The Population Effects of U.S. Deindustrialization

By

Nathan Philip Seltzer

A dissertation submitted in partial fulfillment of

the requirements for the degree of

Doctor of Philosophy

(Sociology)

at the

UNIVERSITY OF WISCONSIN-MADISON

2020

Date of final oral examination: March 18th, 2020

The dissertation is approved by the following members of the Final Oral Committee:

Jenna Nobles, Professor, Sociology
Myra Marx Ferree, Professor Emerita, Sociology
Christine Schwartz, Professor, Sociology
Rourke O'Brien, Assistant Professor, Sociology (Yale University)
James Raymo, Professor, Sociology (Princeton University)

Abstract

Since the 1980s, U.S. labor markets have shifted away from an occupational regime dominated by the production of manufactured goods to one characterized by the provision of services. This economic restructuring has resulted in the decline of middle-wage employment opportunities and the depletion of financial resources for American workers, especially for those without a college degree. Here, I investigate how these structural changes in U.S. labor markets have altered population processes and population health outcomes, reduced upward mobility, and created new fronts of inequality.

Drawing on theories of economic change, including labor market polarization and precarious work, Chapter 1 develops a structural economic explanation for why U.S. fertility rates have declined to record lows in the decade since the Great Recession despite improvements in conventional economic indicators. Combining statistical and survey data with restricted-use vital registration records, I find that changes in industry composition – specifically, the loss of manufacturing and other goods-producing businesses – have a larger effect on reducing total fertility rates than changes in the unemployment rate.

In Chapter 2, I assess how variation in state-level manufacturing decline predicts the rise of the current fatal drug and opioid epidemic that has taken the lives of over 700,000 Americans over the past two decades. The origins of the opioid epidemic are often exclusively attributed to the mechanistic role of pharmaceutical companies and pill mills in expanding the supply of opioid pain relievers to the public. But less recognized are the ecological contexts that shape *demand* for substance use. The findings demonstrate the considerable extent to which declining economic opportunity and the ascendance of economic "despair" are associated with drug mortality.

In the final chapter, I develop a conceptual framework linking the study of labor market change to economic stratification. I examine how deindustrialization has altered opportunities for upward economic advancement in the U.S. Focusing on birth cohorts born in the 1980s, I find strong evidence that declines in manufacturing employment have contributed to growing geographic disparities in upward intergenerational income mobility. Children raised in counties that experienced larger contractions in manufacturing industries throughout adolescence experienced larger economic penalties in adulthood via reduced levels of upward mobility. The results demonstrate how long-term macroeconomic changes can disrupt and redistribute opportunities within societies.

Acknowledgements

This dissertation is the product of immeasurable support, guidance, and encouragement from many mentors over the past five years. As my advisor, Jenna Nobles has taught me how to think like a sociologist and a demographer. She has constantly challenged me to improve the methodological rigor of my research and go above and beyond what is expected. I am fortunate for her taking the time to read countless drafts of my work and provide sharp and constructive feedback.

I also owe a debt of gratitude to the members of my dissertation committee. Myra Ferree has contributed profoundly to my intellectual growth and how I think about research design. She has taught me the craft of writing sociological journal articles. I will forever have her methods course handout, "Some 750 take home points," affixed to my fridge. Rourke O'Brien has been a source of encouragement over the past year and a half. He has helped me develop my research agenda and has provided shrewd advice on professionalization. Incisive feedback from Christine Schwartz has improved the way I frame my research. She has challenged me to think about the underlying mechanisms driving the results presented in this dissertation. Jim Raymo introduced me to demographic techniques during my first year as a graduate student. I failed my first DemTech exam, but Jim was nice enough to give me a B for the semester and allow me to continue on in the program.

Several other faculty at Wisconsin and elsewhere have served as mentors. Marcy Carlson has had unwavering support for me since I moved to Madison. I learned much about family demography as a research assistant, collaborator, and student of hers during my second year in the program. I am extremely fortunate that Elizabeth Wrigley-Field asked me to work with her on a project about job displacement. This project has expanded my knowledge about labor market inequality and informs much of the research conducted in this dissertation. She has also provided me invaluable professional guidance. Pam Herd gets a special thanks for inviting me to be the scribe for the Executive Board of the General Social Survey. This has been an unparalleled opportunity to learn about the challenges currently facing survey research. Finally, Katherine Gregory continues to be a wellspring of knowledge and support.

Prior to entering the Sociology program here at UW-Madison, I received generous encouragement from Mike Hout, Larry Wu, Jeff Manza, and David Greenberg when I worked on my Master’s degree at New York University, and Martha Huggins, Diane Grams, and Mimi Schippers when I worked on my Bachelor’s degree at Tulane University.

I would not have survived the past five years of graduate school without the support of friends and colleagues like Max Coleman, Tiffany Neman, Kaan Jittiang, Sarah Farr, Christian Castro Martinez, Courtney Deisch, Jessica Polos, Ariane Ophir, Kendra Nervik, Masoud Movahed, Javier Rodriguez, Jia Wang, Qian He, Kelsey Wright, Julie Goodwin, Rachel Rosenfeld, Maria Azocar, and Anita Li, among many others. Chloe Haimson was pivotal in developing many of my research ideas. Sherry Zhang, Katie Jajtner, and Wei Xu have provided useful career advice. Additional thanks go to colleagues/friends at other institutions, including Jessie Himmelstern, Daniela Urbina, Leah Glass, and Emma Mishel.

I have benefitted tremendously from the administrative support and friendship of many staff in the Center for Demography and Ecology and the Sociology Department, including Vicki Sekel, Susan Vial, Carol Tetzlaff, Rebekah Turner, Sherry Huhn Gotzler, Charlotte Frascona, Janet Clear, and Mary Lynn Dombrowski. I have also enjoyed being office neighbors on the third floor of Sewell with Charlie Fiss and Lu Chou. Doug Hemken at the SSCC has provided valuable statistical advice.

I also thank my family for supporting me over the years, especially my parents, Natalie and Ben, and my siblings, Daniel, Jennifer, and Peter. My father passed away prior to me entering graduate school, but he continues to be a role model of a scholar and a person. Additional thanks go to both of my grandmothers, Gram and Bohbie.

I am grateful for support from training grant T32 HD007014 awarded to the Center for Demography and Ecology by the Eunice Kennedy Shriver National Institute of Child Health & Human Development, and training grant T32 AG00129 awarded to the Center for Demography of Health and Aging at UW-Madison by the National Institute on Aging. I am also grateful for research support from the U.S. Social Security Administration through grant #RRC08098400-09 to the National Bureau of Economic Research as part of the SSA Retirement Research Consortium. The findings and conclusions expressed are solely those of the author and do not represent the views of SSA, any agency of the Federal Government, or the NBER. Finally, I am thankful for the kindness and generosity of Robert M. and Taissa S. Hauser as a recipient of the Hauser Research Scholar Award.

Table of Contents

Introduction

At the time of writing, the United States is currently experiencing the longest period of continuous economic growth in the nation's modern history.[1] For the past 129 months, since the end of the "Great Recession" in June 2009, unemployment rates have declined, gross domestic product has grown at a steady rate, and median household income has continued to rise to record levels. This ostensible financial prosperity is not just recorded by government statistics, but also by positive public sentiment. According to the most recent national Gallup poll on the economy, 68% of Americans think that now is a good time to find a quality job, up from just 8% in 2009, and only 10% of Americans today think that economic issues are the most important problem facing the country right now, down from 86% in 2009 (Jones and Saad 2020).

Despite these sanguine indicators and beliefs about the economy, demographic trends tell a far different story – at least to the extent that demographic processes are responsive to economic conditions (Chetty, Stepner, et al. 2016; Currie and Schwandt 2014; Preston 1975). Since the Great Recession, U.S. fertility rates have fallen to record lows (Figure 1a) – in 2018, the period total fertility rate (TFR) was 1.73 births per women (Martin et al. 2019) – and U.S. life expectancy experienced its first sustained trend reversal after nearly a century of continuous growth (Figure 1b), largely driven by rising drug- and opioid-related mortality (Arias and Xu 2019; Hedegaard, Miniño, and Warner 2020). Based on decades of empirical and theoretical work in demography, these recent trends would suggest that the economy is not doing well.

[1] The Introduction of this dissertation was drafted in February 2020.

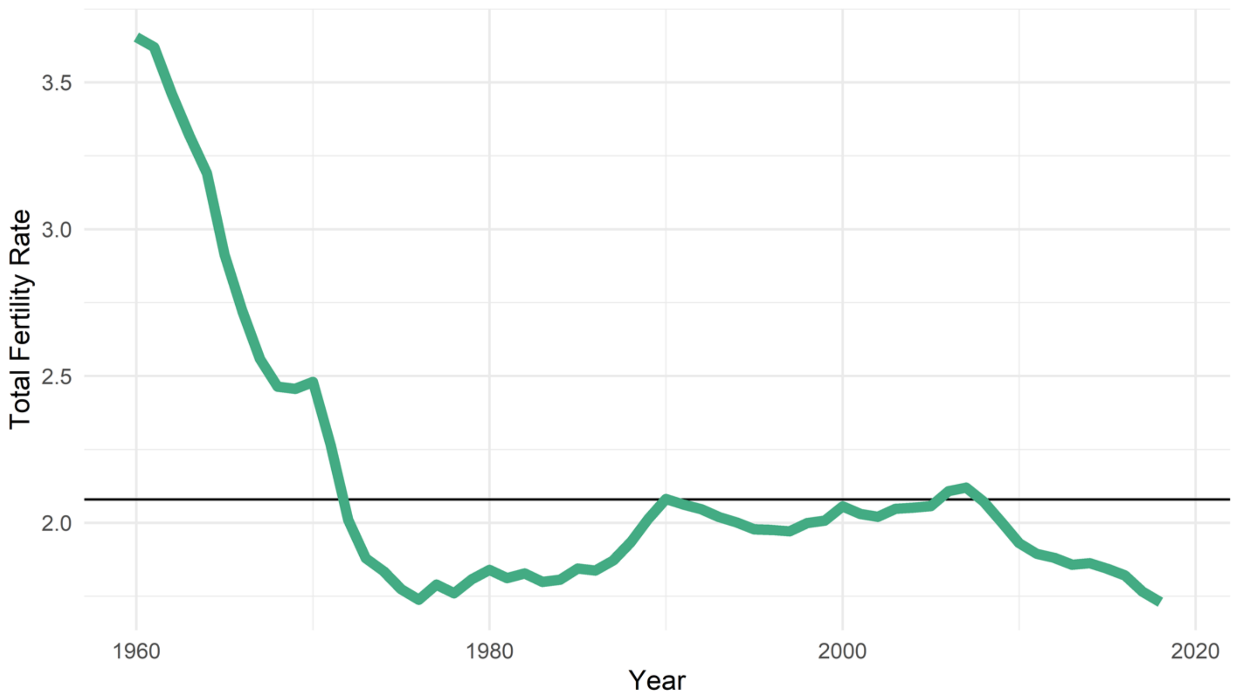


Figure 1a. U.S. Total Fertility Rate, 1960-2018

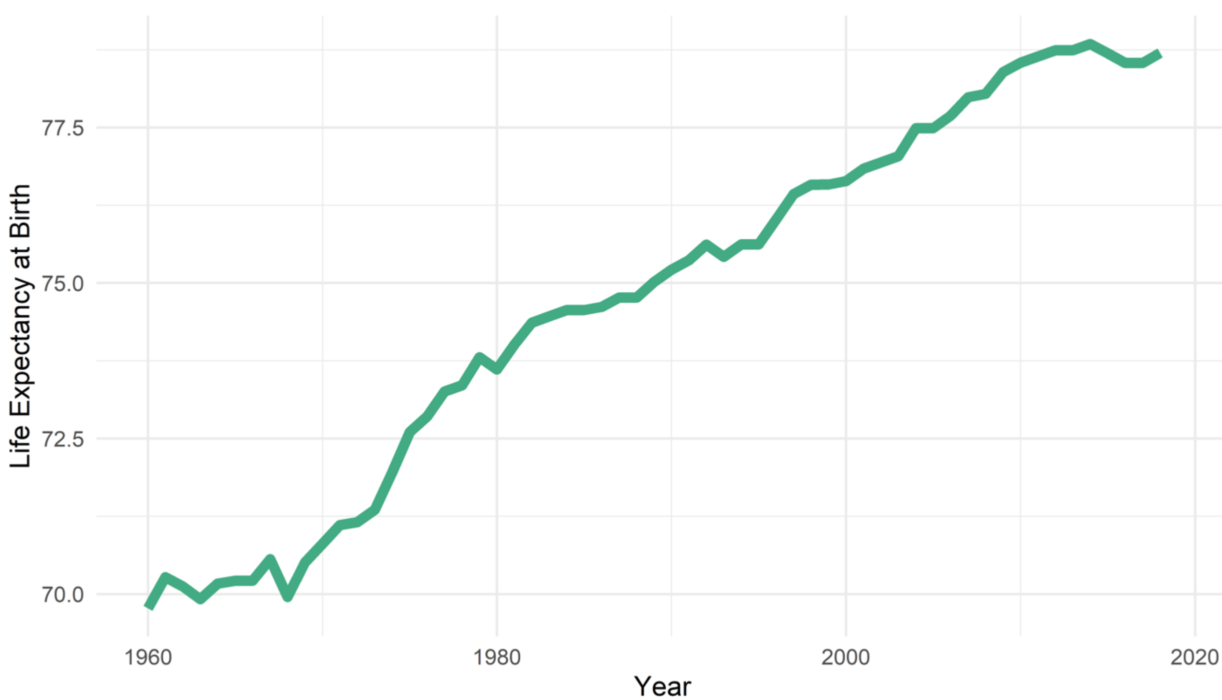


Figure 1b. Overall Life Expectancy at Birth, 1960-2018

The research conducted in this dissertation is motivated by the apparent unmooring of historically linked economic trends from demographic patterns. But rather than casting off economic explanations entirely, I instead focus on how widely-used economic indicators – such as the unemployment rate, gross domestic product, and median household income – are inadequate to describe the state of the U.S. economy in recent decades. Since the 1970s, U.S. labor markets have undergone a process of deindustrialization which has transformed the type of job opportunities available to American workers (Kalleberg 2018). One of the most visible consequences of this transformation has been the decline of occupational opportunities in the middle of the wage distribution, and the accompanying growth of occupational opportunities at the low- and high-end of the wage distribution (Autor 2010; Autor and Dorn 2013). Despite the scale of these changes to the U.S. labor market, sociological and demographic scholarship has largely overlooked the potential implications of this economic restructuring on population dynamics. The principal aim of this dissertation is to explore how the deindustrialization of U.S. labor markets has altered the contexts in which demographic processes occur.

In Chapter 1, “Beyond the Great Recession: Labor Market Polarization and Ongoing Fertility Decline in the United States,” I investigate why U.S. fertility rates have deviated from their previous pro-cyclical trend following the Great Recession in 2007-2009. I draw on theories of economic change, including labor market polarization and work precarity, to develop a model in which long-term structural declines in the supply of middle-skill, middle-wage jobs in goods-producing industries predict decreased fertility rates. This structural economic explanation provides much more analytical leverage in describing the current state of U.S. fertility decision-making because it contends that the decline of middle-wage jobs has prolonged the financial uncertainty faced by people during and after the Great Recession.

In Chapter 2, "The Economic Underpinnings of the Drug Epidemic," I assess how variation in state-level manufacturing decline predicts the rise of the current fatal drug and opioid epidemic that has taken the lives of over 700,000 Americans over the past two decades. The origins of the opioid epidemic are often exclusively attributed to the mechanistic role of pharmaceutical companies and pill mills in over-prescribing opioid pain relievers to patients. Less recognized in academic scholarship – though frequently discussed by journalists and the public – are the ecological contexts that shape *demand* for substance use. This chapter considers the endogenous relationship between supply and demand in the ongoing drug epidemic. The results demonstrate the extent to which declining economic opportunity, and the theorized accompanying ascendance of economic "despair" (Case and Deaton 2015; Shanahan et al. 2019), is associated with drug mortality.

Chapter 3, "Cohort-Specific Experiences of Industrial Decline and Intergenerational Income Mobility," examines *how* deindustrialization has reshaped the economic opportunity structure of U.S. communities. In this study, I use a life course perspective to examine how county-level manufacturing decline has reshaped the upward mobility prospects of birth cohorts born during the 1980s. Children from these cohorts entered the labor market starting in the late 1990s, a period of particularly rapid labor market change. I link subnational business register data with rank-rank estimates of intergenerational income mobility generated by Chetty et al. (2014). I find that cohorts of children raised in counties with larger contractions in manufacturing throughout adolescence faced larger economic penalties as they entered adulthood. This study also documents how manufacturing decline has exacerbated longstanding racial inequalities in upward mobility. In sum, this study leverages cohort-specific experiences of labor market change to observe how deindustrialization has altered processes of intergenerational mobility, both across geographic areas and across time.

Throughout these three chapters, I adopt a macro-level demographic approach that gives precedence to the examination of ecological processes rather than individual-level experiences (Lee 2001). The use of aggregate, population-level data is intentional. Population processes – fertility, mortality, and social mobility – across geographic and historical contexts operate at a macro-scale in which underlying distributions of economic and social characteristics create very different social contexts and milieus. In this sense, an important guiding aim of this research is to understand how places produce populations and population outcomes. This macro-level framework is also beneficial in the aim of evaluating how ecological contexts act to stratify populations and contribute to disparities across subpopulations. At several points in this dissertation, I discuss how individual-level data may answer complementary, but distinct questions. In the Conclusion chapter, I describe my ongoing research that turns the focus to both contextual- and individual-level relationships.

Chapter 1: Beyond the Great Recession: Labor Market Polarization and Ongoing Fertility Decline in the United States

ABSTRACT
In the years since the Great Recession, social scientists have anticipated that economic recovery in the U.S., characterized by gains in employment and median household income, would augur a reversal of declining fertility trends. However, the expected post-recession rebound in fertility rates has yet to materialize. In this study, I propose an economic explanation for why fertility rates have continued to decline regardless of improvements in conventional economic indicators. I argue that ongoing *structural* changes in U.S. labor markets have prolonged the financial uncertainty that leads women and couples to delay or forego childbearing. Combining statistical and survey data with restricted use vital registration records, I examine how cyclical and structural changes in metropolitan-area labor markets were associated with changes in total fertility rates (TFR) across racial/ethnic groups from the early 1990s to the present day, with a particular focus on the period between 2006-2014. The findings suggest that changes in industry composition – specifically, the loss of manufacturing and construction businesses – have a larger effect on TFR than changes in the unemployment rate for all racial/ethnic groups. Since structural changes in labor markets are more likely to be sustained over time, in contrast to unemployment rates which fluctuate with economic cycles, further reductions in unemployment are unlikely to reverse declining fertility trends.

Keywords: Fertility, Great Recession, Labor Market Polarization, Unemployment

INTRODUCTION

The United States experienced an economic recession from December 2007 to June 2009 that had manifold negative consequences on the national and global economy (Bureau of Labor Statistics 2012). Approximately 8.8 million U.S. jobs disappeared and the U.S. unemployment rate rose to a peak of 9.5 percent in 2009 (Bureau of Labor Statistics 2012; Goodman and Mance 2011). All told, the economic damage wrought by the Great Recession resulted in the loss of 19.2 trillion dollars in U.S. household wealth (Department of the Treasury 2012).

In the decade since, demographers have leveraged the Great Recession's adverse economic consequences to examine how economic conditions influence aggregate fertility trends (Sobotka, Skirbekk, and Philipov 2011). These studies have examined economic and labor market variation at the national- and state-level and have found differential outcomes in fertility behavior based on characteristics such as race and ethnicity, socioeconomic status, marital status, and educational attainment (Cherlin et al. 2013; Currie and Schwandt 2014; Percheski and Kimbro 2014; Schneider and Hastings 2015). Researchers interpret these results as indications that women and couples temporarily postpone childbearing as a result of financial uncertainty induced by job loss and decreases in income (Balbo, Billari, and Mills 2013; Brauner-Otto and Geist 2018). Delays in childbearing – even for a couple of years – can reduce lifetime fertility rates for cohorts of women (Bongaarts and Feeney 1998; Currie and Schwandt 2014; Morgan 2003; Ryder 1980). As a result, both brief and sustained changes in macroeconomic conditions have long term implications for population change and renewal.

Despite the importance of these previous studies, a puzzle remains concerning trends in post-recession fertility: while unemployment rates and median household income have returned to pre-recession levels, fertility rates continue to decline and have recently fallen to record lows in the United States (Hamilton et al. 2017; Martin et al. 2018). The total fertility rate for the United States remained below replacement at about 1.77 births per woman in 2017 (Hamilton and Kirmeyer 2017; Martin, Hamilton, and Osterman 2018), down from 2.12 births per woman in 2007. Meanwhile, the national unemployment rate returned to its pre-recession level of 4.7% in May 2016 (Bureau of Labor Statistics 2017) and median household income surpassed pre-recession levels in 2015 (Semega, Fontenot, and Kollar 2017). These patterns raise questions about the relative importance of cyclical economic conditions on fertility behavior and decision-making. If employment and earnings have improved, why do fertility rates continue to decline? Answering this question not only helps explain the contemporary puzzle of why fertility rates have deviated from their historically cyclical trend, but also contributes insight into how longer-term economic processes shape U.S. fertility.

In this study, I propose a structural economic explanation for why fertility rates continue to decline in the United States regardless of improvements in conventional economic indicators since the Great Recession. I argue that ongoing structural changes in the industry composition of U.S. labor markets have prolonged the financial uncertainty that leads women and couples to delay or forego childbearing. Since the 1980s, the U.S. labor market has experienced declines in middle-skill, middle-income jobs in manufacturing and construction as a result of improvements in assembly line automation and the displacement of routine production jobs offshore, among other explanations (Acemoglu and Autor 2011; Autor, Katz, and Kearney 2006; Kalleberg 2009). This process of "labor market polarization" has reduced employment demand for jobs in the middle of the occupational skills distribution while increasing employment demand for lower-paid, low-skill service sector positions. Figure 1 displays the declining share of employment, total annual payroll, and business establishments concentrated in goods-producing industries between 1987 to 2014. The graph shows that the share of workers employed in goods-producing industries declined from 29% in 1987 to 14.7% in 2014. This trend parallels the disappearance of goods-producing business establishments from U.S. labor markets. Economic explanations of demographic behavior should account for structural changes of this magnitude.

Combining statistical and survey data with restricted-use vital registration records, I comparatively examine how cyclical and structural changes in metropolitan-area labor markets were associated with changes in total fertility rates (TFR) across racial/ethnic groups from the early 1990s to the present day, with a particular emphasis on the period between 2006-2014. I focus on variation in TFR across racial/ethnic groups for two reasons. First, the variation in fertility trends across racial/ethnic groups over this period is particularly striking and may reflect the differential economic impacts of the Great Recession in domains ranging from job loss, wealth loss, and housing foreclosure (Hall, Crowder, and Spring 2015; Hout and Cumberworth 2012; Pfeffer et al. 2016). Second, historical inequalities fundamentally shape the distribution of contemporary labor market opportunities (Browne 2000; Jaret, Williams Reid, and Adelman 2003). Since occupational distributions vary by race and ethnicity, we should expect labor market polarization to influence fertility behavior more for groups with larger shares of workers in goods-producing industries.

I focus this analysis on local geographic areas, specifically all 381 metropolitan statistical areas (MSAs) in the United States, since the distribution of labor market outcomes vary considerably across geographic areas (Levine 2012; United States Department of Labor 2012). Past studies on how economic conditions influence fertility behavior in the U.S. mostly focus on state- or national-level trends. However, within states, economic conditions and labor markets vary substantially across metropolitan areas. Furthermore, family formation and fertility are processes that occur primarily at the local level. Social networks, which are mostly concentrated within local geographic areas, are influential in setting the norms of family and fertility decision-making decisions (Arai 2007; Balbo and Barban 2014; Bernardi and Klärner 2014).

The findings of the present study suggest that structural changes in U.S. labor markets have a larger effect on TFR than changes in unemployment rates for all racial/ethnic groups during the 2006-2014 period. Since changes in labor market polarization are more likely to be sustained over time – in contrast to unemployment rates which fluctuate with economic cycles – the results indicate that structural characteristics of U.S. labor markets are as important, if not more important, than short-term swings in unemployment in predicting decreased levels of TFR in recent years. The findings also indicate that Hispanic fertility is substantially more responsive to the loss of goods-producing businesses than white, black, and Asian fertility. Importantly, the findings from this study help explain why fertility rates continues to decline in the United States despite the presence of indicators of employment and income that would otherwise predict a return to pre-recession fertility levels. In addition to making a theoretical contribution to the demographic literature on macroeconomic change and aggregate fertility behavior, the results of this study indicate that further reductions in unemployment are unlikely to reverse declining fertility trends.

CYCLICAL TRENDS IN ECONOMIC CONDITIONS AND FERTILITY BEHAVIOR

The 2007-2009 financial crisis led to immediate reductions in fertility in the United States and Europe (Hamilton and Sutton 2012; Matysiak, Sobotka, and Vignoli 2014). Researchers theorize a pro-cyclical relationship between economic conditions and fertility behavior: fertility rates increase during economic expansions and decrease during economic recessions. As economic prosperity diminishes during cyclical downturns and financial uncertainty and distress increases, women and couples postpone childbearing (Balbo et al. 2013; Buckles, Hungerman, and Lugauer 2018; Currie and Schwandt 2014). Such a perspective is consistent with classical economic theory on fertility that regards children as investments in either future income or future satisfaction (Becker 1960). In economically developed contexts where satisfaction is the primary aim of having children, parents are more likely to afford the costs of bearing and raising children as incomes rise (Sawhill 1977). Other theoretical perspectives posit a counter-cyclical relationship between unemployment and fertility (Butz and Ward 1979; Ermisch 1988). As female unemployment rises during economic recessions, researchers theorize an increase in fertility because women’s time out of the labor force lowers the opportunity costs associated with having a child. However, few empirical studies support this theoretical perspective in contemporary U.S. or European contexts (Cherlin et al. 2013; Morgan, Cumberworth, and Wimer 2011).

Most of the literature on how economic conditions influence fertility behavior use measures of unemployment and median household income to proxy changes in economic conditions. Morgan and colleagues’ (2011) analysis of state-level economic and fertility trends during the Great Recession suggests that larger increases in unemployment are associated with larger decreases in fertility rates. Similarly, Schneider’s (2015) analysis of county- and state-level fertility trends throughout the Great Recession suggests that both national and state trends in unemployment were negatively associated with general fertility rates (GFR).

Two other studies of the Great Recession find similar pro-cyclical patterns pertaining to changes in unemployment and income. First, Currie and Schwandt’s (2014) comprehensive analysis of state-level fertility trends between 1975-2010 suggests that increased unemployment during economic recessions was associated with short-term and long-term reductions in fertility for women in their early 20s. Second, a study by Cherlin and colleagues (2013) likewise finds variation across age groups during the Great Recession: while younger women experienced decreases in age-specific GFR, women in their 40s continued having children at the same pre-recession age-specific GFR levels. As a result, the authors argue that economic cycles differentially influence fertility behavior across age groups.

If the fertility response to the Great Recession was in fact pro-cyclical, then the post-recession recovery period should have predicted increased fertility rates in the same way that the recessionary period predicted decreased fertility rates. However, fertility rates have yet to return to pre-recession levels. Cherlin and colleagues' (2013) analysis indicated an 11 percent decrease in TFR between 2007 and 2011 – a drop from a 2.1 to 1.9. By 2013, six years after the onset of the Great Recession, the national TFR remained below the level of population replacement (Martin et al. 2015). Only in 2014 did the TFR briefly reverse course and increase before decreasing yet more through 2017 (Hamilton and Kirmeyer 2017; Martin et al. 2018). This ongoing fertility decline in the U.S. is at odds with slow, yet steady improvements in economic conditions. Nationally, median household income returned to pre-recession levels in 2015 while the unemployment rate returned to pre-recession levels in 2016.

STRUCTURAL CHANGE IN U.S. LABOR MARKETS

While theories on economic uncertainty and fertility behavior focus almost exclusively on changes in cyclical economic indicators, broader structural changes in U.S. labor markets might help explain the persistence of low fertility in the past decade. Critically, the United States has experienced an economic restructuring that has reshaped the composition of industries that provide jobs to American workers (Kalleberg 2009). Since the 1980s, middle-skill, middle-income jobs in manufacturing and construction have steadily disappeared while service sector positions have rapidly expanded. Although there are many explanations for this labor market restructuring (Janoski, Luke, and Oliver 2014), researchers have identified technological advances in assembly line automation and the offshoring of routine production jobs as major causes (Autor 2011; Autor et al. 2006). This process of "labor market polarization" has reshaped the economic opportunities available for workers, especially those who have less than a college education, by shifting the types of jobs available to workers away from stable middle-class positions (Kalleberg 2009). At the same time, employment demand has grown for low-wage positions which require little education or training as well as for high-wage positions which require a college degree. However, middle-skill, middle-income jobs, long a pathway to middle class economic stability for workers with only a high school degree, have steadily declined (Newman and Winston 2016).

My theoretical argument is motivated in part by recent empirical findings by Autor and colleagues (2017) and Kearney and Wilson (2018) who link long- and short-term industrial changes in U.S. labor markets to changes in fertility rates. Examining the rise of manufacturing import penetration from China between two time periods, 1990-2000 and 2000-2014, Autor et al. (2017) find that commuting zone-level import shocks were associated with decreased fertility rates for U.S. women in their 20s and 30s. In contrast to negative economic shocks, Kearney and Wilson (2018) find that the growth in local-area hydraulic fracturing production between 1997-2012, a positive economic shock, was associated with increases in birth rates for women between the ages of 18-34. These two studies emphasize how the gain and loss of specific industries, in contrast to overall levels of employment, in local labor markets are associated with substantive changes in fertility rates. The findings from these studies also suggest that structural economic changes impact fertility behavior at the community level, influencing perceptions of anticipated growth or decline of industrial sectors.

