entry labor market outcomes. This assumption has been used in other IV analyses of mobility (Cappellari and Jenkins 2004; D'Addio and Rosholm 2005; Cappellari 2007; Mosthaf, Schank, and Schnabel 2014). However, it may be possible that heritable traits that affect productivity could directly father's occupation and workers' mid-career earnings.

Orthogonality can also be assessed using the C statistic, or the difference-in-Sargan statistic, which compares the Sargan-Hansen statistic of a subset of instruments compared to the full set of instruments (including those whose exogeneity is suspect). Failing to reject the null hypothesis indicates that the entire set of instruments are valid. Tests of orthogonality on both the indicators for early-career recession and father's occupation fail to reject the null hypothesis, suggesting the instruments are valid.

Table A3.1. Tests of IV assumptions

Statistic	Value	Interpretation
Kleibergen-Paap Wald LM	70.191 (p<0.0001)	Model is not underidentified
Cragg-Donald Wald F	10.480	Instruments are relevant; bias between 10% (critical value=11.49) and 20% (critical value=6.61)
Hansen J	11.241 (p=0.2595)	Model is not overidentified
Redundancy: recession	3.658 (p=0.0558)	Instrument is not redundant at p<0.10
Redundancy: father occupation	68.079 (p<0.0001)	Instrument is not redundant
C statistic: recession	3.154 (p=0.0757)	Instrument satisfies orthogonality
C statistic: father occupation	11.241 (p=0.2595)	Instrument satisfies orthogonality

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Appendix 4. Chapter 3: Balancing Between Cohorts for Decomposition Analysis

The goal of reweighting in the DFL (DiNardo, Fortin, and Lemieux 1996b) decomposition is to achieve a counterfactual distribution on a set of covariates in a treated group that resembles that distribution in the control group. In this application, the goal is to achieve balance such that each “treated” cohort (the 1950, 1960, and 1970 birth cohorts) resembles the 1940 cohort in its distribution on covariates such as gender and education *and* how those covariates are distributed by early-career rank earnings. These weights are defined as:

$$\omega = (1 - C) + C * \frac{1 - P(C|X, r, X * r)}{P(C|X, r, X * r)}$$

where C is an indicator variable for the weighted cohort, X represents a set of covariates to balance on, and r represents early-career earnings rank, and the propensity score $P(C|X, r, X * r)$ is estimated using the probit regression:

$$\Phi(C) = \beta_0 + \beta_1 X + \beta_2 r + \beta_3 X * r$$

Before proceeding with the decomposition, it is essential to assess that statistical independence between cohort membership and the covariates, early-career earnings rank, and their interaction, was successfully achieved via the reweighting procedure. I do so with linear probability models where the outcome is cohort membership and the predictor variables are the balancing covariate, early-career rank earnings, and their interaction, before (unbalanced) and after reweighting (balanced). From Table A4.1, we see that there is no statistically significant association between any of the predictors and cohort membership after reweighting, indicating that the reweighting procedure successfully achieved the desired counterfactuals.

Table A4.1. Regression coefficients from DFL balance tests

Birth Cohort	1950-1959		1960-1969		1970-1979	
Model	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced
Female	-0.00617	-0.0224	-0.193**	-0.0244	-0.191*	-0.0197
Early-career rank	-0.000113	-0.000222	-0.00207**	-0.000130	-0.00285**	-0.0000561
Early-career rank X female	0.00127	0.000347	0.00476***	0.0000243	0.00467**	0.0000503
Black	0.252***	0.00372	0.310***	0.0220	0.297**	0.0380
Early-career rank	0.000373	0.00000473	0.000650	0.000113	-0.000539	0.000164
Early-career rank X Black	-0.00239	-0.0000824	-0.00361**	-0.000155	-0.00195	-0.000509
College	0.212***	-0.00565	0.0630	0.0384	0.358***	-0.0851
Early-career rank	0.00160**	-0.0000433	0.000729	0.000234	0.0000987	-0.000225
Early-career rank X college	-0.00415***	0.000109	-0.00138	-0.000500	-0.00385**	0.00119
Years experience	0.0138**	0.00192	0.0179***	0.00356	0.0139*	0.00431
Early-career rank	0.00819**	0.00141	0.00887***	0.00183	0.00517	0.00278
Early-career rank X years experience	-0.000345**	-0.0000586	-0.000376***	-0.0000749	-0.000268*	-0.000113
Years tenure	0.00225	-0.000387	0.00631	-0.000475	0.00700	0.000476
Early-career rank	0.000617	0.00000891	0.00195*	0.0000933	0.00215	0.000562
Early-career rank X years tenure	-0.0000504	0.00000162	-0.000152*	0.00000298	-0.000237**	-0.0000300
Experience: manager/professional	0.00566	-0.000567	-0.00518	0.00142	0.00577	-0.000941
Early-career rank	0.00129*	-0.0000831	0.000903	0.000215	0.000932	0.000183
Early-career rank X experience: mgr/prof	-0.000152*	0.0000109	-0.0000140	-0.0000200	-0.000185*	0.00000442
Experience: service	0.0000262	-0.00126	-0.00578	-0.00397	-0.0121	-0.00394
Early-career rank	0.0000470	-0.0000445	-0.0000394	-0.0000233	-0.00122	0.0000401
Early-career rank X experience: service	0.000206	0.0000216	0.000362**	0.0000909	0.000692***	0.000208
Total employer changes	0.0165*	-0.00300	-0.00152	0.00145	-0.0342**	0.00183
Early-career rank	0.000813	-0.000306	-0.000206	0.000236	-0.00386**	0.000533
Early-career rank X total employer changes	-0.0000113	0.0000494	0.0000670	-0.0000200	0.000448*	-0.0000904
Occupation changes: mgr/prof	0.0215	0.00182	0.00557	0.00950	0.000799	0.00842
Early-career rank	0.000416	0.0000474	0.000258	0.000386	0.000270	0.000555
Early-career rank X occupation changes: mgr/prof	-0.000243	-0.0000248	-0.0000772	-0.000138	-0.000349	-0.000172
Occupation changes: service	0.0142	-0.00664	0.0131	0.00428	-0.0363	0.0119
Early-career rank	0.000326	-0.0000881	0.000437	0.000167	-0.00137	0.000348
Early-career rank X occupation changes: service	0.000504	0.000221	0.000858*	-0.0000326	0.00172**	0.000195

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

Note: Each set of rows represents coefficients obtained from separate linear probability models where the outcome is an indicator for belonging to the birth cohort corresponding to the column label. The base category is belonging to the 1940-1949 cohort.

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