I focus this analysis on the decade surrounding the Great Recession because economic downturns have historically played a critical role in accelerating the displacement of middle-skill jobs and goods-producing businesses from U.S. labor markets. However, the modeling strategy also accounts for long-term structural change with an additional analysis that extends back to the early 1990s. Importantly, once manufacturing and other goods-producing jobs disappear, they rarely return during post-recessional recovery periods (Abel and Deitz 2012). For instance, Jaimovich and Siu (2012), examining rebounds in job loss across occupational categories after every economic recession in the U.S. since the 1970s, find that an overwhelming proportion of permanent job loss in middle-skill positions since the 1980s occurred during periods of economic recession rather than periods between economic recessions. The Great Recession was no exception to this trend: between 2007-2009, employment in occupational categories of production, craft, and repair decreased by 17% and employment in occupational categories of operators, fabricators, and laborers decreased by 15% (Autor 2010). The data used in the present analysis indicate that the average percentage of goods-producing businesses in metropolitan statistical areas decreased from 16.66% in 2006 to 14.24% in 2014, a 2.42 percentage point decline (Figure 1). Overall, economic recessions have hastened permanent structural changes in U.S. labor markets and have reduced the demand for middle-wage, middle-income jobs.

The present analysis relies on population-level data and cannot test how individual-level factors influence fertility decision-making. One plausible mechanism through which this macroeconomic relationship may operate is individual-level financial uncertainty, initiated by job displacement from manufacturing, construction, and other goods-producing industries. Workers displaced from positions in goods-producing industries must find new work in service-providing industries which often provide fewer hours, lower pay, and scarcer benefits (Bureau of Labor Statistics and U.S. Department of Labor 2016; Janoski et al. 2014; Kalleberg 2009).[2] Valletta and van der List (2015), for instance, find structural changes in industry composition to contribute to involuntary part-time work in the years following the Great Recession. Re-employment for many who lost jobs during the Great Recession did not necessarily return economic security and stability to pre-recession levels (Janoski et al. 2014; Moretti 2012). This

[2] Alternatively, displaced workers often exit the labor force entirely, enroll in workforce retraining programs, or pursue additional educational degrees and certifications (Janoski et al. 2014; McConnell et al. 2016)

mechanism is consistent with findings on the association between work precarity and fertility and family formation (Brauner-Otto and Geist 2018; Lim 2017; Modena and Sabatini 2012; Piotrowski, Kalleberg, and Rindfuss 2015; White and Rogers 2000; Yu and Sun 2018).

RACIAL/ETHNIC DIFFERENCES IN OUTCOMES DURING THE GREAT RECESSION

The aggregate trend of decreased fertility in the U.S. during the Great Recession conceals substantial variation across racial/ethnic subgroups. First, Hispanic women experienced large decreases in fertility following the start of the Great Recession (Martin et al. 2014). Cherlin and colleagues (2013), for instance, find larger decreases in past-year births for Hispanic women than non-Hispanic women between 2008-2011. Second, black and Asian/Pacific Islander fertility rates decreased more sharply than white fertility rates, but less than Hispanic fertility rates. According to national vital statistics records on fertility between 2007 to 2015 (Hamilton et al. 2017), GFR decreased 3% for non-Hispanic whites, 10% for non-Hispanic blacks, 10% for Asian/Pacific Islanders, and 36% for Hispanics.

The variation in fertility trends across race and ethnicity throughout this period is particularly striking and may reflect differential economic impacts experienced in domains such as housing foreclosure (Hall et al. 2015; Rugh 2015), wealth loss (McKernan et al. 2014; Pfeffer et al. 2016), and job loss (Holder 2015, 2017; Hout and Cumberworth 2012). McKernan et al. (2014), for instance, find that while white families experienced an average decrease in family wealth of approximately 26.2% following the Great Recession, black and Hispanic families lost 47.6% and 44.3%, respectively.

These differential economic consequences of the Great Recession across race/ethnicity also reflect a broader history of labor market stratification. Although black occupational and socioeconomic mobility increased throughout the middle of the 20th century, the economic downturn of the late 1970s largely constrained upward occupational mobility in the years to follow (Bound, Dresser, and Browne 1999; Pattillo 2013). This constrained upward mobility is reflected in the structure of educational and occupational networks which act as barriers to high-level professions for black and Latino workers (Catanzarite and Aguilera 2002; Cohen and Huffman 2007; Kmec 2003; Royster 2003). Racial differences in labor market occupational distributions are also attributed to employer discrimination (Pager and Pedulla 2015). Indeed, research on occupational shifts of African American men during the Great Recession by Holder (2015) indicates that black men experienced declines in representation in high-wage and middle-wage occupational categories between 2005-2006 and 2010-2011, while non-Hispanic white men experienced only minor shifts in their representation in the same occupational categories.

Since occupational distributions vary across race and ethnicity, we should expect labor market polarization to influence fertility behavior more for groups with larger shares of workers in goods-producing industries. Figure 2 displays the percentage of workers age 15-64 employed in goods-producing industries by racial/ethnic group between the years 2006-2014. Throughout this nine-year period, Hispanics had the highest percentage of workers employed in goods-producing industries, followed by whites. Black and Asian workers had the smallest percentage of workers in goods-producing industries.

The statistical approach used in the present study estimates separate regression models for racial/ethnic subgroups and tests for differences across these racial/ethnic subgroups. I expect macroeconomic conditions, both cyclical and structural, will differentially influence fertility behavior across race and ethnicity. Given the variation in the level of employment in goods-producing industries across racial/ethnic groups, we should expect the loss of goods-producing businesses following the Great Recession to have a disproportionate impact on racial/ethnic groups with larger shares of workers in goods-producing industries.

DATA and METHODS

Data

The present study is based on 31.5 million county-level birth certificate records between 2006-2014 from the restricted-use natality detail file from the National Vital Statistics System (NVSS).[3] The restricted-use NVSS natality detail file provides a full enumeration of county-level births in the United States, and includes information on mother's age, race, and Hispanic origin, which allow for the calculation of stratified racial/ethnic total fertility rate (TFR) values (NCHS 2016). County-level birth certificate records were aggregated up to the metropolitan area to match MSA designations defined by the Office of Management and Budget in 2013 (Office of Management and Budget 2013). MSA-level population counts were obtained for each year of the analysis from the National Center for Health Statistics' bridged-race population estimates, which are derived from U.S. Census Bureau population estimates. Female population counts, stratified by 5-year age groups, racial/ethnic group, and county, were aggregated up to the MSA-level.

Data on MSA-level business establishments were accessed from the U.S. Census Bureau's County Business Patterns (CBP) program. Business establishments are physical locations with (1) paid employees and (2) where business activity is conducted. Companies can have multiple business establishments with different numbers of employees. The CBP data provides a complete enumeration of business establishments in the U.S. by industry classification codes which are primarily derived from Internal Revenue Service administrative records.

---

[3] I additionally estimate models using a dataset that extends from 1991-2014, which relies on 82.3 million birth certificate records.

Business establishments are coded according to the Standard Industrial Classification System (SIC) between 1990-1997, and according to the North American Industry Classification System (NAICS) between 1998-2014. I used the Bureau of Labor Statistics' designations of NAICS "domains" to code businesses as either "goods-producing" or "service-providing" (Appendix Table 1).[4] The domain level consists of aggregated industry "supersectors." Industry supersectors within the goods-producing domain include natural resources extraction and mining, construction, and manufacturing.

MSA-level unemployment data were accessed from the Bureau of Labor Statistics' Local Area Unemployment Statistics program (LAUS) and MSA-level Per Capita GDP was accessed from the Bureau of Economic Analysis (BEA). Table 1 displays a full summary of measures and corresponding data sources.

Finally, I calculated metropolitan area statistics for education, past-year migration, homeownership, and marital status from the 1-year American Community Survey (ACS) between 2006-2014 for the overall MSA-level population as well as for racial/ethnic subgroups. ACS data were accessed through the IPUMS-USA database at the University of Minnesota (Ruggles et al. 2017). The smallest identifiable geographic unit in the 1-year public release ACS estimates are public use microdata areas (PUMAs) which have a minimum of 100,000 residents. As a result, ACS estimates used to generate covariates are only available for MSAs with greater than 100,000 residents.[5]

---

[4] To account for comparability issues between SIC and NAICS industry classification codes in the extended period analysis (1991-2014), I construct analogous "domain"-level grouping of SIC codes for CBP data between 1991-1997.

[5] Since PUMAs are nested within states rather than counties, MSA-level estimates have errors of commission and omission in which areas outside of the MSA are included or areas within the MSA are not included, respectively. Most MSAs have a combined error of less than 0.1% or less than 4.9%, but 44 MSAs have an error of 5.0-9.9% and 40 have an error of 10-14.9%. Or in other words, 296 MSAs have less than a 5% geographic boundary error. In this analysis, I make the plausible assumptions that (1) the outlying geographic areas of MSAs are not excessively

Measures

Dependent Variable

I measure population fertility behavior by calculating racial and ethnic-specific total fertility rates (TFR) at the MSA-level for non-Hispanic white women, non-Hispanic black women, Hispanic women, and non-Hispanic Asian women. The TFR measure describes *period* fertility: it provides an aggregate summary of annual age-specific fertility rates for women between the ages of 15-49 in a specific population, thereby generating a measure that can be used for comparisons across populations (Preston et al. 2000). Period TFR is a synthetic measure that describes the number of births a woman could expect to have if she were to experience every current age-specific fertility rate throughout her reproductive life course. To create the TFR measure, I retrieved racial/ethnic-specific and MSA-specific birth counts from the NVSS natality detail file as well as equivalent stratified racial/ethnic- and MSA-specific population counts from the NCHS bridged-race population estimates. I then generated stratified year-, race-, and metropolitan area-specific TFR values according to Eq. 1:

(Eq. 1) $$\mathrm{TFR}_{tmr} = 5 \times \sum_{x=15 \ldots 45} \frac{B^{xtmr}}{N^{xtmr}}$$

where *x* represents birth counts to women age *x* to *x*+5, *t* represents the year of analysis, *m* represents the metropolitan statistical area, and *r* represents the racial/ethnic category.

The use of local-area population estimates in conjunction with birth records to calculate TFR generates a few implausible TFR values. Online Appendix Figure S1 displays a histogram with all TFR values generated through Eq. 1. Of 13,709 total TFR observations, 159 exceed 4.0. I remove these cases from the analytic sample to ensure that outliers are not influencing the

---

biasing the overall MSA population averages, and that (2) sub-population averages in outlying areas of MSAs are similar whether they happen to be immediately inside or outside the MSA boundary.

regression results. The inclusion of these values in the models, however, does not substantively change the results.

Independent Variables

Labor Market Polarization. I operationalize labor market polarization as a relative measure: the percentage of goods-producing business establishments in a MSA. Past research on labor market polarization has established that the goods-producing business sector contains a disproportionate share of middle-skill, middle-income jobs and therefore represents an appropriate measure of local labor market polarization (Abel and Deitz 2012). Additionally, because the availability of goods-producing jobs in a local area is a matter of supply, the distribution of business establishments, rather than the distribution of workers across occupations, is the preferred measurement of structural labor market conditions. In Online Appendix Text S1, I further discuss the conceptual and data limitations of substituting a worker-based measure for the business establishment measure used in the present study.

I calculate the percentage of goods-producing businesses for each MSA by aggregating CBP business establishment data by “domain” classification codes for each year – either goods-producing industries or service-providing industries. I then lag this measure by one year to approximate labor market structure at the time of conception each year rather than the time of birth. As an additional robustness check, I test an absolute measure of labor market polarization: the number of goods-producing businesses in a MSA, log transformed to address its non-normal distribution.

Unemployment. I measure MSA-level unemployment using a one-year lagged annual measure of the unemployment rate from the LAUS dataset. The unemployment rate is calculated by dividing the number of people seeking employment by the total number of people in the civilian labor force. I test the sensitivity of this measure by estimating models which substitute the unemployment rate for (a) the employment-to-population ratio for workers ages 15-64 using ACS data, and (b) *sex-specific* measures of the unemployment rate and employment-to-population ratio for workers ages 15-64 using ACS data.

Control variables

The analytic method used in the present analysis, fixed-effects, controls for time-invariant unobserved heterogeneity that enters the specifications linearly and additively (Allison 2009). Accordingly, fixed characteristics of a metropolitan area are inherently controlled for in this analysis.[6] Fixed-effects analyses, however, do not account for *time-varying* sources of unobserved heterogeneity. To minimize threats to causal inference, I include a set of theoretically relevant covariates that are lagged one year (Table 1).

In the full MSA analysis, covariates include year fixed-effects, a logged measure of population size to adjust for annual changes in metro population size, and per capita gross domestic product (GDP) to adjust for economic growth.

In robustness models using data from the ACS, I additionally adjust for aggregate measures of educational attainment (the percentage with more than a high school diploma), past-year MSA in-migration (the percentage who have in-migrated to the MSA in the past year), homeownership (the percentage who own a home), and marital status (the percentage who have never been married). These covariates are first calculated at the MSA-level for adults age 15-64,

[6] I conceptualize these fixed characteristics as aspects of geography, climate, city-specific cultural norms and mores, shared history, and place-specific socioeconomic and class distributions. To be sure, these metropolitan area characteristics do change over time; but given the relatively brief period of analysis, I make the plausible assumption that metropolitan areas maintain a fixed set of social, cultural, and built-environment characteristics.

and in a further sensitivity check, re-calculated for adults age 15-64 for each racial/ethnic group.

These time-varying covariates have theoretical importance for considering how MSA-level economic and noneconomic indicators might influence racial- and ethnic-specific fertility rates. First, educational attainment is a well-documented determinant of fertility (Rindfuss, Morgan, and Offutt 1996); college attendance for women is associated with lower fertility levels (e.g. Brand and Davis 2012). I account for educational attainment by adjusting for the percentage with more than a high school education. Second, births in an MSA are composed of women residing in the area both prior to and after conception. Consequently, the TFR of a population is partially influenced by births to women which were conceived prior to entering the population. This makes adjusting for MSA in-migration important.[7] I define this measure as the percentage of people in a MSA who have in-migrated to the MSA in the past year.

Third, the Great Recession followed the burst of a housing bubble in the U.S. which reversed a seven-decade trend of increasing homeownership rates. Metropolitan areas experienced sizeable declines in homeownership throughout the 2006-2014 period, although the extent of decline varied across metropolitan areas (Flanagan and Wilson 2013). I account for these changes by including a covariate for the homeownership rate, defined as the percentage of people who own a housing unit, either with or without a mortgage, in a MSA.

Fourth, in addition to impacting population fertility behavior directly, economic conditions might influence fertility behavior indirectly vis-à-vis changes in marriage and partnership trends, which are important proximate determinants of fertility (Bongaarts 1978;

[7] Kothari et al. (2013) note that geographic mobility declined throughout the years of the Great Recession. For the geographic mobility that did occur, labor migration during the Great Recession varied for low- and high-skilled workers as well as across foreign-born and non-foreign-born workers (Cadena and Kovak 2016). In-migration from Mexico, for instance, decreased as a result of economic disruption to the construction and manufacturing sectors in the United States (Calnan and Painter 2017; Villarreal 2014).

Sawhill and Venator 2015; Stevenson and Wolfers 2007). Specifically, economic downturns might alter patterns in union formation and dissolution (for a more detailed discussion, see Morgan et al. 2012). While marriage rates declined and cohabitation rates increased throughout the years of the Great Recession, researchers mostly attribute these changes to continuations of pre-existing trends (Cherlin et al. 2013; Kennedy and Fitch 2012; Morgan et al. 2012; Schneider 2017). In regard to marital union dissolution, research by Cohen (2014) suggests no association between state-level unemployment rates and increases in divorce rates.

To be thorough in the present analysis, I include a covariate in the robustness models for the percentage of people who are single, never-married in a MSA to adjust for changes in marital status over time. Additionally, I estimate a supplemental model in Online Appendix Table S2 which adjusts for MSA-level divorce rates for the population age 15-64. Limitations in the ACS dataset preclude the inclusion of cohabitation measures throughout the entire 2006-2014 period (U.S. Department of Health and Human Services 2008).

In a final set of robustness checks, I test how (a) compositional changes of the Hispanic population throughout the 2006-2014 period and (b) the differential impact of the Great Recession on women and men might influence the results.

Compositional Changes of the Hispanic Population. Declines in Hispanic TFR in the 2006-2014 period attributable to cyclical or structural economic changes might be partially explained by compositional changes of the Hispanic population throughout this period – primarily a drop in Mexico-U.S. migration throughout the 2000s and 2010s (Choi 2014; Parrado 2011; Villarreal 2014). In the present analysis, I am unable to calculate TFR values separately for U.S.-born and foreign-born Hispanics because annual disaggregated county- or metro-level population estimates for these groups are not available. Instead, I conduct a robustness check for the estimates of Hispanic fertility that adjusts for the percentage of reproductive age women who are Mexican immigrants. The inclusion of this measure into the statistical analysis, which captures a form of Recession-driven compositional change in the Hispanic population, does little to alter the results.

Differential Impact of the Great Recession on Women and Men. The timing and magnitude of job loss during the Great Recession varied substantially for men and women (Hartmann, English, and Hayes 2010). Male unemployment increased more rapidly and remained at higher levels than female unemployment between 2007-2009 (Sahin, Song, and Hobijn 2010). Female labor force participation rates were initially unaffected by the recession, whereas male labor force participation rates experienced immediate declines in early 2008 (Cunningham 2018). These differential trends are explained by a larger concentration of men employed in goods-producing industries which were more vulnerable to recessionary impacts (Cunningham 2018; Hout and Cumberworth 2012; Wood 2014). Although women's earnings slightly outpaced men's earnings into the post-recession period (Goodman and Mance 2011), the recovery period (2010-2011) was more financially difficult for women, who began to experience job loss at higher rates than men. In fact, gains during the recovery period in male employment displaced existing female employment in certain service-providing industries (Taylor et al. 2011). To account for these gender-specific trends throughout the years of the Great Recession which might impact fertility behavior, I substitute the overall unemployment rate for gender-specific (a) unemployment rates and (b) labor force participation rates in sensitivity analyses.

Model Specification

The statistical models are estimated as follows. First, I estimate separate two-way fixed-effects regression models for four racial/ethnic subgroups of mothers: non-Hispanic black, non-Hispanic white, Hispanic, and non-Hispanic Asian (Eq. 2):

(Eq. 2) $$TFR_{mt} = \boldsymbol{\beta x}_{mt} + \alpha_m + \mu_{mt}$$

where TFR_{mt} refers to the total fertility rate *TFR* for MSA *m* during year *t*; $\boldsymbol{x}_{mt}$ refers to a set of vectors that includes measures of the two independent variables – labor market polarization and unemployment – as well additional covariates and binary-coded year vectors; $\boldsymbol{\beta}$ refers to a vector of estimated coefficients; α_m refers to a vector of MSA-specific intercepts; and μ_{mt} refers to MSA- and year-specific error terms.

Next, I test for significant differences in coefficients across each racial/ethnic group by (a) pooling observations from the previously separate racial/ethnic subset regressions, and then (b) estimating a model that estimates $\boldsymbol{\beta}$ coefficient values as in Eq. 2, but additionally interacting a set of binary-coded vectors for three of the four racial/ethnic groups $\boldsymbol{g}_r$, using non-Hispanic whites ($\boldsymbol{g}_{white}$) as the reference group, with vectors $\boldsymbol{x}_{mt}$ (Eq. 3). This model is estimated as follows:

(Eq. 3) $$TFR_{mrt} = \boldsymbol{\beta x}_{mt} + \boldsymbol{\gamma}(\boldsymbol{x}_{mt} * \boldsymbol{g}_{mrt}) + \alpha_{mr} + \mu_{mrt}$$

where $\boldsymbol{\gamma}(\boldsymbol{x}_{mt} * \boldsymbol{g}_{mrt})$ represents the interaction coefficients that test for significant differences across racial and ethnic groups. In this equation, $\boldsymbol{\beta}$ coefficients represent the average value for non-Hispanic white women ($\boldsymbol{g}_{white}$), while the $\boldsymbol{\gamma}$ coefficients represent the average difference between each racial/ethnic group and the non-Hispanic white reference group. Critically, Eq. 2 and Eq. 3 are functionally equivalent, but Eq. 3 tests for statistical differences across racial/ethnic-specific coefficients. In the results section, I present regression tables for Eq. 2 and summarize the results from Eq. 3 in the text.

Finally, I estimate a period interaction model that tests whether the coefficient for labor market polarization and the unemployment rate persisted throughout both the pre-recession/recession (2006-2010) and post-recession (2011-2014) time periods.[8] To this end, I re-estimate the racial and ethnic-specific subgroup model (Eq. 2) with an interacted set of binary-coded vectors for the post-recession period $\boldsymbol{p}_{postrecesssion}$ with vectors $\boldsymbol{x}_{mt}$ (Eq. 4). The model is estimated as follows:

(Eq. 4) $$TFR_{mrt} = \boldsymbol{\beta x}_{mt} + \boldsymbol{\gamma}(\boldsymbol{x}_{mt} * \boldsymbol{p}_{mt}) + \alpha_m + \mu_{mt}$$

where the $\boldsymbol{\beta}$ coefficients represent the average value for the post-recession period ($\boldsymbol{p}_{postrecession}$), while the $\boldsymbol{\gamma}$ coefficients represent the average difference in coefficients for the pre-recession/recession and post-recession periods.

RESULTS

Table 2 presents the means and standard deviations of all variables over the entire period of analysis, 2006-2014. Figure 3 displays the average MSA-level TFR values for each racial/ethnic group by year. For all racial/ethnic groups, TFR began to decline in 2008, although at different rates. Hispanic women experienced the largest decline in TFR, from approximately 2.9 in 2006 to 2.2 in 2014, a 24 percent drop. By the end of the period, Hispanic TFR had dropped below black TFR. All other groups experienced declines in TFR between the beginning and end of the period: white TFR declined 7.7%, black TFR declined 7%, and Asian TFR declined 7.8% between 2006-2014.

Figure 4 displays changes in unemployment and goods-producing businesses for all 381 MSAs between 1991-2014. In Panel A, the average MSA unemployment rate increased sharply

---

[8] Because of the lag time between economic conditions during the time of conception and economic conditions at the time birth, the start of the post-recession period aligns with an approximate 1-year lag time.

at the start of the Great Recession in 2008 and then slowly declined after 2011. In contrast to this cyclical trend, Panel B displays a sharp decline in the average share of goods-producing businesses in MSAs at the start of the Great Recession. The rate of decline decreased and leveled off towards the end of the period in 2014. Online Appendix Figure S3 disaggregates the average trend for the share of goods-producing businesses and displays the 2006-2014 drop for each MSA.

Table 3 displays the results of the separate two-way fixed-effects regressions predicting racial- and ethnic-specific TFR for all 381 OMB-designated MSAs in the United States between 2006-2014. (Online Appendix Table S1 displays the full results). All four models include time fixed effects and MSA-level covariates. In 2014, the population residing in these 381 MSAs represented approximately 85% of the U.S. population.

In Model 1, I estimate an equation that aims to reproduce previous findings in family and fertility research that demonstrates a negative association between unemployment and fertility. The results indicate a significant, negative association between the unemployment rate and TFR for non-Hispanic white women (β = -.007 S.E. = .001), non-Hispanic black women (β = -.012; S.E. = .005), non-Hispanic Asian women (β = -.016; S.E. = .007), and Hispanic women (β = -.036; S.E. = .005).

In Model 2, I estimate the effect of labor market polarization, measured as the percentage of goods-producing businesses in a metropolitan area, on TFR without the inclusion of the unemployment rate parameter. In these models, the coefficients are positively and significantly associated with TFR for white, black, Asian, and Hispanic women. A one percentage point increase in goods-producing businesses in a MSA is associated with a .021 increase in TFR for white women (S.E. = .002), a .022 increase in TFR for black women (S.E. = .008), a .027

increase for Asian women (S.E. = .010), and a .058 increase for Hispanic women. (S.E. = .008). Comparing coefficients across racial and ethnic groups (Eq. 3), the results indicate that the effect size for the goods-producing businesses parameters is significantly larger for Hispanics than for whites, blacks, and Asians. There is no significant difference between the coefficients for the latter three groups.

The percentage of goods-producing businesses in all MSAs declined an average of 2.42 percentage points between 2006 and 2014 (Figure 4, Panel B). The estimates in Model 2 suggest that a decline of this magnitude predicts an average decline in TFR of .051 for white women, .053 for black women, .066 for Asian women, and .141 for Hispanic women throughout the entire period. To contextualize these findings, the overall decline in TFR between 2006-2014 was .136 for white women, .139 for black women, .143 for Asian women, .547 for Hispanic women. Altogether, this indicates that declines in the percentage of goods-producing businesses on average account for 37% of overall TFR declines for white women, 38% of overall TFR declines for black women, 46% of overall TFR declines for Asian women, and 26% of overall TFR declines for Hispanic women. These calculations illustrate the average relative differential impact of metropolitan area labor market polarization on fertility rates across population subgroups.

Because parameter estimates of the percentage of goods-producing businesses might be explained by changes in the unemployment rate, Model 3 includes both variables. In this set of models, the effect size of the percentage of goods-producing businesses coefficients remain similar to those estimated in Model 2 for all racial/ethnic groups, although their magnitude slightly diminishes. In contrast, the coefficients for the unemployment rate attenuate in both size and significance in comparison to the coefficients estimated in Model 1. For Hispanic women, the coefficient for the unemployment rate remains sizeable and precisely estimated. Overall, however, these results provide evidence that structural changes in labor markets (i.e. the loss of goods-producing businesses) are more predictive of fertility decline than cyclical changes (i.e. unemployment), at least when examining fertility across racial and ethnic groups at the metropolitan level.

To examine whether labor market polarization and unemployment continued to influence fertility behavior in the recovery period, Model 4 tests whether these two variables maintained their effect sizes during the post-recession period. To estimate the post-recession parameters, I interacted a post-recession dummy variable (2011-2014) with all independent and control variables. I then calculated the pre-recession/recession parameters (2006-2010) in a comparable manner. Both columns of Model 4 estimate the same equation, the only difference is whether the interacted dummy indicator was set as the pre-recession/recession period or the post-recession period.

The results from Model 4 indicate that the effect size of the percentage of goods-producing businesses coefficient remain similar and statistically significant during the post-recession period as they did for the pre-recession/recession period for white, Asian, and Hispanic women. While the coefficient for the percentage of goods-producing businesses does not change across time periods for white women, it slightly increases for Asian women and slightly decreases for Hispanic women. In regard to the unemployment rate, the coefficients remain non-significant for black and Asian women, and close to zero for white women. However, for Hispanic women, the unemployment rate coefficient slightly diminishes between the 2006-2010 period ($\beta = -.033$) and the 2011-2014 period ($\beta = -.026$). To summarize, the results from Model 4 demonstrate how reductions in the percentage of goods-producing businesses in a MSA contributed not only to declines in TFR throughout the recession, but also during the post-recession recovery period.

Robustness Checks

Since the specifications presented above do not account for several unmeasured, time-varying metropolitan area characteristics that might influence the results, I conduct a series of robustness checks which test alternate specifications of these models.

Table 4 displays a set of models which incorporate a set of theoretically-relevant MSA-level covariates, including educational attainment, past-year in-migration, homeownership rates, and marital status. The number of MSAs included in this analysis for each racial/ethnic group is reduced because of ACS 1-year microdata availability. Upon adding these additional covariates, the coefficients and standard errors for the percentage of goods-producing businesses and the unemployment rate remain approximately comparable to those in the previous full 381 MSA analysis for all models estimated above, with several important exceptions. First, the goods-producing businesses coefficients diminish in size and significance for black and Asian women in all models. Second, the unemployment rate coefficient for white women diminishes in size and significance.

In Online Appendix Table S2, I substitute the rate of single/never-married in an MSA for the MSA divorce rate for the population age 15-64. The results from these ACS models are likewise comparable to the previous ACS subset models.

To account for changes in the composition of the Hispanic population, I re-estimate the ACS subset robustness model for Hispanics by swapping past-year in-migration for a measure of Mexican composition: the percentage of reproductive age Hispanic women who are Mexican immigrants (Online Appendix Table S3). The inclusion of this measure into the statistical analysis, which adjusts for compositional changes in the Hispanic population, does little to alter the main results for the goods-producing and unemployment parameter estimates.

Online Appendix Table S4a and S4b displays the results of a further series of robustness and sensitivity checks. I re-estimate the full model, Model 3, using (a) labor market polarization measured as the logged number of goods-producing businesses, (b) MSA-level racial/ethnic-specific covariates in place of MSA-level covariates, (c) labor market polarization measured as the percentage of mid-march workers employed in goods-producing industries, (d) sex-specific unemployment rates in place of the overall unemployment rate, (e) employment-to-population ratios – both overall and sex-specific – in place of the overall unemployment rate, and (f) labor force participation rates – both overall and sex-specific – in place of the overall unemployment rate.

The results from these alternate specifications yield comparable results to those in Table 3. When operationalized as the logged *number* of goods-producing businesses (Models 1-2, Online Appendix Table S4a), labor market polarization similarly explains more variation than the unemployment rate for three out of the four racial/ethnic groups. Substituting racial/ethnic-specific covariates for MSA-specific covariates (Models 4, Online appendix Table S4a) does not substantively change the results of the ACS subset analysis in Table 4 (Model 3). Moreover, accounting for gender-specific trends in unemployment and labor force participation, the results from these models suggest little change from the main results. In total, this battery of alternate specifications yields comparable results to the previously estimated models in Table 3 and Table 4, suggesting that the findings are largely robust.

Long-Term Structural Change, 1991-2014

The prior results indicate that the annual loss of goods-producing business establishments in metropolitan areas throughout the decade spanning the Great Recession was associated with declines in TFR for white, black, Asian, and Hispanic women in the full 381 MSA analysis and for white and Hispanic women in the ACS subset analysis. However, these models do not account for the longer span of time since the 1980s when U.S. labor markets initially began to transition away from the production of goods and towards the provision of services. To evaluate whether these effects have been present over the past several decades, I extend the annual dataset back to the early 1990s to estimate a set of two-way fixed-effects models that cover the years 1991-2014.[9] At the beginning of the period, 1991, goods-producing businesses comprised an average of 18.28% of all businesses in MSAs; by the end of the period, 2014, goods-producing businesses comprised an average of 14.24% of all businesses in MSAs, an overall 4.04 percentage point decrease (Figure 1). Throughout this 24-year period, the average unemployment rate was 6.2%, although cyclical economic expansions and contractions resulted in an average low of 4.2 % in 2001 and an average high of 9.6% in 2011. Online Appendix Table S5 displays the means and standard deviations of variables in the 1991-2014 analysis.

In Table 5, I present the results of these extended period models. The results are substantively comparable to the results from the 2006-2014 analysis for the percentage goods-producing coefficients (Table 3), although the effect size is largest for black women. In Model 3, a one-point increase in the percentage of goods-producing businesses in a MSA is associated with a .020 increase in TFR for white women (S.E. = .001), a .051 increase in TFR for black women (S.E. = .004), a .023 increase for Asian women (S.E. = .005), and a .035 increase for

[9] County-level CBP data on industry composition is available from 1986 and onwards; however, county-level LAU data is available from 1990 and onwards.

Hispanic women. (S.E. = .005). Since the percentage of goods-producing businesses in metropolitan areas declined by an average of 4.04 percentage points over this 24-year period, the estimates from model 3 predict that changes in industry composition accounted for an average decline in TFR of .081 for white women, .206 for black women, .093 for Asian women, and .141 for Hispanic women. For MSA-level unemployment, the coefficients suggest that the relationship between the unemployment rate and racial/ethnic total fertility rate remained pro-cyclical throughout the entire period for white and Asian women, but not for black and Hispanic women.

Overall, the empirical results from this extended period analysis bolster the theoretical argument that ongoing structural trends in the labor market have contributed to fertility decline over the past several decades.

DISCUSSION and CONCLUSION

In the years since the Great Recession, social scientists have anticipated that economic recovery in the U.S., characterized by gains in employment and median household income, would augur a reversal of declining fertility trends. However, the expected post-recession rebound in fertility rates has yet to materialize. In fact, fertility rates continue to decline, with 2017 reaching an unprecedented national low for general fertility rates (Hamilton et al. 2018). The analysis presented here demonstrates how structural changes in U.S. labor markets help explain trends in declining fertility rates. Overlooked in past research on fertility behavior, labor market polarization signifies a permanent change in the financial outlook of American workers, especially for those without a college degree. As businesses, and therefore jobs, in goods-producing industries disappear, displaced workers who wish to remain in the labor force must find employment in the lower paid, lower-skill service sector that provides jobs with fewer hours, lower pay, and scarcer benefits (Bureau of Labor Statistics and U.S. Department of Labor 2016; Janoski et al. 2014; Kalleberg 2009). The "hollowing out" of the middle of the occupational income distribution results in decreased financial security for American workers as they seek to start or expand families. Importantly, once goods-producing businesses disappear from American cities – either as a result of offshoring or improvements in assembly line automation – they tend to not return (Autor and Dorn 2013).

The present analysis suggests that labor market polarization contributed to the decline in fertility rates throughout the entire decade spanning the Great Recession, including the post-recession period between 2011-2014. These findings held even upon adjusting for the unemployment rate and additional economic and noneconomic covariates. As long as goods-producing businesses remain a smaller share of the overall industry composition of U.S. metropolitan areas, the models presented here indicate that fertility rates will remain below their pre-recession levels.

While labor market polarization was found to influence TFR for all racial/ethnic groups throughout the extended period analysis, the effect size is substantially larger in magnitude for women of color than for whites, particularly black and Hispanic women. Job loss in goods-producing industries is more devastating for non-white workers since racial disparities in employment exist even during economically prosperous times (Janoski et al. 2014; Moore 2010). Discrimination in hiring practices by employers has played a significant role in perpetuating these racial disparities, constructing social barriers towards stable and long-term employment (Fryer, Pager, and Spenkuch 2013; Pager, Bonikowski, and Western 2009). Consequently, the search for re-employment for non-white workers after economic recessions has been more drawn out than for whites, entailing lengthier spells of unemployment and therefore increased periods of financial precarity (Couch and Fairlie 2010; Hout and Cumberworth 2012).

The results also suggest a more heterogenous picture regarding the pro-cyclicity of economic cycles and fertility rates during the Great Recession. With exception of the Hispanic models, the unemployment rate parameter estimates were mostly small in size and non-significant once labor market polarization was included in the models. These results were robust to alternative measures of employment, including sex-specific unemployment rates, sex-specific employment-to-population ratios, and the overall employment-to-population ratio. Although this finding contrasts with earlier studies on the Great Recession which find considerable evidence of pro-cyclicality (e.g. Currie and Schwandt 2014; Morgan et al. 2011; Schneider 2015), this discrepancy might be explained by the extended time period of the present study and the geographic level examined.

The magnitude of the coefficient estimates of labor market polarization on fertility rates was nearly three times larger for Hispanic women than for white women. Differences in occupational distributions across racial and ethnic groups might partially explain this finding because groups with a larger share of workers in goods-producing industries would be disproportionately affected by the disappearance of these businesses. In fact, 33% of the Hispanic labor force was employed in goods-producing industries prior to the recession in 2007, whereas only 22.5% of whites, 20% of Asians, and 18% of blacks were employed in goods-producing industries at that time (Figure 2). In absolute terms, as well, there were more Hispanic workers in manufacturing, construction, and mining/extraction industries than there are black and Asian workers combined in 2007 (U.S. Bureau of Labor Statistics 2008). It is therefore likely that compositional differences account for some of the differential impact. The large share of Hispanic workers in the goods-producing sector might also explain why the unemployment rate coefficient remained sizeable and significant for Hispanic fertility.

During the post-recession period, availability and usage of long acting reversible contraceptives (LARCs) increased substantially (Branum and Jones 2015; Finer, Jerman, and Kavanaugh 2012). At the same time, rates of unintended pregnancy declined considerably (Finer and Zolna 2016). Past research suggests that these trends contributed to post-recession fertility declines (Fletcher and Polos 2017; Schneider and Gemmill 2016). Schneider and Gemmill (2016) find that increases in regional LARC usage between 2003-2014 partially accounted for state-level declines in the non-marital fertility rate, especially for Hispanic women. To the extent that labor market restructuring changed the demand for children and the attendant demand for contraception with lower failure rates, LARC take-up is an explanation of post-recession fertility decline that is consistent with the findings presented here. However, the association between structural labor market changes and fertility dates at least to the early 1990s (Table 5) before major increases in LARC availability and usage (Branum and Jones 2015), suggesting that LARCs may be part of but not the entire story of the present findings.

An important question that follows from this analysis is whether declines in fertility rates from labor market polarization are an indicator of delayed or foregone births. One way to approach this question is to identify which age groups were more responsive to declines in goods-producing businesses. In Online Appendix Table S6, I estimate the effect of structural and cyclical economic changes on age-specific fertility rates, binned at five-year age intervals, between 2006-2014. For all racial/ethnic groups, the largest effect sizes for the goods-producing businesses coefficients are concentrated towards women in their 20s. Since the effect size is small and mostly non-significant for women in their 30s and 40s, the results suggest that births are likely being delayed rather than entirely foregone. At the same time, the cohort of women in their 20s at the beginning of the 2006-2014 period might have different birth histories than the cohort of women who began the period in their 30s. Future research will need to determine over the next decade whether increases in fertility rates for women in their 30s are large enough to offset decreases in fertility rates for women who were in their 20s over the past decade.

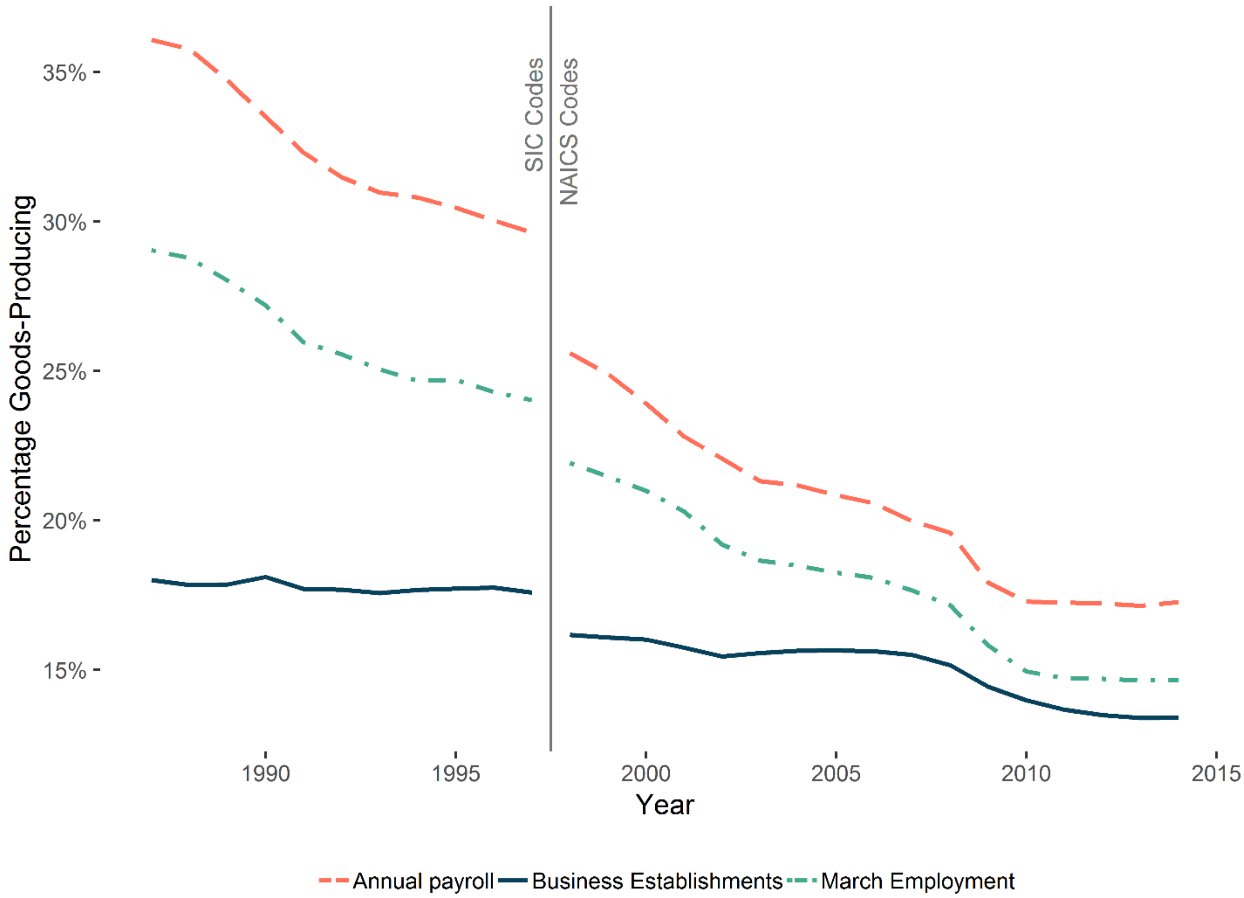
The age-specific fertility rate models also suggest that fertility rates for teenage women ages 15-19 were significantly responsive to changes in structural economic conditions for both white and Hispanic women and changes in cyclical economic conditions for white women. There was no significant effect of structural or cyclical economic conditions on age-specific fertility rates for black or Asian women. Most research examining the influence of the Great Recession on teenage fertility rates finds little empirical evidence of a significant relationship with unemployment rates (Boonstra 2014; Lindberg, Santelli, and Desai 2016; Percheski and Kimbro 2014).

The findings presented here should be interpreted with an understanding of several limitations of the data and analytic method used. First, the present analysis uses aggregate data and is susceptible to ecologically fallacious inference; the findings should only be interpreted in terms of population-level behavior patterns, not individual-level choices. Accordingly, I cannot directly test how individual-level financial uncertainty influences fertility decision-making. Future research should examine how fertility preferences, intentions, and demand are influenced by both individual-level labor market experiences and aggregate labor market conditions. Second, the TFR measure relies on both administrative data and population estimates. While the numerators of the equation, birth counts, represent a full enumeration of all new births in U.S. metropolitan statistical areas between 1991-2014, the denominators of the equation, population counts, draw on bridged-race population *estimates*. However, the bridged-race population estimates used in the present analysis are the same source of population estimates used by the NCHS when they generate and distribute public release vital statistics figures, including fertility rates, and are regarded as the best source of population data for this task.

Despite these limitations, this study offers an innovative economic explanation for why fertility rates in the United States continue to decline. Prevailing theoretical perspectives on how economic conditions influence fertility have primarily relied on cyclical measures of economic change. Researchers have overlooked important long-term structural changes in U.S. labor markets, particularly the decline of manufacturing and construction industries, and the coincident rise of low-paid jobs in service industries. While the present analysis focuses on the impact of economic restructuring in U.S. metropolitan areas on fertility rates, future research should account for whether this relationship is similar in nonmetropolitan and rural areas, which have also experienced considerable declines in goods-producing industries (Low 2017). By proposing a structural economic explanation for why fertility rates continues to decline, this study contributes to the understanding of how macroeconomic conditions influence fertility behavior and decision-making.

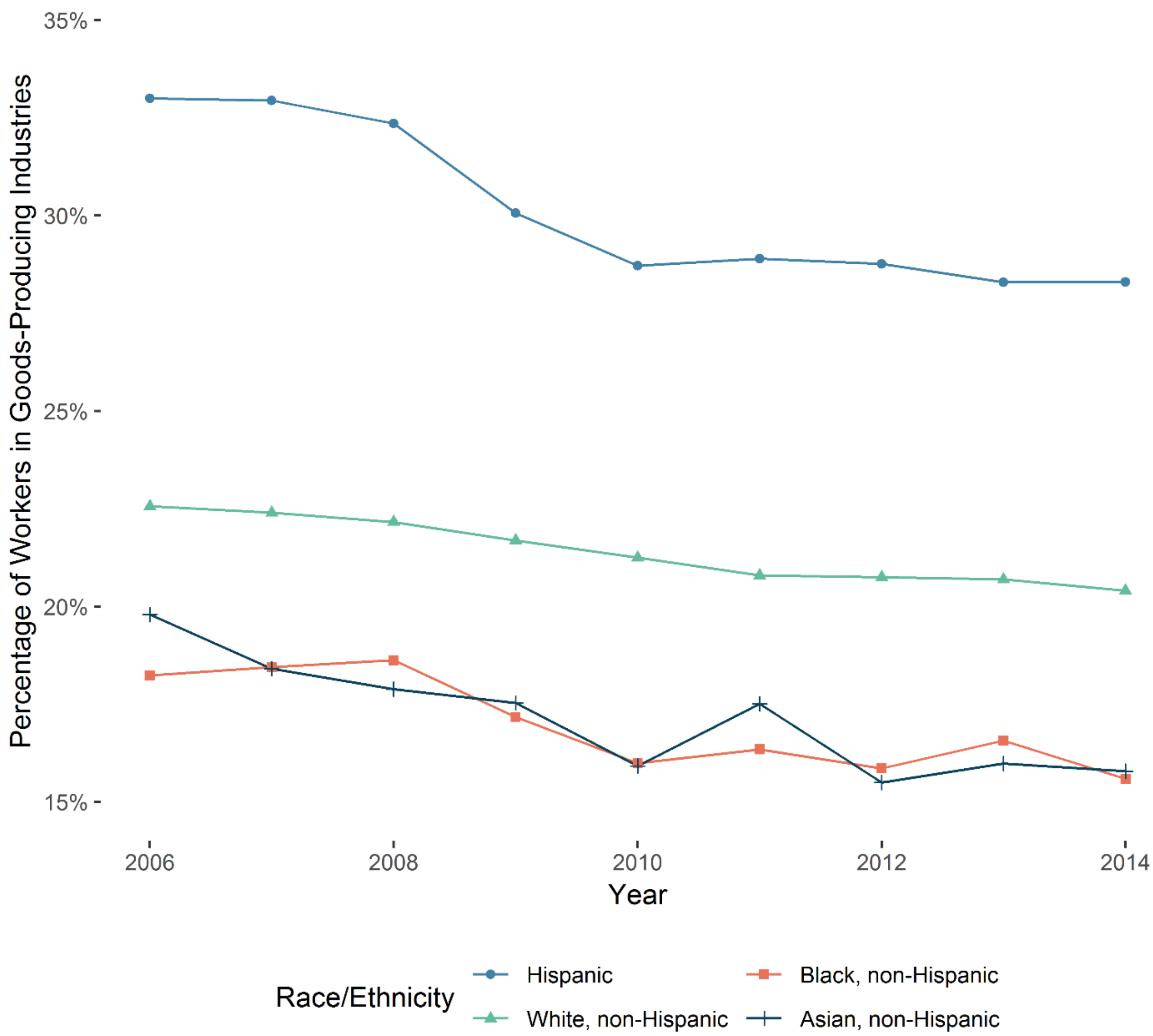
FIGURES

Figure 1. Share of Employment, Payroll, and Business Establishments in Goods-Producing Industries between 1987-2014



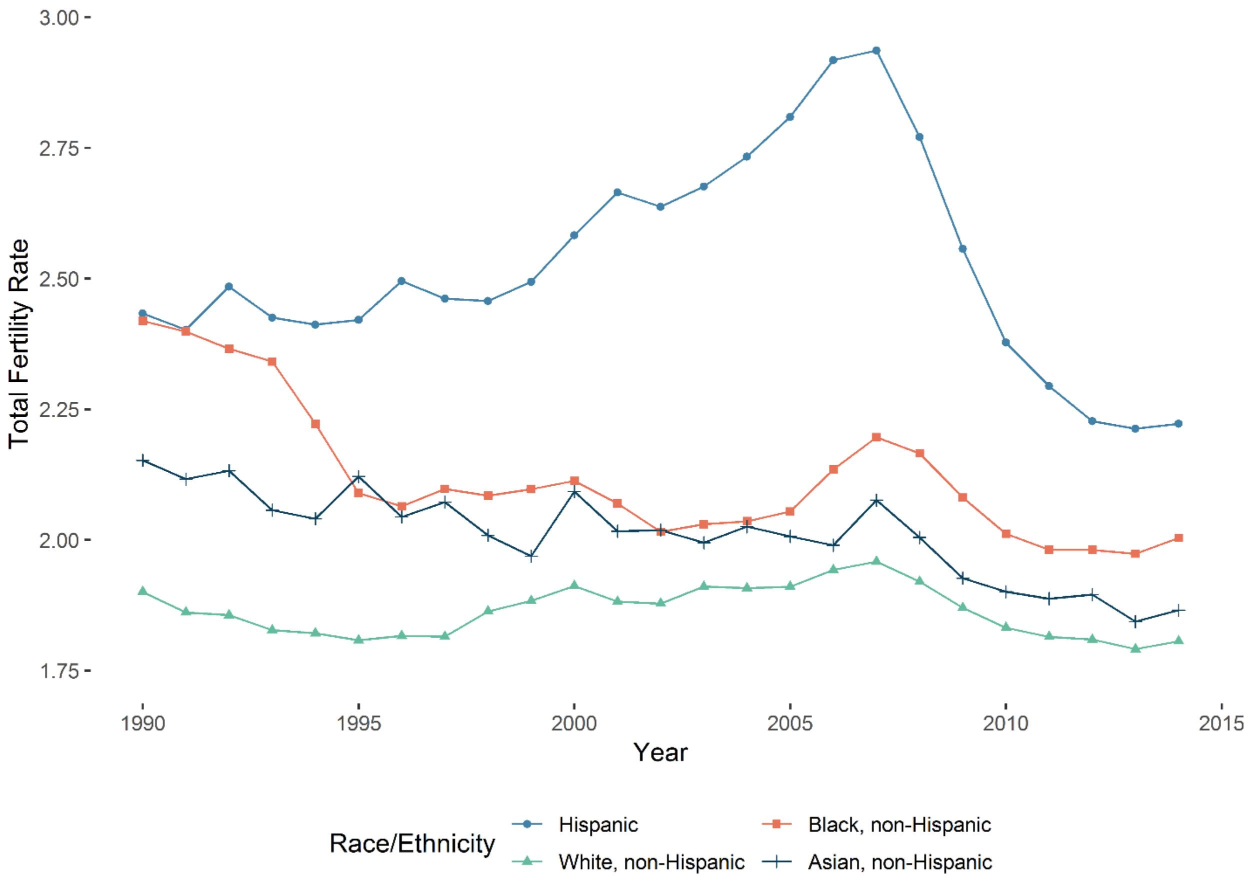
Notes: Data from U.S. Census Bureau's County Business Pattern (CBP) program. Industry classification codes changed in 1998. Dashed lines (1987-1997) are based on Standard Industry Codes (SIC) goods-producing industries; Solid lines (1998-2014) based on North American Industry Classification System (NAICS) goods-producing industries. Calculations are for all metropolitan statistical areas.

Figure 2. Percentage of Workers Ages 15-64 in Goods-Producing Industries by Race/Ethnicity



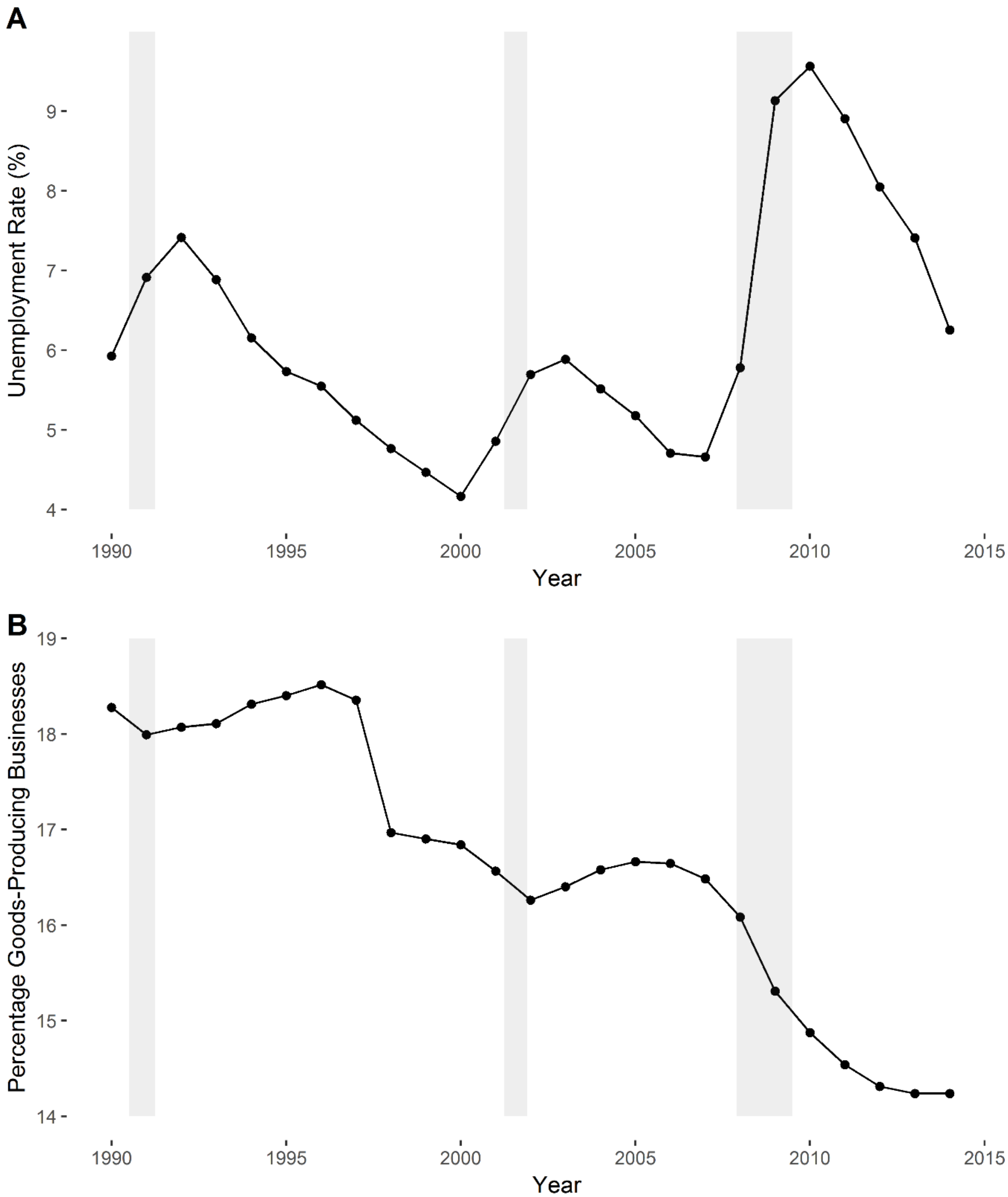
Notes: (a) Goods-producing industries include manufacturing, construction, and extraction/mining, and were classified using NAICS domain codes (b) data from the American Community Survey between 2006-2014 for Metropolitan Statistical Areas with core urban populations larger than 100,000.

Figure 3. Average Total Fertility Rate (TFR) for all 381 Metropolitan Statistical Areas between 1990-2014 by Race/Ethnicity



Notes: Calculated using birth data from restricted-use NCHS Natality Detail Files (1990-2014) and female population data from NCHS bridged-race population estimates. See Online Appendix Figure S2 for TFR by race/ethnicity for entire U.S. metro population.

Figure 4. Average (A) Unemployment Rate and (B) Percentage of Goods-Producing Businesses for all 381 Metropolitan Statistical Areas between 1990-2014.



Note: Shaded areas represent NBER designated recessionary periods (http://www.nber.org/cycles.html): (1) July 1990-March 1991, (2) March 2001-November 2001, and (3) December 2007-June 2009.

TABLES

Table 1. Metropolitan Statistical Area Variables and their corresponding Data Sources

Variable	Data Source(s)
Total Fertility Rate	Restricted-use birth data from the NVSS; population data from the bridged-race population estimates from the NCHS
Unemployment Rate	Bureau of Labor Statistics' Local Area Unemployment Statistics (LAU)
% Goods-Producing Businesses Logged # Goods-Producing Businesses	U.S. Census Bureau's County Business Patterns (CBP)
Per Capita GDP	Bureau of Economic Analysis (BEA)
Never Married Status Education Level Past Year In-Migration[10] Homeownership Rate Unemployment Rate (Male and Female) Share of Hispanic population who are Mexican-origin Labor Force Participation Rate (Overall, Male, and Female) Employment-to-Population Ratio (Overall, Male, and Female) Divorce Rate	1-Year American Community Survey (ACS) via IPUMS-USA

[10] While the ACS includes data for moves within states, these measures do not specify moves between MSAs or from a non-MSA area to a MSA. Measuring MSA in-migration specifically for reproductive-age women would be the ideal measure. However, the ACS has systemic issues in undercounting births to women, especially younger women who are in the first 15 years of their reproductive life-span (O'Hare, Jensen, and O'Hare 2013; U.S. Census Bureau 2016).

Table 2. Descriptive Statistics

Variables	2006-2014 Mean	S.D.	Number of MSAs
Total Fertility Rate			
White TFR	1.86	0.3	381
Black TFR	2.03	0.5	381
Asian TFR	1.90	0.5	381
Hispanic TFR	2.45	0.6	381
MSA-level Covariates			
Unemployment Rate (%)	7.0	2.9	381
Percentage Goods-Producing Businesses	15.5	3.0	381
Number Goods-Producing Businesses (logged)	7.0	1.1	381
Percentage Goods-Producing Workers	18.4	6.7	381
Total Population (logged)	13.6	1.1	381
Per Capita GDP (10,000s)	3.7	0.7	381
MSA-Specific Covariates			
Greater than a HS Degree (%)	54.7	8.1	290
Never Married (%)	36.3	5.3	290
Past Year In-Migration (%)	3.7	2.2	290
Home Ownership (%)	67.5	6.9	290
Divorce Rate 15-64 (%)	11.3	2.2	290
Female Unemployment Rate (%)	8.3	3.1	290
Male Unemployment Rate (%)	8.9	3.5	290
Labor Force Participation Rate 15-64 (%)	73.9	4.3	290
Female Labor Force Participation Rate 15-64 (%)	69.4	5.0	290
Male Labor Force Participation Rate 15-64 (%)	78.4	5.0	290
Employment-to-Population Ratio 15-64 (%)	67.7	5.1	290
Female Employment-to-Population Ratio 15-64 (%)	63.7	5.5	290
Male Employment-to-Population Ratio 15-64 (%)	71.6	6.0	290
Race/Ethnicity-Specific Covariates			
Greater than a HS Degree (%)			
White	60.6	8.7	290
Black	48.0	14.5	260
Asian	66.3	17.2	254
Hispanic	36.7	14.1	277
Never Married (%)			
White	32.3	5.5	290
Black	52.1	13.0	260
Asian	33.1	15.2	254
Hispanic	42.7	10.9	277
Past Year In-Migration (%)			
White	3.7	2.5	290
Black	5.3	8.9	260
Asian	9.3	10.2	254
Hispanic	6.0	6.9	277
Home Ownership (%)			
White	73.0	7.1	290
Black	44.4	16.2	260
Asian	63.9	19.2	254
Hispanic	50.5	15.3	277

Mexican-Origin Composition (%)			
Hispanic Women Ages 15-49	29.5	18.3	282

Notes: (1) All covariates lagged 1-year (2) Different number of MSAs for TFR values reflects removal of TFR values over 4.0 (3) Different number of MSAs for MSA-specific and Race/Ethnicity-specific covariates reflects differential availability of ACS microdata (4) Because yearly sampling variation is assumed to be normally distributed in the ACS, I do not exclude observations that have implausible values. However, I do remove observations with ACS covariate values that indicate the total presence or total lack of a specific social/economic characteristic (e.g. 100% of the population is married). These values are indicative of a very small number of sampled of respondents in a local geography sharing the same characteristic in an annual survey.

Table 3. Fixed-Effects Regression Models of Total Fertility Rate by Race/Ethnicity between 2006-2014 for All MSAs

	2006-2014			2006-2010	2011-2014
Dependent Variable: Total Fertility Rate	Model 1	Model 2	Model 3	Model 4a	Model 4b
White, Non-Hispanic (381 MSAs; N=3429)					
% Goods-Producing Businesses		0.021***	0.020***	0.019***	0.017***
		(0.002)	(0.002)	(0.002)	(0.002)
Unemployment Rate (%)	-0.007***		-0.003*	-0.004*	-0.003*
	(0.001)		(0.001)	(0.002)	(0.001)
Black, Non-Hispanic (380 MSAs; N=3394)					
% Goods-Producing Businesses		0.022**	0.019*	0.019*	0.015
		(0.008)	(0.008)	(0.008)	(0.010)
Unemployment Rate (%)	-0.012*		-0.008	-0.005	-0.009
	(0.005)		(0.006)	(0.007)	(0.006)
Asian, Non-Hispanic (381 MSAs; N=3394)					
% Goods-Producing Businesses		0.027**	0.022*	0.022*	0.027*
		(0.010)	(0.011)	(0.011)	(0.012)
Unemployment Rate (%)	-0.016*		-0.012	-0.011	-0.012
	(0.007)		(0.007)	(0.009)	(0.007)
Hispanic (381 MSAs; N=3333)					
% Goods-Producing Businesses		0.058***	0.046***	0.046***	0.037***
		(0.008)	(0.008)	(0.008)	(0.009)
Unemployment Rate (%)	-0.036***		-0.027***	-0.033***	-0.026***
	(0.005)		(0.006)	(0.007)	(0.006)
MSA Controls	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	No	No

* p<.05, ** p<.01, *** p<.001 (two-tailed tests)

Notes: (a) MSA-level covariates included in all models. Year fixed-effects included only in Model 1 through Model 3. Covariates include annual measures of logged population and per capita GDP. (b) All covariates are lagged one year. (c) Standard errors in parentheses.

Table 4. Fixed-Effects Regression Models of Total Fertility Rate by Race/Ethnicity between 2006-2014 for ACS Subset Sample

	2006-2014			2006-2010	2011-2014
Dependent Variable: Total Fertility Rate	Model 1	Model 2	Model 3	Model 4a	Model 4b
White, Non-Hispanic (290 MSAs; N = 2375)					
% Goods-Producing Businesses		0.022***	0.022***	0.022***	0.022***
		(0.002)	(0.002)	(0.002)	(0.003)
Unemployment Rate (%)	-0.005**		-0.001	-0.003	-0.001
	(0.001)		(0.001)	(0.002)	(0.002)
Black, Non-Hispanic (289 MSAs; N = 2354)					
% Goods-Producing Businesses		0.016	0.013	0.015	0.005
		(0.008)	(0.009)	(0.009)	(0.010)
Unemployment Rate (%)	-0.009		-0.007	-0.006	-0.004
	(0.005)		(0.005)	(0.007)	(0.006)
Asian, Non-Hispanic (290 MSAs; N = 2360)					
% Goods-Producing Businesses		0.013	0.007	0.008	0.025
		(0.011)	(0.012)	(0.012)	(0.014)
Unemployment Rate (%)	-0.016*		-0.014*	-0.012	-0.013
	(0.007)		(0.007)	(0.009)	(0.008)
Hispanic (290 MSAs; N = 2319)					
% Goods-Producing Businesses		0.077***	0.062***	0.064***	0.063***
		(0.009)	(0.009)	(0.009)	(0.010)
Unemployment Rate (%)	-0.042***		-0.031***	-0.038***	-0.024***
	(0.005)		(0.006)	(0.007)	(0.006)
MSA Controls	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes

* p<.05,   ** p<.01,   *** p<.001 (two-tailed tests)

Notes: (a) Year fixed effects and MSA-level covariates included in all models. Covariates include annual measures of logged population, per capita GDP, percentage of homeowners, percentage of one-year in-migration, percentage with more than a high school education, and percentage never married. (b) All covariates are lagged one year. (c) Standard errors in parentheses

Table 5. Fixed-Effects Regression Models of Total Fertility Rate by Race/Ethnicity between 1991-2014 for All MSAs

	1991-2014		
Dependent Variable: Total Fertility Rate	Model 1	Model 2	Model 3
White, Non-Hispanic (381 MSAs; N=9138)			
% Goods-Producing Businesses		0.020***	0.020***
		(0.001)	(0.001)
Unemployment Rate (%)	-0.004***		-0.00000124
	(0.001)		(0.001)
Black, Non-Hispanic (381 MSAs; N=9004)			
% Goods-Producing Businesses		0.045***	0.051***
		(0.004)	(0.004)
Unemployment Rate (%)	0.011***		0.020***
	(0.003)		(0.003)
Asian, Non-Hispanic (381 MSAs; N=8909)			
% Goods-Producing Businesses		0.026***	0.023***
		(0.005)	(0.005)
Unemployment Rate (%)	-0.015***		-0.010*
	(0.004)		(0.004)
Hispanic (381 MSAs; N=8764)			
% Goods-Producing Businesses		0.027***	0.035***
		(0.005)	(0.005)
Unemployment Rate (%)	0.019***		0.025***
	(0.004)		(0.004)
MSA Controls	No	No	No
Year Fixed Effects	Yes	Yes	Yes

* p<.05, ** p<.01, *** p<.001 (two-tailed tests)

Notes: (a) Variables are lagged one year. (b) Standard errors in parentheses. (c) Due to data limitations, these models cannot be adjusted for the covariates included in the full 381 MSA 2006-2014 analysis (i.e. per capita GDP, etc.). Models are adjusted for logged population.

Appendix Table 1. BLS definitions of Industries by Domains, Super-Sectors, and NAICS-Sectors

Domain	Super-Sector	NAICS-Sector (2-Digit Codes)
Goods-Producing	Natural Resources and Mining	11 Agriculture, Forestry, Fishing, and Hunting
		21 Mining
	Construction	23 Construction
	Manufacturing	31-33 Manufacturing
Service-Providing	Trade, Transportation, and Utilities	42 Wholesale Trade
		44-45 Retail Trade
		48-49 Transportation and Warehousing
		22 Utilities
	Information	51 Information
	Financial Activities	52 Finance and Insurance
		53 Real Estate and Rental and Leasing
	Professional and Business Services	54 Professional, Scientific and Technical Services
		55 Management of Companies and Enterprises
		56 Administrative and Waste Services
	Education and Health Services	61 Educational Services
		62 Health Care and Social Assistance
	Leisure and Hospitality	71 Arts, Entertainment, and recreation
		72 Accommodation and Food Services
	Other Services	81 Other Services (Except Public Administration)

ONLINE APPENDIX

Online Appendix Figure S1. Histogram of all TFR values generated by Eq. 1 between 2006-2014

Online Appendix Figure S2. Total Fertility Rate by Race/Ethnicity For all U.S. Metro Areas between 1990-2014

Online Appendix Figure S3. The Decline of Goods-Producing Businesses in the United States, 2006-2014, disaggregated by MSA

Online Appendix Table S1. Full Regression Output of Table 3, Full 381 MSA analysis

Online Appendix Table S2. Fixed-Effects Regression Models of Total Fertility Rate by Race/Ethnicity between 2006-2014 for ACS Subsample, Substituting Divorce Rate for Adults Ages 15-64 for Percent Single, Never-Married

Online Appendix Table S3. Fixed-Effects Regression Models of Total Fertility Rate for Hispanics between 2006-2014 for ACS Subsample, adjusting for the Percentage of Reproductive Age Hispanic Women who are Mexican Immigrants

Online Appendix Table S4a. Robustness and Sensitivity Checks

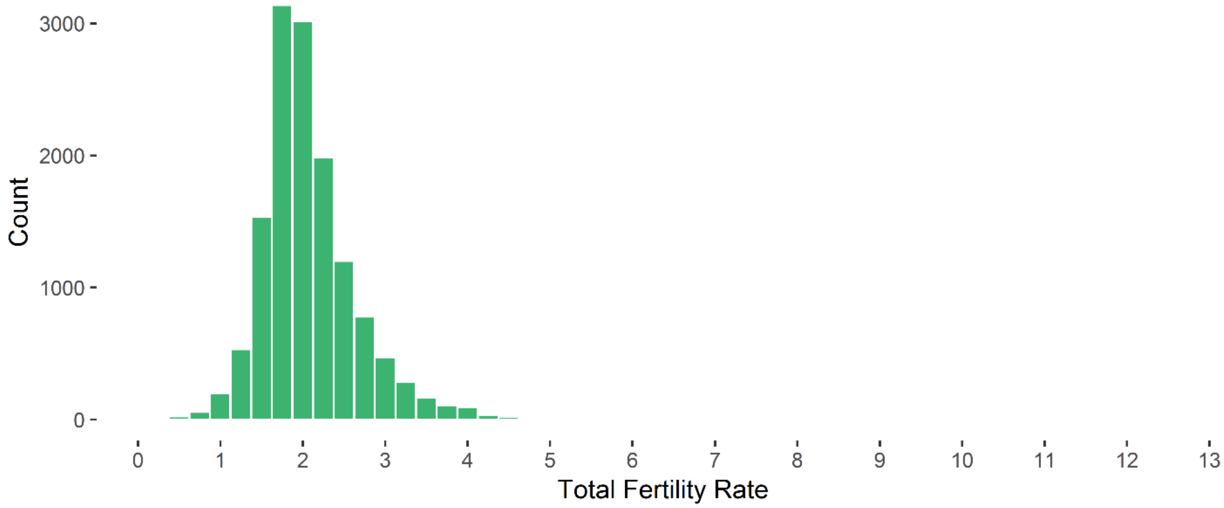
Online Appendix Table S4b. Unemployment Rate and Labor Force Participation Rate Sensitivity Checks

Online Appendix Table S5. Descriptive Statistics, Extended Analysis

Online Appendix Table S6. Fixed-Effects Regression Models of Age-Specific Fertility Rates by Race/Ethnicity between 2006-2014 for All MSAs

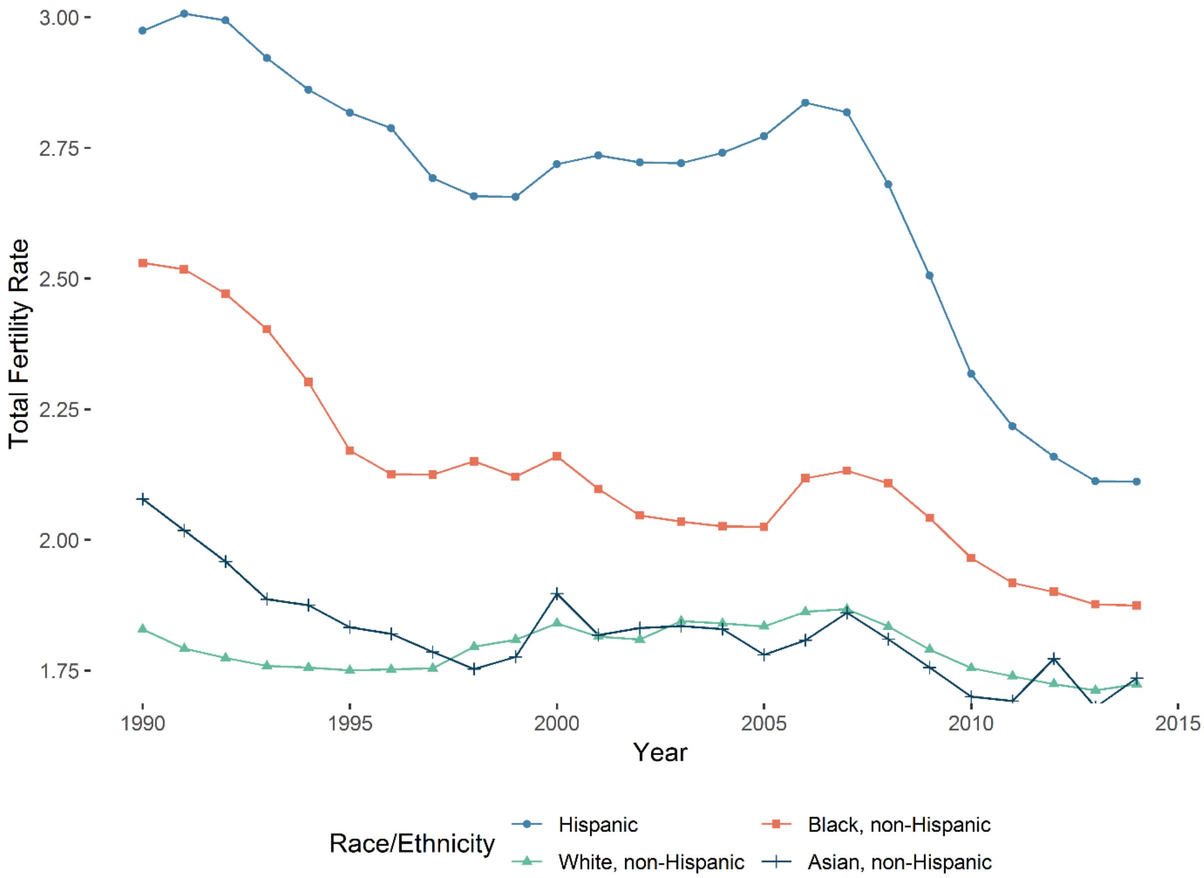
Online Appendix Text S1. Limitations of Employee Data in the County Business Patterns Dataset

Online Appendix Figure S1. Histogram of all TFR values generated by Eq. 1 between 2006-2014 (N=13,709)

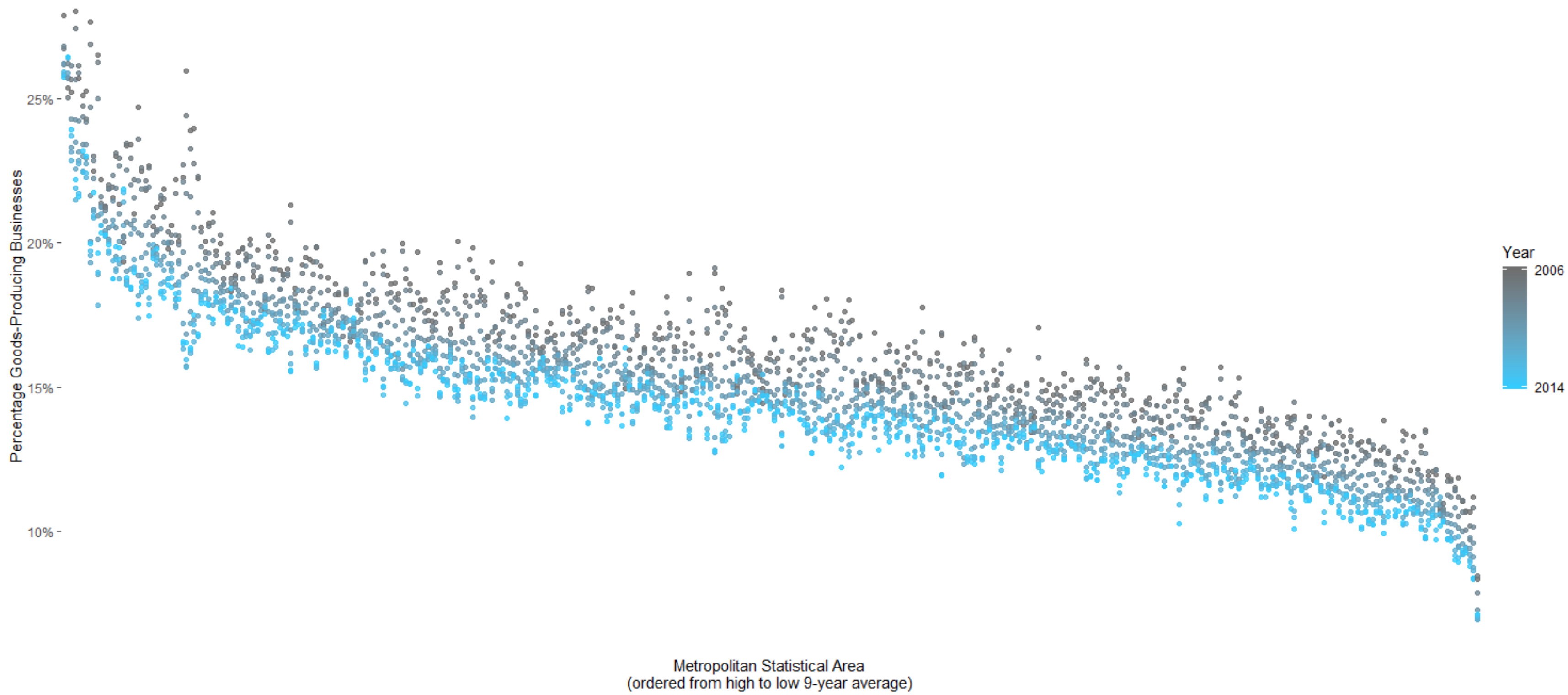


Note: 159 outliers above TFR of four, 38 outliers above TFR of five, and 2 outliers above TFR of eight.

Online Appendix Figure S2. Total Fertility Rate by Race/Ethnicity For all U.S. Metro Areas between 1990-2014



Online Appendix Figure S3. The Decline of Goods-Producing Businesses in the United States, 2006-2014, disaggregated by MSA



Notes: (a) Each vertical set of points represents one MSA over 9 years. (b) MSAs are ordered from high to low based on 9-year average of the share of goods-producing businesses. (c) Data are from the U.S. Census County Business Patterns Program, 2006-2014.

Online Appendix Table S1. Full Regression Output of Table 3, Full 381 MSA analysis

	Non-Hispanic White			Non-Hispanic Black			Non-Hispanic Asian			Hispanic		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
pct_goodsproducing_lag		0.021***	0.020***		0.022**	0.019*		0.027**	0.022*		0.058***	0.046***
		(0.002)	(0.002)		(0.008)	(0.008)		(0.010)	(0.011)		(0.008)	(0.008)
UnemploymentMSA_lag	-0.007***		-0.003*	-0.012*		-0.008	-0.016*		-0.012	-0.036***		-0.027***
	(0.001)		(0.001)	(0.005)		(0.006)	(0.007)		(0.007)	(0.005)		(0.006)
TOT_POP_log_lag	-0.082	0.056	0.050	-0.367	-0.228	-0.245	0.282	0.451	0.424	-2.248***	-1.915***	-1.988***
	(0.056)	(0.057)	(0.057)	(0.226)	(0.232)	(0.232)	(0.291)	(0.299)	(0.299)	(0.238)	(0.242)	(0.241)
gdp_pc_lag	0.051***	0.024*	0.019*	-0.007	-0.025	-0.037	0.375***	0.358***	0.340***	0.345***	0.313***	0.273***
	(0.009)	(0.010)	(0.010)	(0.037)	(0.039)	(0.039)	(0.048)	(0.050)	(0.051)	(0.037)	(0.038)	(0.039)
2006.year	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
2007.year	0.004	0.011*	0.010*	0.050*	0.058**	0.056**	-0.033	-0.024	-0.026	-0.047*	-0.029	-0.032
	(0.005)	(0.005)	(0.005)	(0.021)	(0.021)	(0.021)	(0.027)	(0.027)	(0.027)	(0.022)	(0.022)	(0.022)
2008.year	-0.041***	-0.028***	-0.028***	0.043	0.056*	0.055*	-0.152***	-0.138***	-0.138***	-0.202***	-0.172***	-0.172***
	(0.006)	(0.006)	(0.006)	(0.024)	(0.024)	(0.024)	(0.030)	(0.031)	(0.031)	(0.024)	(0.024)	(0.024)
2009.year	-0.090***	-0.074***	-0.070***	-0.031	-0.021	-0.012	-0.227***	-0.220***	-0.206***	-0.350***	-0.337***	-0.306***
	(0.007)	(0.007)	(0.007)	(0.028)	(0.029)	(0.030)	(0.037)	(0.037)	(0.038)	(0.028)	(0.029)	(0.029)
2010.year	-0.099***	-0.093***	-0.082***	-0.054	-0.071*	-0.038	-0.184***	-0.214***	-0.166***	-0.342***	-0.409***	-0.302***
	(0.009)	(0.007)	(0.009)	(0.036)	(0.029)	(0.037)	(0.046)	(0.037)	(0.047)	(0.036)	(0.029)	(0.037)
2011.year	-0.117***	-0.104***	-0.091***	-0.080*	-0.092**	-0.056	-0.207***	-0.232***	-0.179***	-0.417***	-0.475***	-0.357***
	(0.010)	(0.008)	(0.010)	(0.040)	(0.033)	(0.041)	(0.051)	(0.043)	(0.053)	(0.040)	(0.033)	(0.041)
2012.year	-0.135***	-0.106***	-0.095***	-0.073	-0.067	-0.035	-0.270***	-0.273***	-0.226***	-0.558***	-0.570***	-0.466***
	(0.011)	(0.010)	(0.011)	(0.042)	(0.040)	(0.046)	(0.055)	(0.051)	(0.059)	(0.042)	(0.040)	(0.045)
2013.year	-0.166***	-0.124***	-0.115***	-0.111*	-0.089	-0.063	-0.396***	-0.378***	-0.340***	-0.636***	-0.601***	-0.517***
	(0.011)	(0.011)	(0.012)	(0.044)	(0.046)	(0.049)	(0.056)	(0.059)	(0.063)	(0.044)	(0.045)	(0.049)
2014.year	-0.156***	-0.108***	-0.101***	-0.081	-0.050	-0.029	-0.412***	-0.383***	-0.352***	-0.648***	-0.588***	-0.521***
	(0.011)	(0.011)	(0.012)	(0.043)	(0.047)	(0.049)	(0.055)	(0.060)	(0.063)	(0.043)	(0.047)	(0.049)
_cons	2.840***	0.809	0.938	6.820*	4.691	5.054	-2.707	-5.320	-4.770	30.211***	24.966***	26.346***
	(0.711)	(0.725)	(0.727)	(2.849)	(2.946)	(2.956)	(3.667)	(3.791)	(3.804)	(2.996)	(3.061)	(3.063)
BIC	-8964.134	-9062.759	-9059.313	515.738	512.584	518.285	2193.286	2191.786	2196.777	366.063	357.993	339.903
Log-Likelihood	4530.907	4580.220	4582.567	-209.090	-207.513	-206.299	-1047.865	-1047.115	-1045.545	-134.362	-130.327	-117.226
# MSAs	3429	3429	3429	3394	3394	3394	3394	3394	3394	3333	3333	3333
# Observations	381	381	381	380	380	380	381	381	381	381	381	381

* p<.05, ** p<.01, *** p<.001 (two-tailed tests)

Online Appendix Table S2. Fixed-Effects Regression Models of Total Fertility Rate by Race/Ethnicity between 2006-2014 for ACS Subsample, Substituting Divorce Rate for Adults Ages 15-64 for Percent Single, Never-Married

	2006-2014
Dependent Variable: Total Fertility Rate	Model 1
White, Non-Hispanic (290 MSAs; N=2375)	
% Goods-Producing Businesses	0.021***
	(0.002)
Unemployment Rate (%)	-0.001
	(0.001)
Black, Non-Hispanic (289 MSAs; N=2354)	
% Goods-Producing Businesses	0.014
	(0.009)
Unemployment Rate (%)	-0.007
	(0.005)
Asian, Non-Hispanic (290 MSAs; N=2360)	
% Goods-Producing Businesses	0.007
	(0.012)
Unemployment Rate (%)	-0.014
	(0.007)
Hispanic (290 MSAs; N=2319)	
% Goods-Producing Businesses	0.063***
	(0.009)
Unemployment Rate (%)	-0.031***
	(0.006)
MSA Controls	Yes
Year Fixed Effects	Yes

* p<.05, ** p<.01, *** p<.001 (two-tailed tests)

Notes: (a) Year fixed effects and MSA-level covariates included in all models. Covariates include annual measures of logged population, per capita GDP, percentage of homeowners, percentage of one-year in-migration, percentage with more than a high school education, and percentage divorced. (b) All covariates are lagged one year. (c) Standard errors in parentheses

Online Appendix Table S3. Fixed-Effects Regression Models of Total Fertility Rate for Hispanics between 2006-2014 for ACS Subsample, adjusting for the Percentage of Reproductive Age Hispanic Women who are Mexican Immigrants

	2006-2014			2006-2010	2011-2014
Dependent Variable: Total Fertility Rate	Model 1	Model 2	Model 3	Model 4a	Model 4b
Hispanic (282 MSAs; N = 2023)					
% Goods-Producing Businesses		0.097***	0.082***	0.059***	0.052***
		(0.007)	(0.008)	(0.008)	(0.009)
Unemployment Rate (%)	-0.046***		-0.027***	-0.033***	-0.023***
	(0.005)		(0.005)	(0.006)	(0.005)
MSA Controls	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes

* p<.05,   ** p<.01,   *** p<.001 (two-tailed tests)

Notes: (a) Year fixed effects and MSA-level covariates included in all models. Covariates include annual measures of logged population, per capita GDP, percentage of homeowners, percentage with more than a high school education, and percentage never married, and percentage of reproductive-age Hispanic women who are Mexican immigrants. (b) All covariates are lagged one year. (c) Standard errors in parentheses

Online Appendix Table S4a. Robustness and Sensitivity Checks

Independent Variable	Log Number of Goods-Producing Business Establishments			% Goods-Producing Business Establishments	% Goods-Producing Employees (Mid-March)
Sample	Full	ACS Subset	ACS Subset	ACS Subset	Full
Covariate Set	MSA	MSA	Racial/Ethnic	Racial/Ethnic	MSA
Dependent Variable: TFR	Model 1	Model 2	Model 3	Model 4	Model 5
White, Non-Hispanic					
Goods-Producing Variable	0.138***	0.259***	0.252***	0.022***	0.004***
	(0.022)	(0.032)	(0.032)	(0.002)	(0.001)
Unemployment Rate (%)	-0.011***	-0.001	-0.001	-0.001	-0.005***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Black, Non-Hispanic					
Goods-Producing Variable	0.306***	0.083	0.112	0.013	0.007*
	(0.074)	(0.116)	(0.090)	(0.007)	(0.003)
Unemployment Rate (%)	-0.020***	-0.008	-0.005	-0.005	-0.009
	(0.004)	(0.005)	(0.004)	(0.004)	(0.006)
Asian, Non-Hispanic					
Goods-Producing Variable	0.088	0.168	0.159	0.016	0.012**
	(0.094)	(0.158)	(0.149)	(0.011)	(0.004)
Unemployment Rate (%)	-0.021***	-0.013	-0.016*	-0.015*	-0.012
	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
Hispanic					
Goods-Producing Variable	0.519***	0.915***	0.958***	0.066***	0.007*
	(0.080)	(0.122)	(0.113)	(0.008)	(0.003)
Unemployment Rate (%)	-0.028***	-0.028***	-0.020***	-0.024***	-0.033***
	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)

* p<.05, ** p<.01, *** p<.001 (two-tailed tests)

Online Appendix Table S4b. Unemployment Rate and Labor Force Participation Rate Sensitivity Checks

Independent Variable	% Goods-Producing				
Sample	ACS Subset				
Covariate Set	MSA				
Dependent Variable: TFR	Model 6	Model 7	Model 8	Model 9	Model 10
White, Non-Hispanic (290 MSAs; N=2375)					
% Goods-Producing	0.021***	0.022***	0.022***	0.021***	0.021***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Female Unemployment Rate	-0.001				
	(0.001)				
Male Unemployment Rate	-0.001				
	(0.001)				
Labor Force Participation Rate		0.001			
		(0.001)			
Female Labor Force Participation Rate			0.001		
			(0.001)		
Male Labor Force Participation Rate			0.000		
			(0.001)		
Employment-to-Population Ratio				0.002**	
				(0.001)	
Female Employment-to-Population Ratio					0.001*
					(0.001)
Male Employment-to-Population Ratio					0.001
					(0.001)
Black, Non-Hispanic (289 MSAs; N=2354)					
% Goods-Producing	0.015	0.016	0.017*	0.015	0.016
	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)
Female Unemployment Rate	-0.003				
	(0.003)				
Male Unemployment Rate	-0.001				
	(0.003)				
Labor Force Participation Rate		0.001			
		(0.003)			
Female Labor Force Participation Rate			-0.003		
			(0.002)		
Male Labor Force Participation Rate			0.003		
			(0.002)		
Employment-to-Population Ratio				0.002	
				(0.003)	
Female Employment-to-Population Ratio					-0.001
					(0.002)
Male Employment-to-Population Ratio					0.004

					(0.002)
Asian, Non-Hispanic (290 MSAs; N=2369)					
% Goods-Producing	0.011	0.013	0.014	0.013	0.013
	(0.012)	(0.011)	(0.011)	(0.012)	(0.012)
Female Unemployment Rate	0.006				
	(0.004)				
Male Unemployment Rate	-0.007				
	(0.004)				
Labor Force Participation Rate		-0.001			
		(0.004)			
Female Labor Force Participation Rate			-0.004		
			(0.003)		
Male Labor Force Participation Rate			0.003		
			(0.003)		
Employment-to-Population Ratio				0.000	
				(0.004)	
Female Employment-to-Population Ratio					0.000
					(0.003)
Male Employment-to-Population Ratio					0.000
					(0.003)
Hispanic (290 MSAs; N=2319)					
% Goods-Producing	0.071***	0.076***	0.076***	0.073***	0.072***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Female Unemployment Rate	-0.002				
	(0.003)				
Male Unemployment Rate	-0.006*				
	(0.003)				
Labor Force Participation Rate		0.002			
		(0.003)			
Female Labor Force Participation Rate			0.003		
			(0.002)		
Male Labor Force Participation Rate			-0.001		
			(0.002)		
Employment-to-Population Ratio				0.006*	
				(0.003)	
Female Employment-to-Population Ratio					0.005*
					(0.002)
Male Employment-to-Population Ratio					-0.000
					(0.002)

* p<.05, ** p<.01, *** p<.001 (two-tailed tests)

Notes: unemployment rates, labor force participation rates, and employment-to-population ratios are calculated at the MSA-level and for working age adults 15-64.

Online Appendix Table S5. Descriptive Statistics, Extended Analysis

	1991-2014		
Variables	Mean	S.D.	Number of MSAs
Total Fertility Rate			
White TFR	1.86	0.27	381
Black TFR	2.07	0.52	381
Asian TFR	1.93	0.55	381
Hispanic TFR	2.44	0.68	381
MSA-level Covariates			
Unemployment Rate (%)	6.19	2.85	381
Percentage Goods-Producing Businesses	16.71	3.16	381
Total Population (logged)	12.56	10.37	381

Notes: (1) All covariates lagged 1-year

Online Appendix Table S6. Fixed-Effects Regression Models of Age-Specific Fertility Rates by Race/Ethnicity between 2006-2014 for All MSAs

Dependent Variable: Age-Specific Fertility Rates	**15-19**	**20-24**	**25-29**	**30-34**	**35-39**	**40-44**	**45-49**
White, Non-Hispanic (381 MSAs)							
% Goods-Producing Businesses	0.00028**	0.00158***	0.00067**	0.00097***	0.00031**	0.00012**	0.00003*
	(0.00010)	(0.00020)	(0.00021)	(0.00017)	(0.00010)	(0.00004)	(0.00001)
Unemployment Rate (%)	-0.00022**	-0.00089***	0.00017	0.00021	0.00012	0.00006*	0.00000
	(0.00007)	(0.00013)	(0.00014)	(0.00011)	(0.00007)	(0.00003)	(0.00001)
Black, Non-Hispanic (380 MSAs)							
% Goods-Producing Businesses	0.00039	0.00006	0.00239**	0.00056	0.00049	0.00035	-0.00008
	(0.00040)	(0.00074)	(0.00081)	(0.00070)	(0.00060)	(0.00036)	(0.00017)
Unemployment Rate (%)	0.00040	-0.00135**	-0.00038	-0.00023	0.00032	0.00014	0.00012
	(0.00026)	(0.00049)	(0.00054)	(0.00046)	(0.00038)	(0.00022)	(0.00009)
Asian, Non-Hispanic (380 MSAs)							
% Goods-Producing Businesses	0.00043	0.00275**	0.00101	0.00072	-0.00043	0.00042	-0.00094
	(0.00062)	(0.00099)	(0.00107)	(0.00095)	(0.00069)	(0.00041)	(0.00063)
Unemployment Rate (%)	0.00029	-0.00065	-0.00147*	0.00041	0.00000	0.00008	-0.00074*
	(0.00041)	(0.00067)	(0.00072)	(0.00064)	(0.00047)	(0.00027)	(0.00036)
Hispanic (381 MSAs)							
% Goods-Producing Businesses	0.00227***	0.00470***	0.00221**	0.00051	0.00051	0.00019	-0.00040
	(0.00049)	(0.00071)	(0.00069)	(0.00062)	(0.00046)	(0.00049)	(0.00039)
Unemployment Rate (%)	0.00004	-0.00201***	-0.00180***	-0.00108**	-0.00026	0.00009	-0.00005
	(0.00032)	(0.00047)	(0.00046)	(0.00041)	(0.00030)	(0.00032)	(0.00022)
MSA Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

* p<.05, ** p<.01, *** p<.001 (two-tailed tests)

Online Appendix Text S1. Limitations of Employee Data in the County Business Patterns Dataset

The statistical analyses presented in this study operationalize labor market polarization as the percentage of goods-producing *business establishments* in a MSA. Although the County Business Patterns dataset includes a variable for the number of mid-March employees which could be used to calculate the percentage of *employees* in goods-producing industries, the use of this measure is not without several data and conceptual limitations. Nevertheless, the employee measure and the business establishment measure are strongly correlated (r = .5015).

The main consideration for this decision is the availability and quality of the employee data for business establishments. A nontrivial amount of the employee data is withheld from the dataset since the Census Bureau is prohibited by law from releasing information that would identify the operations of individual employers (CBP Methodology Report). Missing values in the dataset are not missing based on county population size; instead, data is withheld based on the sparseness of the number of business establishments within each sub-classification level of the NAICS coding scheme.

In contrast, none of the data on the number of business establishments for each NAICS sub-classification level are withheld since this data is not considered confidential (CBP Methodology Report).

There are also conceptual reasons for using a business establishment measure over an employee measure. As noted in the Data and Methods section, I conceptualize labor market polarization as more than just the loss of middle-skill, middle-wage jobs in manufacturing and construction industries, but instead the decline of those industries themselves. Closure of business establishments in the goods-producing business sector (e.g. factory closures) are more permanent than layoffs of individual workers in the sense that it is more difficult for jobs to return once a business establishment has been permanently closed. As a result, I argue that structural change in U.S. labor markets is best measured through the loss of business establishments.

As a robustness check, I calculate and estimate models using the employee measure (Online Appendix Table S4a, Model 5), which should be interpreted with an understanding of the limitations noted above.

References:

U.S. Census Bureau. 2018. County Business Patterns Methodology Report. Retrieved from https://www.census.gov/programs-surveys/cbp/technical-documentation/methodology.html.

U.S. Census Bureau. 2018. County Business Patterns, Using Noise for Disclosure Limitation of Establishment Tabular Data. Retrieved from https://www.census.gov/prod/2/gen/96arc/iiaevans.pdf.

Chapter 2: The Economic Underpinnings of the Drug Epidemic

ABSTRACT
U.S. labor markets have experienced transformative change over the past half century. Spurred on by global economic change, robotization, and the decline of labor unions, state labor markets have shifted away from an occupational regime dominated by the production of goods to one characterized by the provision of services. Prior studies have proposed that deterioration of employment opportunities may be associated with the rise of substance use disorders and drug overdose deaths, yet no clear link between changes in labor market dynamics in the U.S. manufacturing sector and drug overdose deaths has been established. Using restricted-use vital registration records between 1999-2017 that comprise over 700,000 drug deaths, I test two questions. First, what is the association between manufacturing decline and drug and opioid overdose mortality rates? Second, how much of the increase in these drug-related outcomes can be accounted for by manufacturing decline? The findings provide strong evidence that restructuring of the U.S. labor market has played an important upstream role in the current drug crisis. Up to 77,000 overdose deaths for men and up to 40,000 overdose deaths for women are attributable to the decline of state-level manufacturing over this nearly two-decade period. These results persist in models that adjust for other social, economic, and policy trends changing at the same time, including the supply of prescription opioids. Critically, the findings signal the value of policy interventions that aim to reduce persistent economic precarity experienced by individuals and communities, especially the economic strain placed upon the middle class.

Keywords

Drug Overdose Deaths, Mortality, Deindustrialization, Social Determinants; Economic Conditions

1. INTRODUCTION

The ongoing drug epidemic is arguably one of the most consequential public health issue in the United States right now. Drug overdose deaths in the United States continued to rise through 2017, reducing overall life expectancy for the third year in a row – a trend in life expectancy that has not occurred in over a century (Hedegaard, Warner, and Miniño 2018; Murphy et al. 2018; Woolf and Schoomaker 2020). Nationally, drug overdose death rates increased from 6.1 deaths per 100,000 population in 1999 to 21.7 deaths per 100,000 population in 2017 (Murphy et al. 2018). Despite a slight decline in 2018, drug overdose mortality remains high at 20.7 deaths per 100,000 population (Hedegaard et al. 2020). Researchers have debated the extent to which social and economic determinants of health are meaningful explanations of the U.S. drug and opioid epidemic, with a particular emphasis on the opioid epidemic (Case and Deaton 2015, 2018; Dasgupta, Beletsky, and Ciccarone 2018; Ruhm 2019). While some emphasize the importance of pharmaceutical companies in increasing the legal supply of prescription opioids (e.g. Ruhm 2019), others emphasize the role of structural economic change and economic despair as demand-side drivers of rising rates of substance use (e.g. Case and Deaton 2015a, 2017; Monnat 2019). Yet, this framing of dueling supply-side and demand-side explanations overlooks the endogenous interrelationship between both supply and demand. While pharmaceutical companies such as Purdue Pharma played a central, mechanistic role in increasing the supply of legal prescription opioids available to patients (DeShazo et al. 2018; Haffajee and Mello 2017), they did not send their pharmaceutical sales representatives or marketing dollars to communities across the U.S. at random (Hadland et al. 2019). Rather, analyses of the geospatial patterning of the opioid epidemic indicate that areas with higher economic precarity – higher rates of poverty, higher rates of unemployment, and lower median home values, for instance – also had higher rates of filled opioid prescriptions, opioid-related hospital visits, and ultimately, opioid overdose deaths (Ghertner and Groves 2018; Monnat 2019; Schoenfeld et al. 2019). Moreover, counties that received more pharmaceutical company opioid marketing to physicians also had higher rates of opioid prescribing and opioid overdose deaths (Hadland et al. 2019). In conjunction, these empirical findings suggest that pharmaceutical companies were likely responding in part to demand-side factors, focusing their marketing strategy on communities struggling from economic stagnation. A full accounting of the origins of the opioid epidemic therefore necessitate a broader examination of how contextual economic conditions are associated with the rise of opioid deaths.

Prior studies have proposed that long-term changes in economic conditions, including the deterioration of employment opportunities in U.S. labor markets and the rise of economic insecurity for families, may be associated with the rise of substance use disorders and drug overdose mortality rates more generally (Betz and Jones 2018; Case and Deaton 2017; Ghertner and Groves 2018; Hederos et al. 2017; McLean 2016; Monnat 2018; Nosrati et al. 2017). Understanding this relationship is necessary for multiple reasons. Establishing whether drug-related overdose deaths are attributable to upstream social and economic factors opens additional avenues of clinical, public health, and public policy intervention to stem the ongoing rise of drug overdose deaths. It may also shed light on regional variation in epidemic intensity and facilitate prediction of trends in these rates. Many of the hardest hit regions of the ongoing drug and opioid crisis have also endured decades of deteriorating economic conditions (Dasgupta et al. 2018; Ezzati et al. 2008; Zoorob and Salemi 2020). Investigating this relationship informs social scientists about the scope conditions under which social and economic contexts are salient predictors of population-level health outcomes.

The present study considers how structural economic change – specifically, the decline of employment opportunities in the manufacturing sector – are associated with the rise of drug deaths since the late 1990s. Over the past half century, the United States labor market has experienced an industrial restructuring that has fundamentally reshaped the employment opportunities available to American workers, particularly for those with only a high school degree (Acemoglu and Autor 2011; Autor and Dorn 2013; Autor et al. 2006; Kalleberg 2009). Spurred on by global economic change, robotization, and the decline of labor unions, U.S. labor markets have shifted away from an occupational regime dominated by the production of manufactured goods to one characterized by the provision of services. This new occupational structure has prompted the job polarization of U.S. labor markets, wherein the decline of largely middle-wage employment in manufacturing sectors has been accompanied by the rise of employment growth in low-wage and high-wage service sectors (Autor et al. 2006).

Although this structural transformation of U.S. labor markets began in the 1970s, the decline of employment opportunities in the manufacturing sector accelerated rapidly during the 2000s with the loss of nearly 5.4 million jobs (Atkinson et al. 2012). In comparison to the 1980s and the 1990s, when manufacturing employment decreased on average by about 0.5% per year, manufacturing employment decreased on average by 3.7% per year in the 2000s (Figure 1). And although the manufacturing sector experienced a resurgence of employment growth following the Great Recession throughout the 2010s, only about 1.3 million manufacturing jobs were regained out of the initial 5.4 million that were loss since the early 2000s; these new manufacturing jobs are less likely to pay as well as manufacturing jobs in past decades (Jacobs et al. 2016). Overall, the decline of manufacturing jobs has resulted in the stagnation of wage growth and the depletion of financial resources for the American middle class (Kalleberg 2009; Kalleberg and von Wachter 2017). Middle-income households held 62% of aggregate household income at the start of the 1970s. They now hold less than 43% of aggregate household income, largely the result of declining middle-wage jobs (Pew Research Center 2015).

Recent research in the social and biomedical sciences has raised important questions about the implications of these and other structural economic changes on the mental health and emotional well-being of the middle class. Scholars theorize that the restructuring of labor markets, the rise of precarious work arrangements, and an overall stagnation of economic opportunity for many, has stimulated the rise of economic anxiety (Brand 2015; Case and Deaton 2015; Kalleberg 2018; Kirsch and Ryff 2016; Lim 2017; McCall et al. 2017; Thiede and Monnat

2016). Job loss, economic disinvestment, and out-migration from local labor markets and communities influence perceptions of economic opportunity, which in turn are associated with several indicators of worsened physical and mental health (Burgard, Brand, and House 2009; Catalano 1991; Charles and DeCicca 2008; McLean 2016; Zivin, Paczkowski, and Galea 2011). One of the clearest manifestations of this hypothesized process is the recent intensification of diagnoses of substances use disorders (SUDs) and drug overdose deaths (Gaydosh et al. 2019; Murphy et al. 2018). Both quantitative and qualitative research accounts suggest that local risk environments characterized by dampened economic opportunity can influence substance use (McLean 2016; Monnat 2019; Venkataramani et al. 2020). In this sense, drug deaths may represent a particularly extreme version of individual-level responses to societal pressures.

The present study contributes a sociological perspective to literature on the ongoing drug and opioid epidemic by emphasizing the role of institutions in shaping both social and economic contexts that impact health outcomes. Legislative and regulatory strategies for spurring industrial growth and addressing the oversupply of prescription opioids vary considerably across state borders, which motivates the importance of state-level comparisons that account for heterogenous social, economic, and political contexts.

Using this state-level framework, I combine economic and business activity data from multiple sources with annual drug and opioid overdose mortality data from the National Center for Health Statistics to answer two questions. First, what is the association between manufacturing decline and drug and opioid overdose mortality rates? Second, how much of the increase in these overdose mortality outcomes can be accounted for by manufacturing decline? I use a research design that leverages variation both within states and within time periods to sidestep endogeneity concerns that complicate identification. I use data from the Census

Bureau's County Business Patterns program to examine how the decline in the relative share of state-level employment and earnings in manufacturing industries impacts drug and opioid mortality, net of factors that shape the supply of opioids and changes in other state-level contextual and compositional processes. This analysis is augmented by the estimation of a series of alternate specifications, including county-level models, to further evaluate the robustness of the results. The findings suggest strong evidence that the industrial restructuring of the U.S. labor market – the decline of manufacturing, in particular – has played an important upstream role in the current opioid crisis. Up to 77,000 overdose deaths for men and up to 40,000 overdose deaths for women are attributable to the decline of state-level manufacturing over this nearly two-decade period.

2. BACKGROUND

2.1 Economic Deterioration and Negative Health Outcomes

Social scientists have increasingly turned their attention towards the link between macroeconomic conditions, individual-level experiences of the labor market, and physical and mental health outcomes. Prior individual-level analyses on job displacement and plant closures in the U.S. and in European countries have demonstrated that involuntary job loss is associated with an array of negative health related outcomes, including decreased mental and physical health functioning (Riumallo-Herl et al. 2014; Schaller and Stevens 2015), decreased self-reported health (Huijts et al. 2015; Strully 2009), increased cigarette smoking and alcohol consumption (Black, Devereux, and Salvanes 2015; Gallo et al. 2001), and short-term and long-term increased risks of all-cause mortality (Browning and Heinesen 2012; Sullivan and von Wachter 2009). Studies have documented how increased economic strain (Schaller and Stevens 2015; Strully 2009; Sullivan and von Wachter 2009), decreased employment prospects and precarious employment situations (Janoski et al. 2014; Strully 2009), and reduced access to health insurance and reduced health care use (Jolly and Phelan 2017; Schaller and Stevens 2015; Sullivan and von Wachter 2009) increase the likelihood of experiencing adverse health outcomes and behaviors, including alcohol and cigarette usage.

Population substance use, including opioid use, may increase during periods of economic deterioration through multiple pathways. This may occur directly through the heightened stress of job displacement on individuals and their families, or indirectly through population health impacts initiated by dampened economic opportunity and increased economic insecurity within labor markets. The individual-level experience of job displacement, and the resultant economic strain and reduction of resources, fosters a risk-environment that increases the likelihood of substance abuse (Mclean 2018; Merline et al. 2004; Rhodes 2009; Rolfs et al. 2012).

Yet, the direct experience of job displacement for laid off workers does not fully account for the massive growth of substance use disorders and drug overdose deaths in communities that have experienced economic deterioration over the past several decades. Several pathways operate outside of individual-level effects. For example, the economic consequences of job loss and business disinvestment from labor markets extend beyond displaced workers to their families and to the broader community; these effects appear to have spillover health costs (Adda and Fawaz 2019; Broman, Hamilton, and Hoffman 1990; Colantone, Crinò, and Ogliari 2019; Lang, McManus, and Schaur 2019). Long-term economic change like manufacturing decline alters the opportunity structures of labor markets and influences perceptions of economic uncertainty, which in turn increases physical and mental health issues (Colantone et al. 2019; Lang et al. 2019).

Indeed, several new studies have suggested a link between economic deterioration in labor markets and increased opioid deaths. Monnat (2018), found a cross-sectional association between manufacturing dependence and average drug-related mortality rates across U.S. counties. In a separate analysis, Monnat (2019) found that drug mortality rates for non-Hispanic whites are larger in counties designated as service sector-dependent in comparison to counties designated as non-specialized. Likewise, Pierce and Schott (2016), examining the impact of U.S. trade policy on cause-specific mortality from three categories of deaths of despair, found that the implementation of trade liberalization policies predicted increased mortality rates from accidental poisonings for white men and women, but not for other racial/ethnic groups. In contrast to these findings, Ruhm (2018), examining changes in county-level drug mortality rates between 1999-2015, reported a positive, albeit non-significant, association between Chinese import penetration and overall increased drug mortality rates; but overall, he concludes that economic conditions (including other economic measures) explain less than 10% of the drug epidemic. Finally, Venkataramani et al. (2020) research on the relationship between automotive plant closures in local communities and opioid overdose mortality suggests that discrete economic shocks are associated with community-level increases in opioid overdose deaths.

The present study builds on and contributes to this literature by using an identification strategy that supports attribution of drug and opioid deaths to upstream economic change—and the shift from manufacturing to service employment in particular. I leverage annual variation in state-level manufacturing change to estimate drug and opioid overdose mortality. The panel design models a data generating process in which yearly fluctuations in employment conditions have immediate impacts on substance use and drug overdose deaths.

Though past findings have asserted that the rise of drug deaths throughout this time period are mostly concentrated among middle-age white men (e.g. Case and Deaton 2015), recent studies have documented a counter-narrative: deaths of despair have substantially increased for a more expansive set of racial/ethnic groups, as well as for women (Alexander, Kiang, and Barbieri 2018; Gaydosh et al. 2019; Woolf et al. 2018). In light of these findings, I further investigate whether structural economic changes have differentially influenced drug deaths across racial/ethnic and gender subgroups by estimating a set of sensitivity models that predict age-, sex-, and race/ethnicity-specific drug mortality rates.

2.2 State-Level Heterogeneity in Socio-Political Policy Regimes

Rising differentiation in state-level health and economic policies have contributed to an increasingly common practice of conceptualizing the state as a laboratory to study population welfare (Montez, Hayward, and Zajacova 2019). Indeed, state-level contexts and policies are important determinants of population health outcomes, specifically (Bradley et al. 2016; Kim and Jennings 2009; Montez et al. 2019). State legislative and regulatory decisions influence population health outcomes directly through health policies such as tobacco control and Medicaid expansion, but also indirectly through social and economic policies in domains such as education and the criminal justice system (Massoglia and Remster 2019; Miller et al. 2019), which stratify health outcomes within and across state populations. Policies concerning economic development and the rise of opioid prescriptions vary dramatically across states, and rather than being viewed as distinct, separate state policies, are better conceptualized as components of broader socio-political policy regimes that influence the daily lives of residents. As noted by Montez et al. (2019), state-level authority has increasingly taken precedence over both federal- and local-level authority over the past several decades.

Additionally, the pace and character of industrial change over the past three decades has differed markedly across states. These differences arise in part because of differences across state labor markets in how easily occupational tasks can be routinized and offshored in certain manufacturing sectors (Acemoglu and Autor 2011; Autor and Dorn 2013),[11] but also because of state-level policies that create incentives for manufacturers to stay or relocate plants. That is, states actively contend with one another as well as with international competitors to retain and attract manufacturing jobs. In order to promote economic development and industrial growth, policy approaches used by states have included financial incentives, corporate tax subsidies, labor deregulation, and the softening of environmental regulations, among others (Eisenger 1988; Eisneger 1995; Grant and Wallace 1994; Bartik 1988; Gray and Lowery 1990; Brace 2002; Giroud and Rauh 2015). The variation in the legislation and implementation of these state-level industrial policies and labor contexts as well as the outcomes of these policies further motivate the importance of state-level comparisons and the usage of state fixed effects. Nationally, the share of jobs in manufacturing industries declined by an average of 5.8 percentage points between 1998-2016, from 15.2% in 1998 to 9.4% in 2016 (Figure 2a, data and measurement described below). In this same time period, the share of total annual payroll in manufacturing industries declined by an average of 7.2 percentage points, from 18.6% in 1998 to 11.4% in 2016 (Figure 2b). This average national decline masks substantial state-level variation. Arkansas, Rhode Island, Tennessee, North Carolina, and South Carolina experienced large declines in manufacturing employment of over 8 percentage points, while states such as Nevada, Wyoming, and Hawaii experienced declines of less than 2 percentage points.

An analysis examining the effects of state-level economic change on health and mortality must also be attentive to other contemporaneous social, economic, and compositional changes that might confound estimation. To address this concern, the models adjust for a set of

[11] For instance, manufacturing employment in the automobile industry decreased substantially for midwestern states while increasing for southern states (Cutcher-Gershenfeld, Brooks, and Mulloy 2015).

theoretically relevant, time-varying compositional and contextual population-level characteristics, including educational attainment, race/ethnicity, nativity, marital status, and self-reported health (Chetty, Stepner, et al. 2016; Schoenfeld et al. 2019). Based on prior literature that documents how companies move production operations to labor markets with cheaper labor costs and labor protections (Grant and Wallace 1994), I adjust for state-level trends in the percentage of workers represented by labor unions.[12] I adjust for state-level trends in unemployment rates because shifts in unemployment are associated with changes in population health outcomes and cause-specific mortality rates, including deaths from drugs and alcohol (Granados et al. 2014; Ruhm 2003, 2011). The unemployment rate is conceptually distinct from the relative share of manufacturing employment since it quantifies joblessness rather than the industrial characteristics or qualities of jobs in a labor market.

For the study of opioids specifically, there is also relevant state-level variation in policies that have facilitated the local *supply* of opioids. State governments have enacted an array of policy strategies to address the opioid epidemic. For instance, the creation of Prescription Drug Monitoring Program's (PDMPs), state-run electronic databases that allow prescribers, dispensers, and other health authorities to track the prescription patterns of controlled substances for individual patients, has become a widely adopted policy intervention used by states to reduce the amount of opioid painkillers prescribed to patients (Bao et al. 2017; Cerdá et al. 2020; Fink et al. 2018). States have also enacted other policy interventions such as laws that aim to regulate pain management clinics, increase access to naloxone, and improve legal protections for bystanders who report drug overdoses. The outcomes of these policies, whether effective in

[12] I also tested for the percentage of workers in a state labor force who were *members* of labor unions rather than those covered/represented by labor unions. The results are approximately the same.

reducing substance use and opioid deaths or not, has varied (e.g. Doleac and Mukherjee 2018). I adjust for the implementation of PDMPs, naloxone access laws, and Good Samaritan laws, to account for these principal drug policy interventions. Given data availability limitations for the full 19-year time period, I adjust for state-level trends in the supply of legally dispensed opioid prescriptions in sensitivity analyses that span the years 2007-2017, thereby netting out the supply of legal opioids.

Situating the present analysis at the state-level therefore facilitates modeling how regional variation in ecological risk environments contributes to variation in the concentration of a pressing public health concern, specifically, drug overdose mortality and opioid-related hospitalizations. It also facilitates an opportunity to address the implementation of several important state-level policy changes that are widely considered relevant to the unfolding of the U.S. opioid epidemic. Capturing annual variation in these processes both increases the precision of identification and advances a theoretical model of how labor market dynamics shape contexts of substance use and drug overdose.

3. DATA and METHODS

3.1 Drug Overdose Mortality Rates

Data on annual state-level, drug and opioid overdose mortality between 1999-2017 were calculated using the restricted-use multiple cause of death file from the National Center for Health Statistics (NCHS) in combination with bridged-race population estimates from the NCHS. Mortality data used in this study are based on approximately 47.7 million death certificate records of U.S. residents reported to the National Vital Statistics System (NVSS) between 1999-2017. For drug overdose mortality rates, this data represents approximately 260,000 deaths to women and 440,000 deaths to men, among which 326,000 of those male deaths are for non-Hispanic white men ages 15-64. For opioid mortality rates, this data represents approximately 134,000 deaths to women and 262,000 deaths to men.

Drug overdose mortality rates were constructed and defined using the International Statistical Classification of Diseases and Related Health Problems 10th Revision (ICD10) underlying cause of death codes X40-44, X60-64, X85, and Y10-14 (Hedegaard et al. 2018). These classifications include drug deaths recorded as unintentional, suicide, homicide, or of undetermined intent, although nearly 90% are recorded as unintentional. Opioid overdose mortality rates were constructed using the previous ICD10 underlying cause of death codes in conjunction with any of the following IC10 multiple cause of death codes T40.0 (Opium), T40.1 (Heroin), T40.2 (Other Opioids), T40.3 (Methadone), T40.4 (Other Synthetic Narcotics), or T40.6 (Other Unspecified Narcotics). Table S1 presents the full description of all ICD10 codes used to define drug and opioid mortality rates.

I calculated age-adjusted mortality rates to account for shifts in the age distribution of state populations over time as well as differences in the age distribution of populations across states. I then log-transformed the age-adjusted mortality rates because the non-transformed mortality rates are right-skewed and nonnormal (Figure S1). Since there were only a few state-year observations with drug or opioid death rates of zero, I allowed the log transformation to render these values as undefined and excluded them from my analysis. I used the “direct” method of age standardization to derive age-adjusted death rates based on the weighted age distribution of the total U.S. population in the year 2000 as the standard (Anderson and Rosenberg 1998). I accessed bridged-race population estimates from the NCHS for population denominators. I evaluated the accuracy of the calculated age-adjusted mortality rates by comparing equivalent non-suppressed, publicly available age-adjusted mortality rates for state-year observations that had more than 9 deaths through the CDC Wonder database. The correlation between the rates I calculated and those accessed through CDC Wonder ranged from *r*=.9998 to *r*=.9999, indicating that the calculations were performed correctly. The advantage of using the restricted-use multiple cause of death file is that the present analysis includes non-zero, state-year observations that would otherwise be suppressed in the public-use file.

3.2 Measures

3.2.1 Manufacturing decline

The decline of the U.S. manufacturing sector in state labor markets was assessed using relative measures of the total number of employees and total annual payroll concentrated in the manufacturing sector. Both measures were lagged one-year to achieve appropriate temporal ordering. I obtained state-level data on annual employment and payroll between 1998-2016 from the U.S. Census Bureau’s County Business Patterns program (CBP) which compiles subnational business establishment data according to 6-digit North American Industry Classification System (NAICS) codes (U.S. Census Bureau 2018). CBP relies primarily on business establishment data from the Census Bureau’s Business Register (BR) which contains a complete list of all business establishments in the United States with paid employees. The relative share of annual employment and payroll was calculated by dividing the number of employees and payroll in the manufacturing sector (NAICS 2-digit codes 31-33) by the number of employees and payroll in all other business sectors.

3.2.2 Covariates

I included a set of theoretically relevant, time-varying covariates in the models which might plausibly confound the direct association between shifts in manufacturing employment and mortality rates. Based on extant literature on the economic and geographic determinants of mortality and life expectancy (Chetty, Stepner, et al. 2016), the models adjust for state-level compositional and contextual characteristics including the share of workers covered by labor unions, the unemployment rate, the percentage of the population with a college degree, the percentage of the population ever married, the percentage of the population who are Hispanic, the percentage of the population who are black, and the average self-reported health score.

The findings of several recent studies (Currie, Jin, and Schnell 2019; Krueger 2017) have suggested a reverse causal direction between economic conditions and the opioid epidemic: that is, these researchers argue that substance use might be causally impacting rates of unemployment and labor force participation. I use an estimation strategy that lags all predictors by one year to achieve well-defined temporal ordering, but I additionally test specifications that adjust for a set of state-specific drug regulatory policies that might plausibly be associated with both changes in manufacturing sectors (or labor markets more broadly) and drug use. These policies include annual binary indicators for the initial and ongoing implementation of Prescription Drug Monitoring Programs (PDMPs), naloxone access laws, and Good Samaritan laws. The outcomes of these policies, whether effective in reducing substance use and opioid deaths, has varied (for Naloxone access laws, see Doleac and Mukherjee 2018; for PDMPs, see Fink et al. 2018, Finley et al. 2017, or Grecu et al. 2019); yet, they represent the implementation of extensive state-level interventions that might explain trends in drug and opioid deaths.

Data on annual state-level union coverage come from the Union Membership and Coverage Database (Hirsch and Macpherson 2003) which estimates statistics on union membership using the Current Population Survey (CPS). Data on state-level unemployment rates were accessed from the U.S. Census Bureau’s Local Area Unemployment Statistics program (LAUS) (Bureau of Labor Statistics 2018). Data on other state-level social, economic, health, and compositional characteristics between 1999-2017 were calculated using micro-data from the U.S. Census Bureau's CPS Annual Social and Economic Supplement accessed through the Integrated Public Use Microdata System (IPUMS) at the University of Minnesota (Flood et al. 2018). I applied person-level weights when generating these state-level characteristics. Data on the implementation of state-level drug policies were acquired from the Prescription Drug Abuse Policy System (PDAPS) (Bao et al. 2017). Table 1 displays the means and standard deviations of the entire sample for the entire period of the study, 1999-2017.

3.3 Analytic Approach and Model Specification

This study leverages annual variation within state labor markets over nearly two decades to evaluate how declining shares of manufacturing jobs and earnings contribute to changes in drug and opioid overdose mortality. I estimated a set of two-way, state-level fixed effects regression equations predicting log-transformed age-adjusted rates of drug and opioid overdose deaths, for women and men separately. The first specification adjusted for state and year fixed effects as well as contextual and economic characteristics. I then introduced measures of several state-level time-varying policies that might plausibly confound the association between manufacturing decline and overdose mortality. To test the robustness of the results to measurement choices, I operationalized the decline of manufacturing in two separate ways: first, as the percentage of workers employed in the manufacturing sector, and second, as the percentage of total annual payroll concentrated in the manufacturing sector. Parameter estimates and clustered standard errors at the state-level are reported for all estimated regression models. The models are estimated as follows:

Eq. 1 $$\log(M_{st}) = \boldsymbol{\beta} \boldsymbol{x}_{st} + \boldsymbol{\alpha}_s + \boldsymbol{\mu}_{st}$$

where log (M_{st}) refers to the log-transformed age-adjusted mortality rate for state *s* during year *t*; $\boldsymbol{\beta}$ refers to a vector of estimated coefficients; $\boldsymbol{x}_{st}$ refers to a vector that measures the relative share of state-level manufacturing, either the percentage of employment or annual payroll concentrated in manufacturing industries, and vectors of state-level compositional and contextual characteristics as well as additional state-level policies, in addition to binary-coded year vectors; $\boldsymbol{\alpha}_s$ refers to a vector of state-specific intercepts; and $\boldsymbol{\mu}_{st}$ refers to state- and year-specific error terms.

3.4 Subgroup and Sensitivity Analyses

I conducted several additional analyses to (1) further investigate subgroup heterogeneity, (2) adjust for the supply of prescription opioids, (3) evaluate whether the results persist when predicting *county*-level drug and opioid overdose mortality rates, and (4) test whether the results persist using additional outcome of substance use: opioid-related inpatient hospitalizations and emergency department visits.

First, I constructed models that predicted age-specific rates of drug deaths, binned across 10-year age intervals between the ages 25-64, for non-Hispanic whites and blacks separately by sex.[13] I estimate these models using log-transformed values according to Eq. 1. Second, the relationship between economic conditions and drug-related mortality and hospitalizations might be confounded by issues of drug supply (Monnat 2019; Ruhm 2019). Several recent studies have argued that the supply of prescription opioids is negatively associated with labor force outcomes, including unemployment rates and labor force participation (Currie et al. 2019; Hollingsworth,

[13] In the age-, sex-, and race/ethnicity-specific set of sensitivity models, I include whites and blacks, but not other racial/ethnic groups because most state-year drug death rate values for other racial/ethnic groups are below 10 deaths and unreliable.

Ruhm, and Simon 2017; Krueger 2017). State-level opioid supply might therefore confound the identification in Eq. 1 that models the relationship between lagged manufacturing decline and drug overdose mortality rates and opioid-related hospitalizations. Therefore, I conducted a set of sensitivity tests that adjusted for the state-level rate of retail opioid prescriptions dispensed per 100 population, which accounts for the full supply of legally dispensed prescription pills. These sensitivity models only cover the years 2007-2017 because of data availability. Data on the prescription opioid rate were accessed from the CDC which acquired prescription data from IQVIA, a health information technology and clinical research company (Centers for Disease Control and Prevention 2019; Guy et al. 2020). Unfortunately, there is no comparable dataset which measures the supply of illegal drugs.

To further assess the impact of changes in manufacturing employment and earnings on drug and opioid mortality rates, third, I estimated models predicting county-level drug and opioid mortality rates. In these robustness analyses, I estimated multiple model specifications that vary by the incorporation of (a) state- or county-level manufacturing measures and (b) state or county fixed effects. I use log-transformed mortality rates in this analysis and include all state-level covariates with exception for state-level unemployment rates, which are swapped out for county-level unemployment rates. The 1999-2017 time period of this analysis and the county-level of analysis precludes the availability of as rich of a county-level covariate set as in the main state-level models. Moreover, for the model specifications that include county-level manufacturing measures, county-year observations are dropped according to data availability.

Mortality is the most dismal consequence of drug and opioid misuse; however, the drug epidemic has also devastated individuals and communities through an array of negative physical and mental health outcomes that require medical interventions. In a final sensitivity analysis, I consider whether structural changes in manufacturing employment and annual payroll are associated with two types of medical utilization: opioid-related emergency department visits and inpatient hospitalization stays. I accessed data on these outcomes through the Healthcare Cost and Utilization Project (HCUP) database from the Agency for Healthcare Research and Quality (AHRQ) at the U.S. Department of Health and Human Services. AHRQ draws on an annual sample of treat-and-release visits to emergency departments from the State Emergency Department Databases (SEDD) and a sample of short-term inpatient stays at community hospitals from the State Inpatient Databases (SID). Opioid-related emergency department visits and inpatient stays are coded according to ICD-9-CM codes (Weiss et al. 2017). These samples cover 98% of all inpatient discharges and 98.5% of all emergency department visits in the states that partner with AHRQ. For both measures, data are only available from 2005-2017, and the maximum number of states participating in the databases are 36 for the emergency department visits and 47 for the inpatient stays.

4. RESULTS

4.1 Manufacturing Decline and Logged Mortality from Drug Overdoses

Figure 3 presents a series of maps of the U.S. that display the variation in age-adjusted drug overdose mortality rates across states in 1999, 2008, and 2017. For both men and women, rates of overdose mortality increased throughout the time period and were highest in West Virginia, Virginia, Ohio, and Washington, D.C. at the end of the period in 2017.

Table 2, Panel A presents the regression results predicting state-level logged mortality rates from drug overdoses for women and men using both measures of manufacturing decline (Full model output is presented in Table S2A). For the full age-adjusted log-transformed drug mortality rate models, Model 2, a one percentage point increase in the share of workers employed in manufacturing is associated with a 2.6% decrease in drug mortality rates for women and a 4.1% decrease in drug mortality rates for men.[14] This is equivalent to a decrease of -0.24 deaths per 100,000 population in the drug mortality rate for women and a decrease of -0.65 deaths per 100,000 population in the drug mortality rate for men. Using the annual payroll measure, a one percentage point increase in the share of overall annual payroll in manufacturing is associated with a 2.7% decrease in drug mortality rates for women and a 3.3% decrease in drug mortality rates for men. This is equivalent to a reduction of -0.26 in the drug mortality rate for women and a decrease of -0.52 in the drug mortality rate for men. For both measures, the results are statistically significant below the $p<.01$ threshold for men, but only the annual payroll measure is statistically significant below the $p<.05$ level for women. Manufacturing jobs, as a share of all jobs in state labor markets, declined by an average of 5.8 percentage points throughout the entire 1999-2017 period. Accordingly, changes in manufacturing employment accounted on average for an additional 1.4 drug deaths per 100,000 for women and 3.8 drug deaths per 100,000 for men based on the point estimates between the start and end of this period. Similarly, the average decline of manufacturing annual payroll by 7.2 percentage points accounts for an additional 1.7 drug deaths per 100,000 for women and 4.7 drug deaths per 100,000 for men between the start and end of this period.

The point estimates indicate that manufacturing decline between 1999-2017 predicts an additional 77,610 (annual payroll) to 77,282 (employment) drug overdose deaths for men and an additional 29,756 (employment) to 40,059 (annual payroll) drug overdose deaths for women over this 19-year period, had the share of manufacturing employment and annual payroll remained at 1999 levels during each year of the present analysis. This means that manufacturing decline

[14] For women, (exp(-0.026) – 1)*100 = -2.566; for men, (exp(-0.042) – 1)*100 = -4.113.

accounts for approximately 17.6% of all overdose deaths for men and 11.4% to 15.4% of all overdose deaths for women between the start and end of this period.

Figure 4 displays the percentage of deaths between 1999-2017 attributable to changes in state-specific decreases in manufacturing employment and annual payroll for both women and men between 1999-2017. For states such as South Dakota, North Carolina, Mississippi, Nebraska, Iowa, and Arkansas, manufacturing decline accounts for 40% or more of all overdose deaths for men and approximately 20% of all overdose deaths for women. Meanwhile, manufacturing decline accounts for less than 5% of all overdose deaths for men and less than 2.5% of all overdose deaths for women in the District of Columbia and states such as Wyoming, Nevada, Hawaii, Alaska, and New Mexico. This map demonstrates the substantial and meaningful variation in state-level differences in manufacturing decline on drug overdose death rates – a range of 50 percentage points for men and 27 percentage points for women. Table S3 presents the predicted number of deaths in each state attributable to manufacturing decline based on the employment and annual payroll point estimates.

4.2 Manufacturing Decline and Mortality from Opioid Overdoses

Out of the 700,000 drug overdose deaths over the 1999-2017 period, approximately 400,000 deaths involved the use of opioids, including prescription opioids, heroin, and synthetic opioids such as fentanyl and fentanyl analogs. To investigate the role of manufacturing decline on the opioid crisis specifically, Table 2, Panel B presents regression results predicting state-level logged opioid mortality for women and men using both measures of manufacturing decline (Full model output is presented in Table S2B). For the full age-adjusted opioid mortality rate models, Model 2, a one percentage point increase in the share of workers employed in the manufacturing sector is associated with a 4.6% decrease in opioid mortality for women and a

6.2% decrease in opioid mortality for men. Using the annual payroll measure yields similar results: a one percentage point increase in the share of overall annual payroll in manufacturing is associated with a 4.5% reduction in opioid mortality for women and an 4.8% reduction in opioid mortality for men. Similar to the overall logged drug overdose mortality rate models (Table 2, Panel A), the results are only statistically significant for the annual payroll measure for women, but are statistically significant for both measures for men. Since manufacturing jobs declined an average of 5.8 percentage points throughout the entire 1999-2017 period, changes in manufacturing employment accounted on average for an additional 1.4 opioid deaths per 100,000 for women and 3.6 opioid deaths per 100,000 for men based on the point estimates. Similarly, the average decline of manufacturing annual payroll by 7.2 percentage points accounts for an additional 1.7 opioid deaths per 100,000 for women and 3.4 opioid deaths per 100,000 for men.

4.3 Subgroup Analysis: Manufacturing Decline and Overdose Mortality across Racial/Ethnic-Specific 10-Year Age Groups

Researchers have documented how the rise of drug deaths – particularly opioid drug deaths – is concentrated among middle-age, non-Hispanic white males (Case and Deaton 2015). The third column of Figure 3 presents a set of maps which display the rapid and widespread increase in overdose deaths among non-Hispanic white males ages 45-54 in 1999, 2008, and 2017.

Table 4A estimates regression models predicting state-level, crude age-specific death rates from drug overdoses for non-Hispanic white males and females between the age of 25 to 64, binned at 10-year intervals. With exception to the 55-64 age group, the coefficients for these subpopulations are substantially larger than the results from the prior overall male and female population models. Regardless of the measure of manufacturing decline, the results for the 25-

34, 35-44, and 45-54 age groups are substantively large and statistically significant for white males, with the effect size largest for white men ages 25-34. For the female age-specific models, the results are substantively large and statistically significant for both manufacturing measures in 25-34 and 35-44 age groups. The estimates suggest that manufacturing decline accounts for 24.9% to 31.3% of the overall increase in drug deaths for white males ages 25-34, 28.6% to 30.9% of the overall increase in drug deaths for white males ages 35-44, and 24.3% to 26.6% of the overall increase in drug deaths for white males ages 45-54 between 1999-2017. For white females ages 35-44, manufacturing decline accounts for 22.2% to 22.3% of the overall increase in drug deaths, or approximately 10,000 deaths, according to the annual payroll measure. In contrast to whites, manufacturing decline generally does not have a significant effect on the rise of drug deaths for non-Hispanic black males and females, although the effect sizes are similar in direction and often similar in magnitude to whites in the 25-34, 35-44, and 45-54 age groups (Table 4B).

4.4 Sensitivity Analyses

In a first set of sensitivity analyses (Table S4), I estimated a set of models that adjust for the legal supply of opioid prescriptions per 100 population using data accessed from the CDC. For models estimating log-transformed age-adjusted rates of drug deaths, the models do not substantively change for men – the magnitude and statistical significance of both manufacturing measures remains – but the coefficient for percentage of annual payroll concentrated in manufacturing slightly attenuates and loses precision for women. In contrast, the inclusion of this additional covariate into the models predicting log-transformed age-adjusted rates of opioid deaths increases the standard errors in the male models as well as the female models. While caution should be used to interpret these models (they only cover the years 2007-2017 and have a reduced number of state-year observations), they indicate that the role of manufacturing decline on the broader drug epidemic cannot be simply explained away by state-level trends in the legal supply of opioid pain prescriptions, but there is evidence that this might be the case for deaths specifically from opioids.

In a second set of analyses (Table S5), I estimated models predicting logged county-level drug and opioid rates, testing measures of both (a) state-level and (b) county-level changes in manufacturing employment and payroll, and including different levels of fixed effects, at either the state- or county-level. These models incorporate the full set of state-level covariates as in the prior models, but swap out state-level unemployment rates for county-level unemployment rates.[15] For the models predicting logged county-level drug and opioid mortality using state-level manufacturing decline, the magnitude and significance level of the coefficients persists; but the effect size is smaller for the models that use county-level manufacturing decline to predict logged county-level drug and opioid mortality.

In a final set of sensitivity models, I swap out the estimation of opioid mortality rates for another outcome of substance use: opioid-related emergency department visits and inpatient hospitalizations. Data on these outcomes are only available between 2007-2017 and most states do not have observations spanning those entire 11 years. The estimates, presented in Table S6, are consistent in direction and substantive magnitude as the primary findings presented above, though the estimate precision varies by the years of the study. Overall, these three additional sensitivity analyses indicate that the findings from the main analysis generally hold up when accounting for, first, the legal supply of prescription opioids, second, the scale at which mortality

[15] I am unable to include a more extensive set of time-varying county-level covariates because of data availability over this 19-year time period.

rates and manufacturing decline are measured, and third, a separate set of outcome measures that drug use.

5. DISCUSSION

The drug epidemic continues to disrupt the lives of individuals, families, and communities throughout the country. Since 1999, over 700,000 people in the U.S. have died from drug overdoses (including approximately 400,000 from opioid overdoses), and according to the most recent estimates, 2.1 million people suffered from an opioid use disorder in 2017 (Center for Behavioral Health Statistics and Quality 2018). This study documents a large and substantively important state-level relationship between annual declines in the U.S. manufacturing sector and increases in drug and opioid overdose mortality rates between 1999-2017. These findings demonstrate how the ongoing transformation of U.S. labor markets has altered ecological-level risk environments that shape population health outcomes.

Manufacturing decline, measured either as the share of manufacturing jobs in a state labor market or the share of total annual payroll concentrated in the manufacturing sector, accounts for approximately 17.6% of all overdose deaths for men and 11.4% to 15.4% of all overdose deaths for women between the start and end of the time period studied, 1999-2017. This represents an upward bound of an excess 77,000 male and 40,000 female drug overdose deaths that would otherwise have been avoided if the share of manufacturing employment and annual payroll had remained at 1999 levels. These results persist in models that adjust for a set of state-level contextual, compositional, and labor and drug policy characteristics as well as sensitivity models which adjust for trends in the supply of legally filled opioid prescriptions and models that estimate this relationship at the county-level.

Even more striking, state-level manufacturing decline predicts upwards of 30.9% of the increase in drug overdose deaths for non-Hispanic white males between the ages of 35-44 and 26.6% of the increase in drug overdose deaths for non-Hispanic white males between the ages of 45-54, a demographic group that has been particularly hard-hit by the rise in drug deaths (Case and Deaton 2015, 2017; Okie 2010).

Many explanations of the rise of the overdose epidemic emphasize the important, mechanistic role of pharmaceutical companies and pill mills in deluging communities with inexpensive opioid pain relievers (Kolodny et al. 2015). The results presented here do not conflict with this supply-side explanation since it is likely that workers in manufacturing industries, already more likely to experience workplace-related pain ailments such as repetitive strain injuries (van Tulder, Malmivaara, and Koes 2007), were at higher risk to becoming addicted to prescription painkillers upon job loss and financial hardship (Dasgupta et al. 2018; Nagelhout et al. 2017). Economically depressed regions were also more likely to be targeted by pharmaceutical companies pushing opioid medications (Hadland et al. 2019). In fact, the results suggest that state-level differences in manufacturing decline represent a substantial amount of variation in drug and opioid overdose deaths. Future research would benefit from moving beyond the current scholarly debate of the opioid and broader drug epidemic that sets in opposition social/economic explanations and drug-supply explanations.

The modeling strategy used in the present study – two-way fixed effects – is well suited for evaluating the relationship between manufacturing decline and overdose mortality because it adjusts for all observed and unobserved time-invariant, state-specific confounders as well as for aggregate time trends (Allison 2009).[16] In addition, the models adjust for time-varying characteristics – state-level contextual, compositional, and drug and labor policy– that might potentially confound the relationship between manufacturing decline and drug mortality/opioid-related hospitalizations. Equivalent county-level models that include county-level fixed effects further indicate that the results are robust when examining this process in local communities specifically. This evidence indicates strong support for the labor market explanation that has been widely theorized, but until now, not well supported empirically (Case and Deaton 2015; Monnat 2018; Ruhm 2019).

The findings of the present study emphasize the importance of understanding the role of upstream social and economic factors when addressing the ongoing opioid epidemic in the U.S. State-level differences in drug policies, labor environments, and broader socio-political policy regimes are salient facets of drug-risk environments that shape the health of populations. Critically, the results signal the value of policy interventions and solutions that would reduce the persistent economic precarity experienced by individuals and communities, especially the economic strain placed upon American workers. The value of implementing these upstream social and economic policies do not conflict with efforts made by government entities to hold pharmaceutical companies and pill mills accountable for over-prescribing opioid medications to the public, nor does it conflict with the value of health policies aimed at reversing the opioid epidemic. Future research should further investigate the complex relationship between structural unemployment, pain management, prescription drug use, and drug mortality.

[16] Recent methodological work by Goodman-Bacon (2019b, 2019a) illustrates how two-way fixed effects estimators are biased in circumstances when treatment effects change over time. Given the relatively short period considered here, I make the assumption that the effect of manufacturing decline on drug and opioid mortality is uniform throughout this time period.

This analysis should be interpreted with an understanding of the limitations of the data and analytic method. The data are ecological and do not model how individual-level labor market histories or perceptions of local economic opportunity are associated with mortality. As such, future research should identify datasets which allow for the modeling of individual-level labor market experiences and perceptions in conjunction with macro-level structural economic changes in labor markets. This sort of multi-level approach would further clarify the interrelationship between individual-level risk factors and ecological-level risk environments.

Second, although fixed-effects analyses adjust for time-invariant confounders which enter the model specifications linearly and additively, this method does not account for the full set of known and unknown confounders which vary across time. To address this issue, this study adjusted for several important known sources of time-varying unobserved heterogeneity which have been identified by past research to impact mortality rates. Third, the covariates that adjust for state-specific supply-side factors of prescription painkillers (i.e. PDMPs, prescription opioid rates) are imprecise measures of the misuse of prescription opioids and have a number of limitations (Bao et al. 2017; Horwitz et al. 2018); yet, they represent the best available measures for evaluating policy changes that have altered the flow of prescription drugs. Fourth, drug and opioid overdose mortality rates used in this analysis were calculated according to deaths coded as having an underlying cause related directly to drug or opioid poisonings. Classifying individual-level death records that involve drug and opioid use as a *contributing* cause is not possible with NCHS vital statistics mortality records, but recent findings from Glei and Preston (2020) suggest that the scale of deaths from the drug epidemic was about two times larger in 2016 than drug-coded deaths when taking into account drug-associated mortality from indirect causes such as circulatory diseases, respiratory diseases, neoplasms, and external causes, to name a few.

6. CONCLUSIONS

Manufacturing decline over the past two decades represents a continuation of long-term structural economic changes which have fundamentally altered the types of jobs available to U.S. workers, particularly those with only a high school degree. Since the 1980s, job growth has been concentrated in low-skill service industries that provide lower pay, fewer benefits, and decreased job security (Autor et al. 2006; Kalleberg 2018). The findings of this study suggest that these economic changes can account for a substantial proportion of recent increases in U.S. mortality rates over the past two decades, especially for drug overdose deaths. Additionally, state-level differences in manufacturing decline during this time period account for a considerable amount of the geographic variation in drug overdose deaths.

Policymakers and clinicians alike may benefit from understanding the extent to which drug overdose deaths have social and economic determinants which impact the structure of opportunities available to U.S. workers. While it is most likely unfeasible to rebuild the country's manufacturing base back to 20th century levels, the findings of the present study would suggest that improvements in wages, benefits, and job stability for workers in low-wage service positions might decrease economic uncertainty and therefore provide a pathway towards reducing opioid and drug overdose mortality. Future research should further investigate and test specific mechanisms through which deteriorating economic conditions and employment prospects impact health and mortality.

FIGURES

Figure 1a. Total Number of Workers Employed in the Manufacturing Sector, 1980-2019

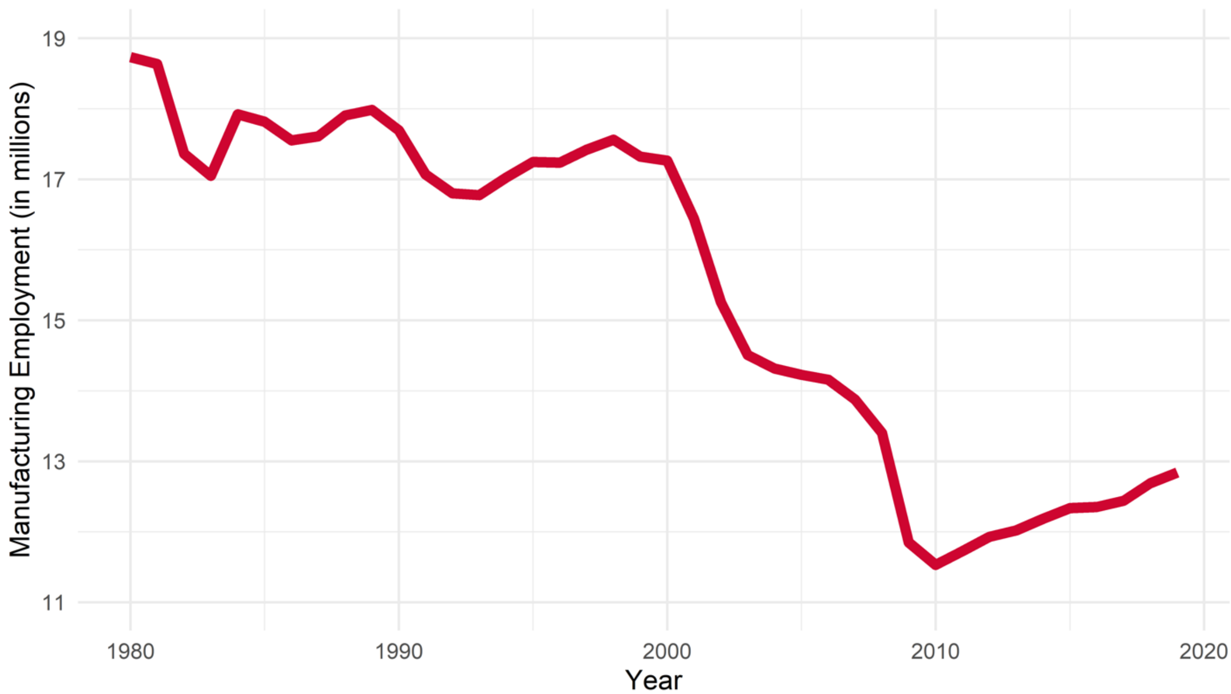
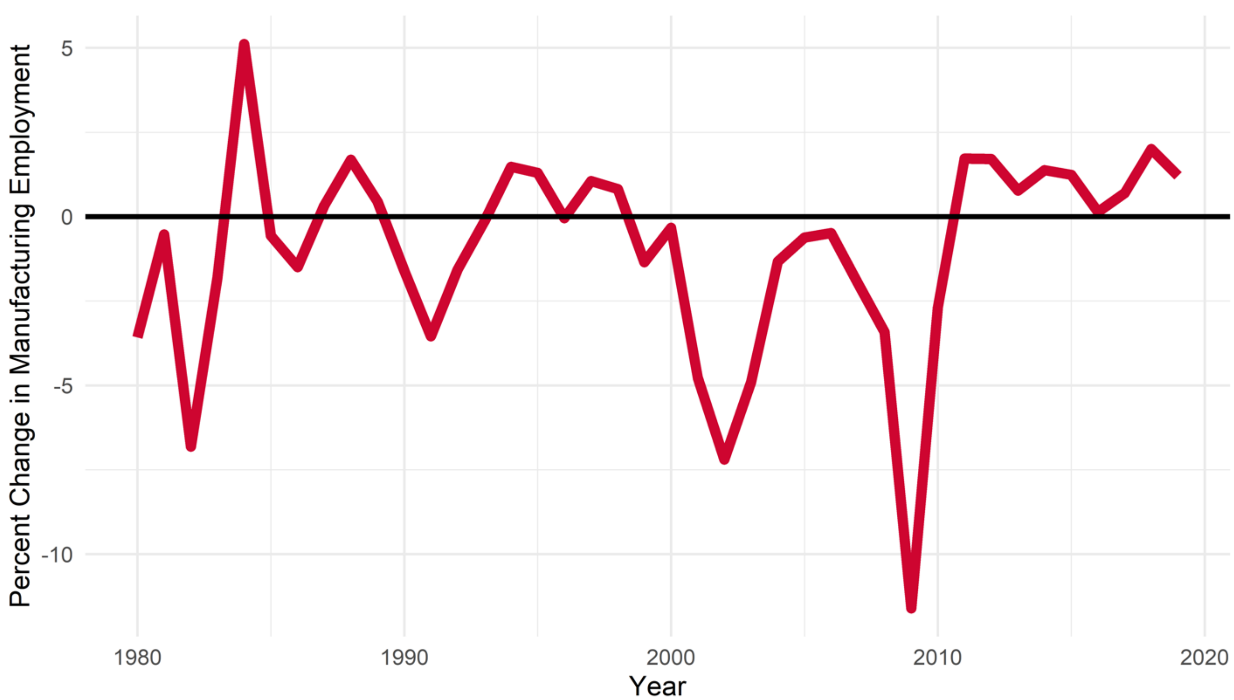
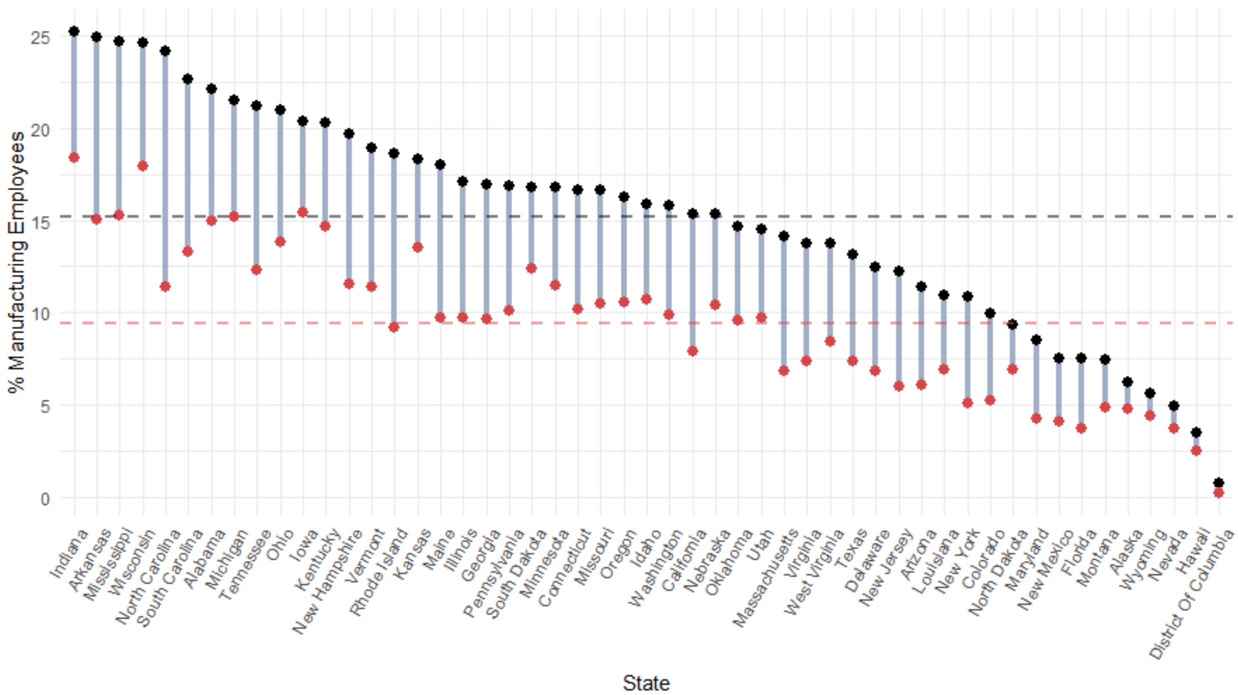


Figure 1b. Annual Percent Change in Manufacturing Employment, 1980-2019



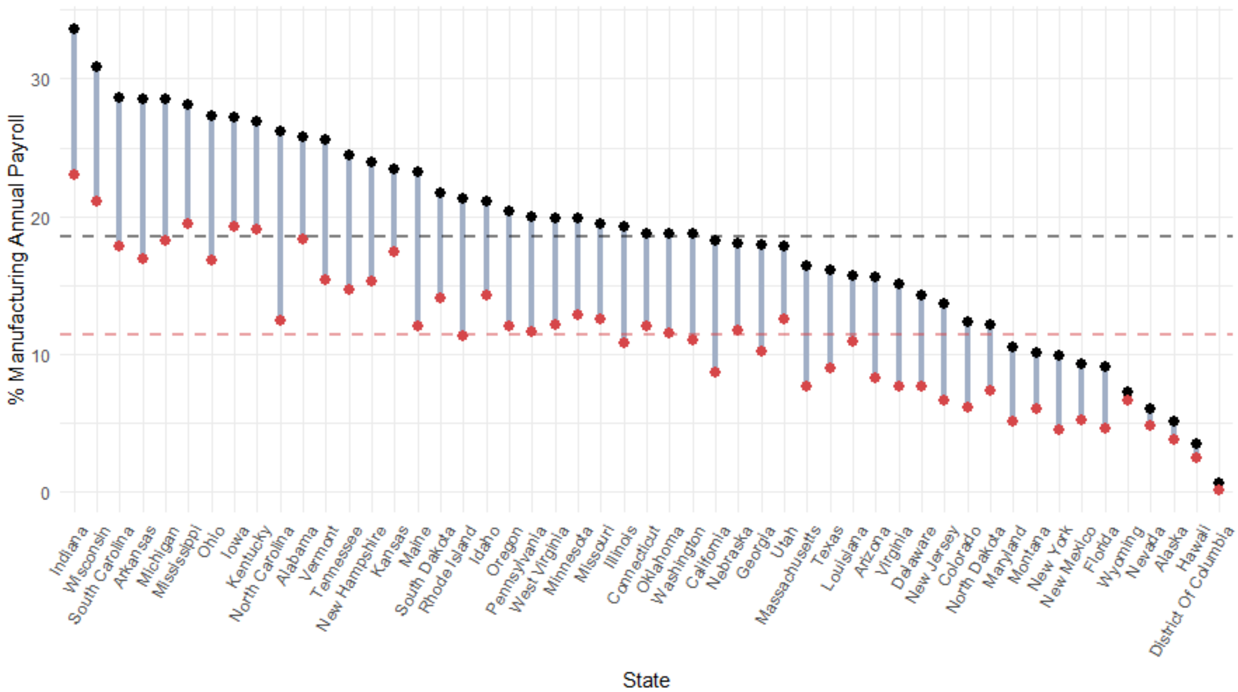
Data Source: U.S. Bureau of Labor Statistics, All Employees, Manufacturing [MANEMP], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/MANEMP, January 28, 2020.

Figure 2a. Change in the Share of Employees in Manufacturing Sector by State, 1998-2016



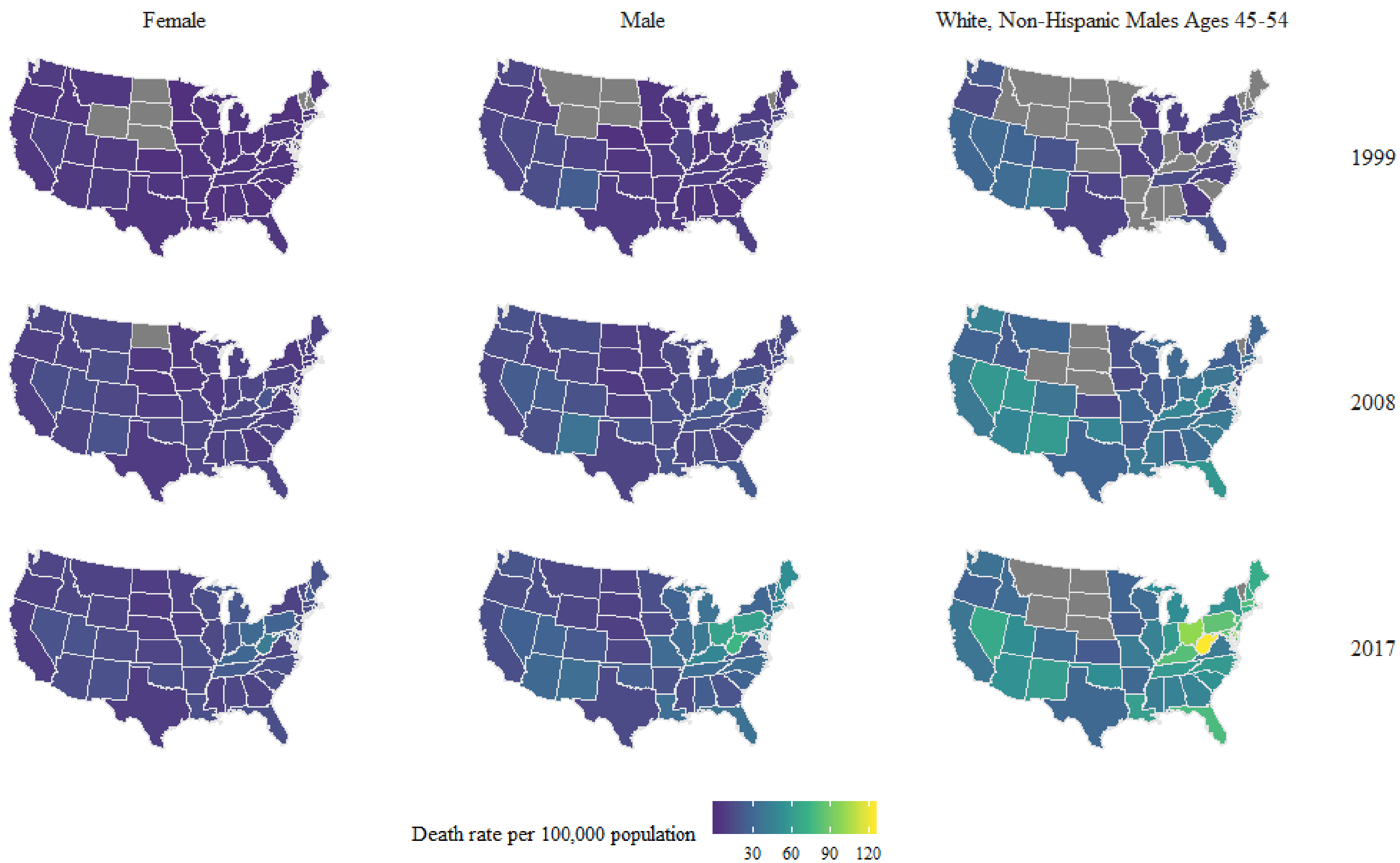
Notes: Black dots represent percentage of workers employed in manufacturing in 1998; Red dots represent percentage of workers employed in manufacturing in 2016; Vertical lines represent percentage point decline between 1998-2016. Horizontal grey dotted line represents state average in 1998; Horizontal pink dotted line represents state average in 2016. Data: U.S. Census Bureau, County Business Patterns Program

Figure 2b. Change in the Share of Annual Payroll in Manufacturing Sector by State, 1998-2016



Notes: Black dots represent percentage of manufacturing annual payroll in 1998; Red dots represent percentage of manufacturing annual payroll in 2016; Vertical lines represent percentage point decline between 1998-2016. Horizontal grey dotted line represents state average in 1998; Horizontal pink dotted line represents state average in 2016. Data: U.S. Census Bureau, County Business Patterns Program.

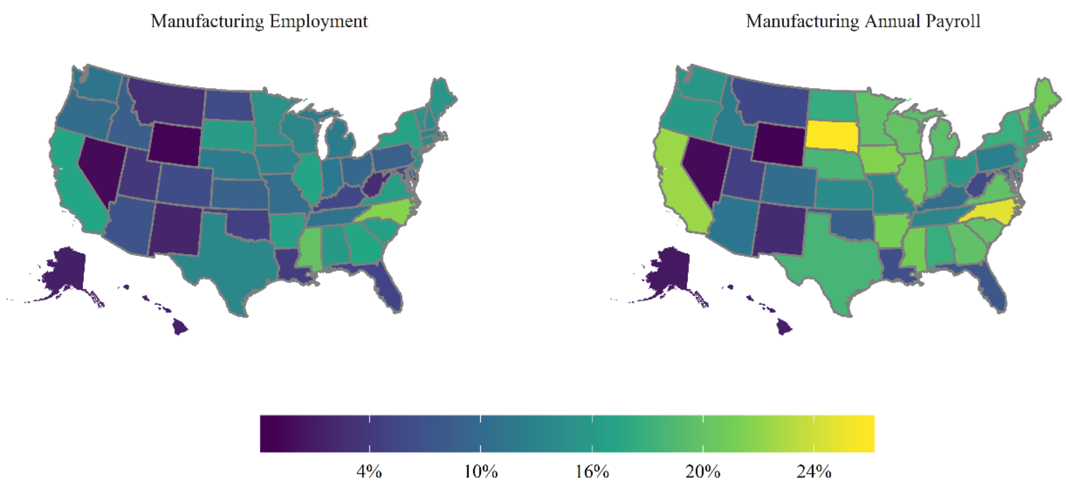
Figure 3. State-Level Overdose Rates for Females, Males, and White, Non-Hispanic Males Ages 45-54



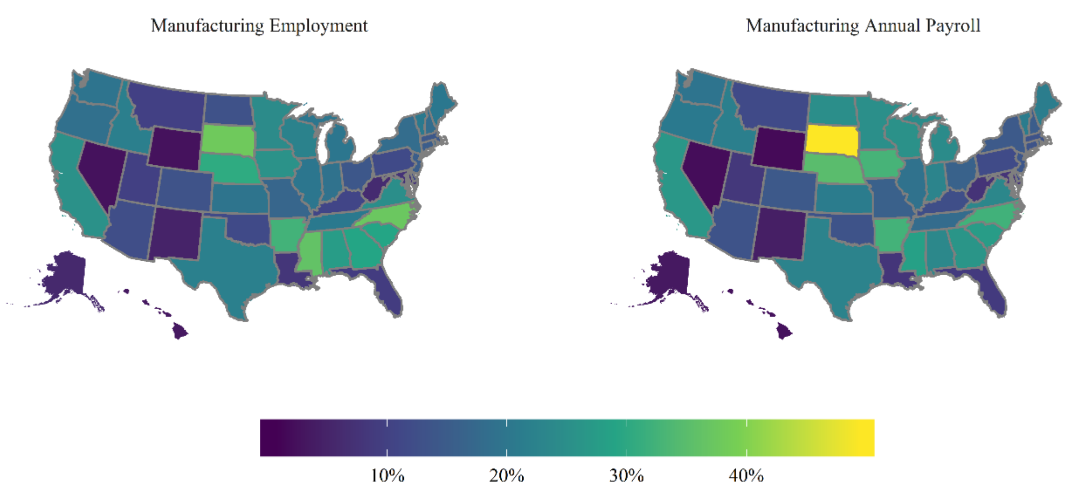
Notes: Death rates are age-adjusted for females and males. Grey shading represents states with less than 10 deaths per year; rates are not displayed in accordance with requirements of the data use agreement with the NCHS.

Figure 4. Percentage of Drug Deaths between 1999-2017 Predicted by Manufacturing Decline

A. Women



B. Men



TABLES

Table 1. Descriptive Statistics

	1999-2017		
Variables	Mean	S.D.	State-Year Observations
Drug Overdose Age-Adjusted Death Rate (per 100,000 population)			
Female	9.5	5	969
Male	15.9	9.4	969
Opioid Overdose Age-Adjusted Death Rate (per 100,000 population)			
Female	5.3	4.1	969
Male	9.9	8.3	969
Logged Drug Overdose Age-Adjusted Death Rate (per 100,000 pop.)			
Female	2.1	0.6	969
Male	2.6	0.6	969
Logged Opioid Overdose Age-Adjusted Death Rate (per 100,000 pop.)			
Female	1.4	0.8	967
Male	2	0.8	968
Logged Emergency Department Visits (per 100,000 population)			
Female	4.8	0.6	381
Male	4.9	0.7	381
Logged Inpatient Hospital Stays (per 100,000 population)			
Female	5.3	0.5	553
Male	5.2	0.6	553
Manufacturing Measures			
Manufacturing Employment (%)	11.5	5.0	969
Manufacturing Annual Payroll (%)	13.9	6.3	969
State-Level Covariates			
Unemployment Rate	5.6	2	969
College Graduates (%)	19.6	5	969
Ever-Married (%)	56.5	3.5	969
Hispanic (%)	9.3	9.7	969
Black (%)	11.3	11.5	969
Self-Reported Health Score (1-Excellent to 5-Poor)	2.2	0.12	969
State-Level Labor and Drug Policy Covariates			
Union Coverage (%)	12.8	5.5	969
Prescription Drug Monitoring Program			
# of states in 1999	16	-	950
# of states in 2017	50	-	950
Naloxone Access Laws			
# of states in 1999	0	-	969
# of states in 2017	48	-	969
Good Samaritan Laws			
# of states in 1999	0	-	969
# of states in 2017	37	-	969
Opioid Prescriptions Filled (per 100 population)	81	23	561

Note: All covariates are lagged one year.

Table 2. Regression Analyses Predicting Logged Drug and Opioid Overdose Mortality Rates

A. Logged Drug Overdose Mortality		
Manufacturing Measure	Model 1	Model 2
Female		
% Employees in Manufacturing	-0.024	-0.026
	(0.014)	(0.013)
% Annual Payroll in Manufacturing	-0.026*	-0.027*
	(0.012)	(0.011)
Male		
% Employees in Manufacturing	-0.040**	-0.042**
	(0.015)	(0.014)
% Annual Payroll in Manufacturing	-0.033**	-0.034**
	(0.012)	(0.012)
B. Logged Opioid Overdose Mortality		
Manufacturing Measure	Model 1	Model 2
Female		
% Employees in Manufacturing	-0.043	-0.047
	(0.026)	(0.024)
% Annual Payroll in Manufacturing	-0.043*	-0.046*
	(0.020)	(0.019)
Male		
% Employees in Manufacturing	-0.059*	-0.064*
	(0.028)	(0.026)
% Annual Payroll in Manufacturing	-0.046*	-0.049*
	(0.022)	(0.021)
State and Year Fixed Effects	Yes	Yes
Compositional and Economic Covariates	Yes	Yes
Labor and Drug Policy Covariates	No	Yes

* p<.05, ** p<.01, *** p<.001 (two tailed tests)

Notes: (a) All covariates are lagged one year. (b) All male models have 969 observations, representing 50 states and the District of Columbia over 19 years. (c) Compositional and economic covariates include state-level measures of the unemployment rate, the percentage of the population with a college degree, the percentage of the population who have ever been married, the percentage of the population who are Hispanic, the percentage of the population who are black, and the average self-reported health score. (d) Labor and drug policy covariates include state-level measures of the percent of workers covered or represented by labor unions, and binary indicators of whether states have implemented three types of drug policies: PDMPs, naloxone access laws, and Good Samaritan laws for reporting drug overdoses.

Table S3A. Regression Analyses Predicting Logged Crude Age-Specific Drug Overdose Death Rates for White, non-Hispanic Males and Females for 10-year age groups.

Logged Age-Specific Drug Death Rate	White Females, non-Hispanic		White Males, non-Hispanic	
	Model 1	Model 2	Model 1	Model 2
Ages 25-34				
% Employees in Manufacturing	-0.049**	-0.050**	-0.051*	-0.052*
	(0.016)	(0.016)	(0.020)	(0.020)
% Annual Payroll in Manufacturing	-0.041**	-0.042***	-0.036*	-0.036*
	(0.013)	(0.012)	(0.017)	(0.016)
N	969	969	969	969
Ages 35-44				
% Employees in Manufacturing	-0.024	-0.028	-0.052**	-0.054**
	(0.026)	(0.025)	(0.018)	(0.019)
% Annual Payroll in Manufacturing	-0.026	-0.028	-0.044**	-0.044**
	(0.022)	(0.021)	(0.015)	(0.014)
N	969	969	969	969
Ages 45-54				
% Employees in Manufacturing	-0.049	-0.050	-0.061**	-0.061**
	(0.026)	(0.025)	(0.023)	(0.022)
% Annual Payroll in Manufacturing	-0.042	-0.043	-0.048*	-0.048*
	(0.022)	(0.021)	(0.019)	(0.018)
N	969	969	969	969
Ages 55-64				
% Employees in Manufacturing	-0.010	-0.012	-0.042	-0.045
	(0.025)	(0.024)	(0.024)	(0.024)
% Annual Payroll in Manufacturing	-0.001	-0.001	-0.026	-0.027
	(0.021)	(0.020)	(0.020)	(0.020)
N	969	969	969	969

* p<.05, ** p<.01, *** p<.001 (two tailed tests)

Notes: (a) Two-way fixed effects models include state and year fixed effects. (b) models adjust for state-level characteristics including the unemployment rate, the percentage of the population with a college degree, the percentage of the population who have ever been married, and the average self-reported health score. (c) All covariates are lagged one year. (d) state clustered standard errors in parentheses.

Table S3B. Regression Analyses Predicting Logged Crude Age-Specific Drug Overdose Death Rates for Black, non-Hispanic Males and Females for 10-year age groups.

Logged Age-Specific Drug Death Rate	Black Females, non-Hispanic		Black Males, non-Hispanic	
	Model 1	Model 2	Model 1	Model 2
Ages 25-34				
% Employees in Manufacturing	-0.046	-0.055	-0.021	-0.022
	(0.037)	(0.041)	(0.035)	(0.035)
% Annual Payroll in Manufacturing	-0.037	-0.039	-0.021	-0.022
	(0.029)	(0.031)	(0.029)	(0.029)
N	621	621	729	729
Ages 35-44				
% Employees in Manufacturing	-0.041	-0.038	-0.032	-0.036
	(0.030)	(0.029)	(0.025)	(0.026)
% Annual Payroll in Manufacturing	-0.036	-0.032	-0.045*	-0.047*
	(0.022)	(0.021)	(0.021)	(0.020)
N	716	716	748	748
Ages 45-54				
% Employees in Manufacturing	-0.051	-0.053	-0.010	-0.014
	(0.032)	(0.034)	(0.030)	(0.031)
% Annual Payroll in Manufacturing	-0.037	-0.037	-0.013	-0.012
	(0.029)	(0.029)	(0.024)	(0.023)
N	713	713	775	775
Ages 55-64				
% Employees in Manufacturing	-0.010	-0.021	-0.080*	-0.087*
	(0.044)	(0.044)	(0.034)	(0.033)
% Annual Payroll in Manufacturing	-0.018	-0.018	-0.081**	-0.080**
	(0.034)	(0.033)	(0.026)	(0.024)
N	559	559	689	689

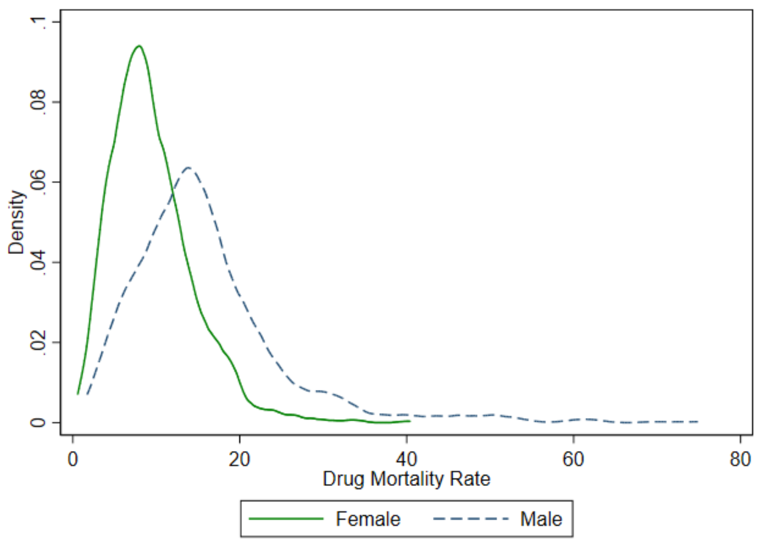
* p<.05, ** p<.01, *** p<.001 (two tailed tests)

Notes: (a) Two-way fixed effects models include state and year fixed effects. (b) models adjust for state-level characteristics including the unemployment rate, the percentage of the population with a college degree, the percentage of the population who have ever been married, and the average self-reported health score. (c) All covariates are lagged one year. (d) state clustered standard errors in parentheses.

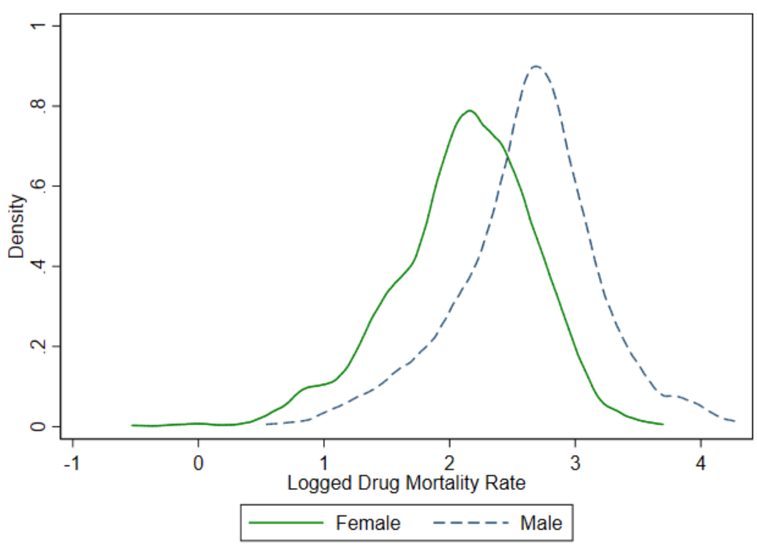
ONLINE SUPPLEMENT

Figure S1. Distributions of Age-Adjusted Mortality Rates, 1999-2017

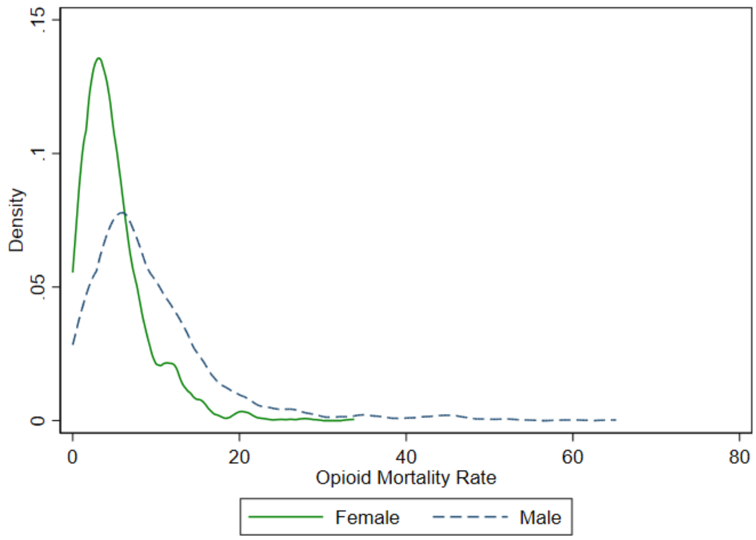
A1. Drug Mortality Rate



A2. Logged Drug Mortality Rate



B1. Opioid Mortality Rate



B2. Logged Opioid Mortality Rate

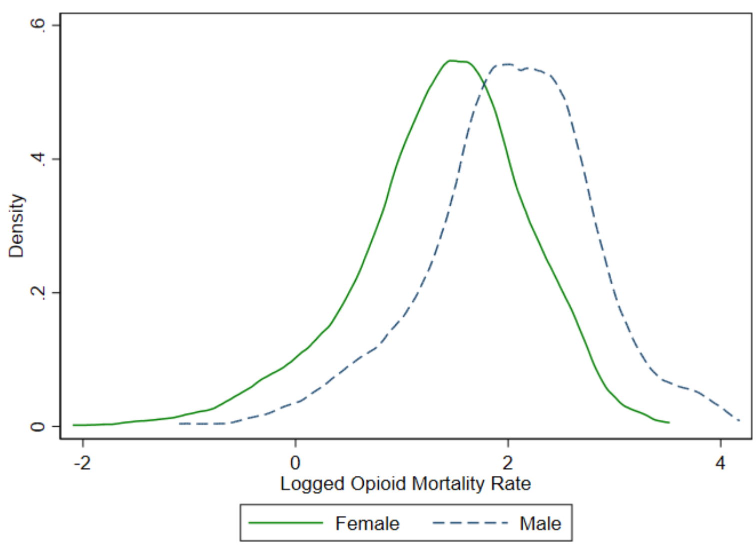


Table S1. ICD10 Codes for Drug Overdose Deaths

ICD10 Code	Description
Underlying Causes	
X40	Accidental poisoning by and exposure to nonopioid analgesics, antipyretics and antirheumatics
X41	Accidental poisoning by and exposure to antiepileptic, sedative-hypnotic, antiparkinsonism and psychotropic drugs, not elsewhere classified
X42	Accidental poisoning by and exposure to narcotics and psychodysleptics [hallucinogens], not elsewhere classified
X43	Accidental poisoning by and exposure to other drugs acting on the autonomic nervous system
X44	Accidental poisoning by and exposure to other and unspecified drugs, medicaments and biological substances
X60	Intentional self-poisoning by and exposure to nonopioid analgesics, antipyretics and antirheumatics
X61	Intentional self-poisoning by and exposure to antiepileptic, sedative-hypnotic, antiparkinsonism and psychotropic drugs, not elsewhere classified
X62	Intentional self-poisoning by and exposure to narcotics and psychodysleptics [hallucinogens], not elsewhere classified
X63	Intentional self-poisoning by and exposure to other drugs acting on the autonomic nervous system
X64	Intentional self-poisoning by and exposure to other and unspecified drugs, medicaments and biological substances
X85	Assault by drugs, medicaments and biological substances
Y10	Poisoning by and exposure to nonopioid analgesics, antipyretics and antirheumatics, undetermined intent
Y11	Poisoning by and exposure to antiepileptic, sedative-hypnotic, antiparkinsonism and psychotropic drugs, not elsewhere classified, undetermined intent
Y12	Poisoning by and exposure to narcotics and psychodysleptics [hallucinogens], not elsewhere classified, undetermined intent
Y13	Poisoning by and exposure to other drugs acting on the autonomic nervous system, undetermined intent
Y14	Poisoning by and exposure to other and unspecified drugs, medicaments and biological substances, undetermined intent
Contributing Causes	
T40.0	Opium
T40.1	Heroin
T40.2	Other Opioids
T40.3	Methadone
T40.4	Other Synthetic Narcotics
T40.6	Other Unspecified Narcotics

Table S2A. Full Models: Regression Analyses Predicting Logged Drug Overdose Mortality Rates

Outcome: Logged Drug Overdose Mortality Rates	Men				Women			
	Manufacturing Employment		Manufacturing Annual Payroll		Manufacturing Employment		Manufacturing Annual Payroll	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
1999	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
2000	0.100**	0.100**	0.102**	0.102**	0.109	0.108	0.106	0.105
	(0.035)	(0.036)	(0.034)	(0.035)	(0.060)	(0.060)	(0.058)	(0.058)
2001	0.222***	0.211***	0.224***	0.215***	0.320***	0.308***	0.312***	0.302***
	(0.047)	(0.049)	(0.044)	(0.046)	(0.063)	(0.065)	(0.061)	(0.063)
2002	0.378***	0.365***	0.360***	0.349***	0.484***	0.470***	0.458***	0.446***
	(0.060)	(0.063)	(0.061)	(0.063)	(0.059)	(0.062)	(0.059)	(0.062)
2003	0.427***	0.411***	0.418***	0.405***	0.593***	0.575***	0.568***	0.553***
	(0.073)	(0.076)	(0.070)	(0.073)	(0.078)	(0.082)	(0.077)	(0.080)
2004	0.474***	0.451***	0.461***	0.443***	0.678***	0.653***	0.647***	0.625***
	(0.093)	(0.097)	(0.091)	(0.094)	(0.084)	(0.089)	(0.083)	(0.086)
2005	0.527***	0.495***	0.522***	0.496***	0.725***	0.692***	0.697***	0.668***
	(0.089)	(0.094)	(0.085)	(0.089)	(0.081)	(0.085)	(0.077)	(0.080)
2006	0.683***	0.650***	0.672***	0.645***	0.850***	0.815***	0.814***	0.784***
	(0.102)	(0.106)	(0.097)	(0.100)	(0.095)	(0.099)	(0.093)	(0.096)
2007	0.697***	0.658***	0.688***	0.656***	0.938***	0.898***	0.900***	0.864***
	(0.107)	(0.113)	(0.101)	(0.105)	(0.096)	(0.099)	(0.094)	(0.095)
2008	0.728***	0.690***	0.716***	0.685***	0.992***	0.952***	0.949***	0.915***
	(0.121)	(0.128)	(0.116)	(0.121)	(0.099)	(0.102)	(0.097)	(0.098)
2009	0.676***	0.646***	0.659***	0.636***	0.937***	0.905***	0.892***	0.865***
	(0.126)	(0.133)	(0.125)	(0.130)	(0.090)	(0.094)	(0.092)	(0.093)
2010	0.648***	0.623***	0.618***	0.599***	1.024***	0.996***	0.971***	0.947***
	(0.155)	(0.163)	(0.155)	(0.161)	(0.127)	(0.134)	(0.131)	(0.134)
2011	0.721***	0.688***	0.703***	0.676***	1.091***	1.054***	1.044***	1.013***
	(0.163)	(0.173)	(0.161)	(0.168)	(0.144)	(0.153)	(0.147)	(0.154)
2012	0.742***	0.703***	0.725***	0.694***	1.113***	1.071***	1.065***	1.029***
	(0.162)	(0.173)	(0.158)	(0.166)	(0.136)	(0.146)	(0.137)	(0.144)
2013	0.832***	0.782***	0.818***	0.776***	1.166***	1.114***	1.118***	1.071***
	(0.166)	(0.176)	(0.163)	(0.170)	(0.137)	(0.147)	(0.139)	(0.146)
2014	0.926***	0.865***	0.912***	0.858***	1.260***	1.202***	1.209***	1.157***
	(0.164)	(0.171)	(0.161)	(0.166)	(0.131)	(0.141)	(0.132)	(0.140)
2015	1.069***	0.997***	1.058***	0.995***	1.323***	1.259***	1.272***	1.214***
	(0.162)	(0.167)	(0.157)	(0.162)	(0.140)	(0.150)	(0.139)	(0.148)
2016	1.257***	1.175***	1.243***	1.168***	1.431***	1.362***	1.373***	1.312***
	(0.169)	(0.169)	(0.162)	(0.165)	(0.150)	(0.161)	(0.150)	(0.161)

2017	1.336***	1.244***	1.324***	1.240***	1.509***	1.435***	1.451***	1.385***
	(0.177)	(0.178)	(0.169)	(0.172)	(0.160)	(0.174)	(0.158)	(0.173)
Unemployment Rate	0.009	0.006	0.012	0.010	0.007	0.005	0.007	0.005
	(0.014)	(0.014)	(0.014)	(0.014)	(0.016)	(0.015)	(0.015)	(0.015)
% with College Degree	-0.007	-0.008	-0.007	-0.008	-0.011	-0.011	-0.011	-0.011
	(0.011)	(0.012)	(0.011)	(0.012)	(0.010)	(0.010)	(0.010)	(0.010)
% Ever-Married	-0.013	-0.011	-0.012	-0.011	-0.010	-0.008	-0.009	-0.008
	(0.010)	(0.010)	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
% Hispanic	-0.033**	-0.034**	-0.032**	-0.033**	-0.029**	-0.029**	-0.027**	-0.027**
	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)
% Black	0.010	0.012	0.009	0.011	0.004	0.006	0.003	0.005
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)
Self-Reported Health	0.246	0.243	0.212	0.207	-0.272	-0.280	-0.286	-0.297
	(0.254)	(0.254)	(0.254)	(0.254)	(0.305)	(0.310)	(0.303)	(0.308)
% Labor Union Coverage		-0.018*		-0.017		-0.017		-0.016
		(0.009)		(0.009)		(0.008)		(0.008)
Good Samaritan Law Implementation		0.014		0.020		0.010		0.017
		(0.061)		(0.061)		(0.050)		(0.050)
Naloxone Access Law Implementation		0.025		0.024		0.003		-0.001
		(0.063)		(0.063)		(0.055)		(0.055)
Prescription Drug Monitoring Program Implementation		0.001		0.000		0.003		0.002
		(0.051)		(0.050)		(0.045)		(0.044)
% Manufacturing Employment	-0.040**	-0.042**			-0.024	-0.026		
	(0.015)	(0.014)			(0.014)	(0.013)		
% Manufacturing Annual Payroll			-0.033**	-0.034**			-0.026*	-0.027*
			(0.012)	(0.012)			(0.012)	(0.011)
Intercept	2.898**	3.090***	2.926**	3.101***	3.066***	3.244***	3.171***	3.339***
	(0.829)	(0.863)	(0.848)	(0.884)	(0.735)	(0.729)	(0.724)	(0.718)
N	969	969	969	969	969	969	969	969
R-Squared	0.743	0.745	0.743	0.746	0.756	0.758	0.758	0.760
BIC	-77.301	-59.178	-79.360	-60.365	15.973	36.784	9.943	31.056

* p<.05, ** p<.01, *** p<.001 (two tailed tests)

Table S2B. Full Models: Regression Analyses Predicting Logged Opioid Overdose Mortality Rates

Outcome: Logged Opioid Overdose Mortality Rates	Men				Women			
	Manufacturing Employment		Manufacturing Annual Payroll		Manufacturing Employment		Manufacturing Annual Payroll	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
1999	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
2000	0.113	0.112	0.119*	0.118*	0.175*	0.175*	0.172*	0.172*
	(0.058)	(0.058)	(0.056)	(0.055)	(0.086)	(0.085)	(0.085)	(0.084)
2001	0.321***	0.298***	0.328***	0.309***	0.485***	0.469***	0.476***	0.462***
	(0.077)	(0.078)	(0.074)	(0.075)	(0.099)	(0.101)	(0.097)	(0.099)
2002	0.530***	0.504***	0.510***	0.487***	0.772***	0.755***	0.736***	0.717***
	(0.100)	(0.102)	(0.102)	(0.103)	(0.113)	(0.116)	(0.118)	(0.121)
2003	0.532***	0.497***	0.528***	0.497***	0.817***	0.794***	0.784***	0.761***
	(0.107)	(0.110)	(0.103)	(0.103)	(0.116)	(0.119)	(0.114)	(0.117)
2004	0.665***	0.616***	0.656***	0.613***	0.981***	0.948***	0.939***	0.907***
	(0.143)	(0.145)	(0.138)	(0.138)	(0.136)	(0.138)	(0.132)	(0.134)
2005	0.724***	0.659***	0.728***	0.671***	1.094***	1.049***	1.058***	1.016***
	(0.154)	(0.156)	(0.144)	(0.143)	(0.138)	(0.139)	(0.130)	(0.131)
2006	0.885***	0.814***	0.881***	0.819***	1.217***	1.169***	1.170***	1.124***
	(0.170)	(0.173)	(0.164)	(0.163)	(0.147)	(0.147)	(0.140)	(0.140)
2007	0.926***	0.843***	0.925***	0.852***	1.345***	1.289***	1.295***	1.242***
	(0.174)	(0.178)	(0.168)	(0.167)	(0.155)	(0.159)	(0.151)	(0.154)
2008	1.043***	0.959***	1.041***	0.966***	1.456***	1.398***	1.399***	1.345***
	(0.206)	(0.210)	(0.198)	(0.196)	(0.173)	(0.173)	(0.166)	(0.164)
2009	1.036***	0.965***	1.026***	0.964***	1.415***	1.367***	1.354***	1.308***
	(0.225)	(0.225)	(0.220)	(0.215)	(0.182)	(0.178)	(0.173)	(0.167)
2010	0.988***	0.921**	0.959***	0.898***	1.486***	1.440***	1.411***	1.366***
	(0.263)	(0.265)	(0.262)	(0.256)	(0.217)	(0.218)	(0.215)	(0.211)
2011	1.040***	0.956**	1.028***	0.954***	1.548***	1.491***	1.485***	1.430***
	(0.282)	(0.284)	(0.272)	(0.267)	(0.230)	(0.232)	(0.220)	(0.219)
2012	1.095***	0.998**	1.087***	1.000***	1.603***	1.535***	1.539***	1.474***
	(0.282)	(0.286)	(0.270)	(0.267)	(0.238)	(0.239)	(0.225)	(0.223)
2013	1.215***	1.093***	1.210***	1.100***	1.715***	1.626***	1.651***	1.565***
	(0.279)	(0.281)	(0.267)	(0.261)	(0.229)	(0.233)	(0.219)	(0.221)
2014	1.392***	1.259***	1.388***	1.265***	1.879***	1.779***	1.811***	1.715***
	(0.285)	(0.284)	(0.274)	(0.267)	(0.235)	(0.236)	(0.222)	(0.223)
2015	1.558***	1.411***	1.561***	1.425***	1.972***	1.860***	1.905***	1.797***
	(0.282)	(0.280)	(0.268)	(0.263)	(0.245)	(0.249)	(0.231)	(0.237)
2016	1.791***	1.632***	1.790***	1.640***	2.128***	2.001***	2.053***	1.930***
	(0.286)	(0.282)	(0.275)	(0.270)	(0.257)	(0.267)	(0.244)	(0.260)

2017	1.876***	1.707***	1.879***	1.720***	2.233***	2.101***	2.158***	2.030***
	(0.305)	(0.302)	(0.290)	(0.289)	(0.278)	(0.289)	(0.262)	(0.281)
Unemployment Rate	0.011	0.007	0.016	0.013	0.012	0.009	0.013	0.011
	(0.020)	(0.019)	(0.021)	(0.021)	(0.019)	(0.018)	(0.019)	(0.019)
% with College Degree	-0.025	-0.025	-0.025	-0.026	-0.025*	-0.027*	-0.024	-0.026*
	(0.013)	(0.013)	(0.014)	(0.014)	(0.012)	(0.012)	(0.012)	(0.012)
% Ever-Married	-0.018	-0.015	-0.017	-0.014	-0.024	-0.021	-0.023	-0.020
	(0.013)	(0.014)	(0.013)	(0.013)	(0.014)	(0.014)	(0.013)	(0.014)
% Hispanic	-0.066***	-0.067***	-0.065***	-0.065***	-0.057***	-0.057***	-0.054***	-0.054***
	(0.014)	(0.015)	(0.014)	(0.014)	(0.015)	(0.015)	(0.015)	(0.015)
% Black	-0.002	0.001	-0.003	0.000	-0.004	-0.002	-0.005	-0.004
	(0.011)	(0.011)	(0.011)	(0.012)	(0.015)	(0.015)	(0.015)	(0.015)
Self-Reported Health	0.375	0.337	0.323	0.280	-0.244	-0.280	-0.274	-0.315
	(0.339)	(0.331)	(0.351)	(0.346)	(0.372)	(0.386)	(0.361)	(0.377)
% Labor Union Coverage		-0.032*		-0.030*		-0.023		-0.021
		(0.013)		(0.013)		(0.014)		(0.013)
Good Samaritan Law Implementation		0.084		0.092		0.116		0.127
		(0.115)		(0.115)		(0.106)		(0.107)
Naloxone Access Law Implementation		-0.026		-0.026		-0.040		-0.047
		(0.095)		(0.096)		(0.084)		(0.085)
Prescription Drug Monitoring Program Implementation		0.028		0.028		0.018		0.017
		(0.081)		(0.080)		(0.075)		(0.074)
% Manufacturing Employment	-0.059*	-0.064*			-0.043	-0.047		
	(0.028)	(0.026)			(0.026)	(0.024)		
% Manufacturing Annual Payroll			-0.046*	-0.049*			-0.043*	-0.046*
			(0.022)	(0.021)			(0.020)	(0.019)
Intercept	3.026**	3.426**	3.026**	3.401**	3.445***	3.775***	3.578***	3.904***
	(1.056)	(1.033)	(1.113)	(1.093)	(0.873)	(0.883)	(0.890)	(0.905)
N	968	968	968	968	967	967	967	967
R-Squared	0.683	0.687	0.683	0.687	0.726	0.729	0.728	0.731
BIC	737.644	750.562	737.679	751.359	865.939	883.549	860.414	877.578

* p<.05, ** p<.01, *** p<.001 (two tailed tests)

Table S3. Number of Drug Overdose Deaths Attributable to Manufacturing Decline Between 1999-2017, by State and Measure of Manufacturing

	Men		Women	
State	Employment	Annual Payroll	Employment	Annual Payroll
Alabama	1430	1224	570	661
Alaska	61	36	21	16
Arizona	1363	1469	515	752
Arkansas	997	1000	383	520
California	10953	11499	4132	5874
Colorado	992	1088	361	536
Connecticut	944	843	375	453
Delaware	189	181	76	98
District of Columbia	13	9	5	5
Florida	2755	2653	1085	1415
Georgia	2950	2636	1148	1388
Hawaii	57	41	21	21
Idaho	326	325	121	162
Illinois	3569	3437	1355	1767
Indiana	1814	2172	688	1116
Iowa	545	699	201	350
Kansas	510	553	189	277
Kentucky	1007	1171	383	603
Louisiana	594	589	230	308
Maine	425	453	174	250
Maryland	894	906	355	488
Massachusetts	1857	1752	731	933
Michigan	2936	3585	1128	1865
Minnesota	1076	1118	396	557
Mississippi	1083	850	431	458
Missouri	1538	1442	589	747
Montana	105	123	39	62
Nebraska	285	324	105	162
Nevada	131	100	48	49
New Hampshire	446	372	173	196
New Jersey	2068	1867	808	988
New Mexico	242	207	93	107
New York	4197	3363	1657	1799
North Carolina	4799	4131	1879	2190
North Dakota	44	83	15	38
Ohio	3194	3664	1232	1914
Oklahoma	708	815	264	412
Oregon	882	967	333	495
Pennsylvania	3150	3177	1206	1648

Rhode Island	388	344	156	187
South Carolina	1687	1578	671	850
south Dakota	166	217	60	106
Tennessee	2148	1898	843	1009
Texas	5413	5552	2011	2792
Utah	491	420	171	198
Vermont	174	180	69	98
Virginia	2151	2026	816	1040
Washington	1941	1935	727	981
west Virginia	320	396	120	200
Wisconsin	1583	1804	592	913
Wyoming	15	10	5	5

Note: Estimates based off Table 2, Panel A, Model 2.

Table S4. Sensitivity Analyses Adjusting For Opioid Prescriptions per 100 Population.

A. Logged Drug Overdose Mortality		
Manufacturing Measure	Model 1	Model 2
Female		
% Employees in Manufacturing	-0.031	-0.031
	(0.029)	(0.029)
% Annual Payroll in Manufacturing	-0.021	-0.019
	(0.019)	(0.019)
Male		
% Employees in Manufacturing	-0.068*	-0.065*
	(0.031)	(0.031)
% Annual Payroll in Manufacturing	-0.047*	-0.042*
	(0.021)	(0.020)
B. Logged Opioid Overdose Mortality		
Manufacturing Measure	Model 1	Model 2
Female		
% Employees in Manufacturing	-0.052	-0.040
	(0.061)	(0.059)
% Annual Payroll in Manufacturing	-0.001	0.005
	(0.039)	(0.038)
Male		
% Employees in Manufacturing	-0.098	-0.089
	(0.058)	(0.057)
% Annual Payroll in Manufacturing	-0.041	-0.033
	(0.036)	(0.034)
State and Year Fixed Effects	Yes	Yes
Compositional and Economic Covariates	Yes	Yes
Labor and Drug Policy Covariates	No	Yes
Opioid Prescription Rate	Yes	Yes

* p<.05, ** p<.01, *** p<.001 (two tailed tests)

Notes: (a) All covariates are lagged one year. (b) Model 1 has 561 observations, representing 50 states and the District of Columbia over 11 years (2007-2017); Model 2, which has 550 observations, excludes Missouri which has not passed legislation implementing a PDMP. (c) Compositional and economic covariates include state-level measures of the unemployment rate, the percentage of the population with a college degree, the percentage of the population who have ever been married, the percentage of the population who are Hispanic, the percentage of the population who are black, and the average self-reported health score. (d) Labor and drug policy covariates include state-level measures of the percent of workers covered or represented by labor unions, and binary indicators of whether states have implemented three types of drug policies: PDMPs, naloxone access laws, and Good Samaritan laws for reporting drug overdoses.

Table S5A. Male. Regression Analyses Predicting County-Level Drug and Opioid Overdose Death Rates

A. Logged Drug Overdose Mortality				
	County-Level Manufacturing		State-Level Manufacturing	
Manufacturing Measure	Model 1	Model 2	Model 1	Model 2
County Fixed Effects				
% Employees in Manufacturing	-0.005*	-0.005*	-0.048**	-0.046**
	(0.002)	(0.002)	(0.017)	(0.014)
	47484	47484	48965	48965
% Annual Payroll in Manufacturing	-0.005**	-0.005**	-0.045**	-0.043**
	(0.002)	(0.002)	(0.016)	(0.014)
	48504	48504	49912	49912
State Fixed Effects				
% Employees in Manufacturing	-0.013***	-0.013***	-0.048**	-0.046**
	(0.002)	(0.002)	(0.016)	(0.013)
	47484	47484	48965	48965
% Annual Payroll in Manufacturing	-0.009***	-0.009***	-0.046**	-0.043**
	(0.001)	(0.001)	(0.015)	(0.013)
	48504	48504	49912	49912
B. Logged Opioid Overdose Mortality				
	County-Level Manufacturing		State-Level Manufacturing	
Manufacturing Measure	Model 1	Model 2	Model 1	Model 2
County Fixed Effects				
% Employees in Manufacturing	-0.007*	-0.006*	-0.077**	-0.074**
	(0.003)	(0.003)	(0.024)	(0.022)
	47484	47484	48965	48965
% Annual Payroll in Manufacturing	-0.006**	-0.006**	-0.067**	-0.064**
	(0.002)	(0.002)	(0.020)	(0.018)
	48504	48504	49912	49912
State Fixed Effects				
% Employees in Manufacturing	-0.012***	-0.012***	-0.078**	-0.075**
	(0.001)	(0.001)	(0.024)	(0.021)
	47484	47484	48965	48965
% Annual Payroll in Manufacturing	-0.009***	-0.009***	-0.068***	-0.065***
	(0.001)	(0.001)	(0.019)	(0.018)
	48504	48504	49912	49912
Compositional and Economic Covariates	Yes	Yes	Yes	Yes
Labor and Drug Policy Covariates	No	Yes	No	Yes

* p<.05, ** p<.01, *** p<.001 (two tailed tests)

Table S5B. Female. Regression Analyses Predicting County-Level Drug and Opioid Overdose Death Rates

A. Logged Drug Overdose Mortality				
	County-Level Manufacturing		State-Level Manufacturing	
Manufacturing Measure	Model 1	Model 2	Model 1	Model 2
County Fixed Effects				
% Employees in Manufacturing	-0.006***	-0.006***	-0.031	-0.030*
	(0.002)	(0.002)	(0.017)	(0.014)
N	47484	47484	48965	48965
% Annual Payroll in Manufacturing	-0.005***	-0.005***	-0.036**	-0.033**
	(0.001)	(0.001)	(0.013)	(0.011)
N	48504	48504	49912	49912
State Fixed Effects				
% Employees in Manufacturing	-0.010***	-0.010***	-0.033	-0.032*
	(0.002)	(0.002)	(0.016)	(0.013)
N	47484	47484	48965	48965
% Annual Payroll in Manufacturing	-0.006***	-0.006***	-0.038**	-0.034**
	(0.001)	(0.001)	(0.013)	(0.010)
N	48504	48504	49912	49912
B. Logged Opioid Overdose Mortality				
	County-Level Manufacturing		State-Level Manufacturing	
Manufacturing Measure	Model 1	Model 2	Model 1	Model 2
County Fixed Effects				
% Employees in Manufacturing	-0.006***	-0.006**	-0.061*	-0.058*
	(0.002)	(0.002)	(0.023)	(0.022)
N	47484	47484	48965	48965
% Annual Payroll in Manufacturing	-0.006***	-0.006***	-0.054**	-0.051**
	(0.001)	(0.001)	(0.018)	(0.017)
N	47484	47484	48965	48965
State Fixed Effects				
% Employees in Manufacturing	-0.009***	-0.009***	-0.062**	-0.059**
	(0.001)	(0.001)	(0.022)	(0.021)
N	47484	47484	48965	48965
% Annual Payroll in Manufacturing	-0.006***	-0.006***	-0.055**	-0.052**
	(0.001)	(0.001)	(0.017)	(0.016)
N	47484	47484	48965	48965
Compositional and Economic Covariates	Yes	Yes	Yes	Yes
Labor and Drug Policy Covariates	No	Yes	No	Yes

* p<.05, ** p<.01, *** p<.001 (two tailed tests)

Table S6. Regression Analyses Predicting Rates of Emergency Department Visits and Inpatient Stays

A. Logged Emergency Department Visits Per 100,000 Population		
Manufacturing Measure	Model 1	Model 2
Female		
% Employees in Manufacturing	-0.015	-0.016
	(0.031)	(0.031)
% Annual Payroll in Manufacturing	-0.008	-0.005
	(0.025)	(0.024)
N	381	381
Male		
% Employees in Manufacturing	-0.024	-0.024
	(0.035)	(0.037)
% Annual Payroll in Manufacturing	-0.022	-0.017
	(0.027)	(0.027)
N	381	381
B. Logged Hospital Stays Per 100,000 Population		
Manufacturing Measure	Model 1	Model 2
Female		
% Employees in Manufacturing	-0.002	-0.003
	(0.024)	(0.023)
% Annual Payroll in Manufacturing	-0.007	-0.007
	(0.015)	(0.015)
N	553	553
Male		
% Employees in Manufacturing	-0.004	-0.007
	(0.026)	(0.025)
% Annual Payroll in Manufacturing	-0.006	-0.006
	(0.017)	(0.017)
N	553	553
State and Year Fixed Effects	Yes	Yes
Compositional and Economic Covariates	Yes	Yes
Labor and Drug Policy Covariates	No	Yes

* p<.05, ** p<.01, *** p<.001 (two tailed tests)

Notes: (a) All covariates are lagged one year. (b) Compositional and economic covariates include state-level measures of the unemployment rate, the percentage of the population with a college degree, the percentage of the population who have ever been married, the percentage of the population who are Hispanic, the percentage of the population who are black, and the average self-reported health score. (d) Labor and drug policy covariates include state-level measures of the percent of workers covered or represented by labor unions, and binary indicators of whether states have implemented three types of drug policies: PDMPs, naloxone access laws, and Good Samaritan laws for reporting drug overdoses.

Chapter 3: Cohort-Specific Experiences of Industrial Decline and Intergenerational Income Mobility

ABSTRACT

The U.S. manufacturing industry has long been regarded as the economic engine that built and sustained the middle class. In recent decades, this pillar of economic opportunity has eroded substantially. Though much has been written about the decline of manufacturing sectors in U.S. communities, the potential consequences for economic mobility, and stratification processes more generally, remain largely unexplored. In this study, I develop a conceptual framework linking the study of labor market change to economic stratification. I examine how structural changes to U.S. labor markets have altered opportunities for economic advancement in the U.S. I focus the analysis on birth cohorts in the 1980s, whose labor market entry spans the large-scale erosion of the manufacturing industry in the 2000s. I find strong evidence that declines in manufacturing employment have contributed to growing geographic disparities in upward intergenerational income mobility. Children raised in counties that experienced large contractions in manufacturing industries throughout adolescence experienced large economic penalties in adulthood via reduced levels of upward mobility. The results demonstrate how long-term macroeconomic changes can disrupt and redistribute opportunities within societies.

BACKGROUND

The U.S. manufacturing industry has long been regarded as the economic engine that built and sustained the middle class (Janoski et al. 2014). For much of the 20th century, employment in manufacturing industries acted as a ladder that raised poor- and working-class families and individuals into the middle class through stable full-time and well-paying jobs. Yet, in recent decades, this pillar of economic opportunity has rapidly declined. In 1980, one out of four workers were employed in a goods-producing industry; now, in 2020, the share has dropped to one in ten workers.[17] Although employment in manufacturing has modestly increased since the end of the Great Recession in 2009, wages for new production jobs are substantially lower than in prior decades (Jacobs et al. 2016). The rapid pace of job destruction in manufacturing industries is further compounded by the lack of wage growth in the expanding low-skill service

[17] Authors calculations using BLS data from the Federal Reserve Bank of St. Louis (FRED).

sector as well as by the rise of nonstandard and contingent work arrangements (Kalleberg 2018; Schneider and Harknett 2019). Workers who lack a four-year college degree in this new occupational environment have progressively found their employment opportunities constrained and their prospects for upward mobility diminished (Autor and Dorn 2013; Autor et al. 2006).

The decline of manufacturing in the U.S. is now popularly viewed as the "cause" of many social, demographic, and political changes that have occurred in recent decades. Scientific and journalistic accounts suggest that the economic deterioration initiated by manufacturing decline in traditional blue-collar communities is associated with the rise of "deaths of despair" from alcohol, drugs, and suicide (Case and Deaton 2015; Monnat 2019; Venkataramani et al. 2020). In a similar line of inquiry, researchers have also documented how the rearrangement of opportunities in the U.S. labor market has contributed to shifts in other demographic processes, including fertility behavior and migration patterns, vis-à-vis increases in economic insecurity (Charles, Hurst, and Notowidigdo 2017; Seltzer 2019). Despite the scholarly and public interest in understanding how labor market changes might be impacting social and demographic trends, we know little about how this postindustrial transition has impacted economic attainment and the intergenerational transmission of socioeconomic status.

In the present study, I develop a conceptual framework for examining how deindustrialization in U.S. communities has reshaped the upward mobility prospects of birth cohorts born during the 1980s. I focus on birth cohorts born during this period because the entered the labor force during a pivotal moment in the history of U.S. deindustrialization (the late 1990s and early 2000s) that coincided with the start of what would ultimately be the loss of approximately 5.7 million jobs in the manufacturing sector over the course of the 2000s.[18] In relative terms, the percentage of jobs in the manufacturing sector dropped from 15.5% of all jobs in the U.S. labor market to 10.5% of all jobs in the U.S. labor market between 2000-2010. Linking subnational business records on industrial change with county-level and cohort-specific estimates of intergenerational income mobility, I examine how long-term manufacturing decline in the U.S. has altered economic opportunity structures across and within communities.

I begin by asking three questions: First, to what extent does variation in relative levels of manufacturing employment explain spatial differences in intergenerational mobility across labor markets? That is, do communities that have maintained a thriving manufacturing sector provide better opportunity prospects for new labor market entrants than communities that have little or no remaining employment in manufacturing industries? Second, do community-specific histories of industrial change and restructuring explain differences across labor markets in intergenerational mobility outcomes? And finally, third, how do successive birth cohorts born within communities differentially experience labor market change?

I additionally evaluate whether the decline of middle-wage occupational opportunities in the manufacturing sector has increased inequities in intergenerational mobility across population subgroups, specifically across race/ethnicity and gender. This research aim seeks to test whether the consequences of manufacturing decline have been more severe for certain population subgroups.

The findings provide strong empirical evidence of the large role of labor market changes on economic opportunity. The evidence provides four contributions to literature on social

[18] About 3.4 million of these lost manufacturing jobs (or about 60%) disappeared prior to the start of the Great Recession in 2007.

stratification, labor market inequality, and life course trajectories. First, children from the 1980-1988 cohorts who lived in counties with a higher share of manufacturing sector opportunities upon labor force entry – operationalized as either the share of employment, earnings, or business establishments concentrated in manufacturing industries at age 18 – experienced higher income mobility than those who lived in counties with a lower share of manufacturing upon labor force entry. Second, children from these cohorts who lived in counties that experienced larger contractions in manufacturing throughout their adolescence faced larger economic penalties in adulthood via reduced levels of upward intergenerational mobility. Third, the specific experiences of birth cohorts within counties upon entry into the labor force impacted their prospects for upward mobility. Finally, I find that the effect size of manufacturing decline on upward intergenerational income mobility is about three times the size for Black men relative to white men, indicating that the transition to a postindustrial society is exacerbating pre-existing racial disparities in intergenerational mobility. Overall, these findings demonstrate how long-term, but ongoing, structural changes in social structures can disrupt and redistribute opportunities within societies.

INDUSTRIAL CHANGE AND INTERGENERATIONAL MOBILITY PROCESSES

Despite a longstanding interest in the relationship between occupational hierarchies and the persistence of socioeconomic status, social scientists have often overlooked the role of industrial change on intergenerational mobility processes (for some notable exceptions, see: DiPrete 1993; Hauser et al. 1975). This oversight in the literature is unfortunate since the industrial composition of labor markets determines the distribution of occupational opportunities. Economic restructurings and transitions also alter the contexts of occupational hierarchies for both the parent and offspring generations. Recent research by Song et al. (2019), for instance, emphasizes the importance of accounting for historical transitions in labor markets when analyzing long-term trends in intergenerational occupational mobility. They find that without accounting for the transition from an agriculture society to manufacturing-dependent society in the late 19th and early 20th century, there is a higher rank-rank correlation between fathers' and sons' intergenerational occupational mobility. Other studies on intergenerational occupational mobility that have not properly accounted for the transition from farming to manufacturing (e.g. Long & Ferrie, 2013) have resulted in exaggerated estimates of intergenerational persistence (Xie and Killewald 2020).

Rather than merely a peripheral concern, the present study seeks to refocus the scholarly conversation around the changing industrial composition of labor markets as instead an important driver of variation in upward intergenerational mobility.

Why might we be concerned that this industrial transition is associated with reductions in upward mobility? First, rising job displacement from manufacturing industries is associated with unstable employment and/or underemployment as well as reductions in short- and long-term earnings (Carrington and Fallick 2015; Couch et al. 2018; Fallick 1996; Parrado, Asena, and Wolff 2007). Worker movement across occupations and industries became increasingly more common during the second half of the 20th century (Parrado et al. 2007) and displacement-induced moves from manufacturing to other industries are associated with substantial earnings losses (Cha and Morgan 2010). Overall, the decline in manufacturing jobs has destabilized once stable, well-paying occupational career trajectories, thereby reducing the availability of occupational opportunities for upward movement.

Second, the geography of manufacturing decline varies considerably across and within regions, which might exacerbate pre-existing spatial trends in intergenerational mobility.

Between 1980-2010, the Northeast experienced the sharpest losses in manufacturing employment while the West Coast experienced slight increases in manufacturing employment (Helper, Krueger, and Wial 2012). While the Midwest had a slight resurgence in manufacturing employment growth in the 1990s after a decline in the 1980s, it then experienced substantial losses in the 2000s along with all other regions of the country. Within regions and states during this time period, manufacturing jobs shifted from metropolitan areas to small metropolitan and non-metropolitan areas (Helper et al. 2012). On the surface, these trends correlate with the geography of upward intergenerational mobility: Findings by Chetty et al. (2014) indicate that regions such as the Southeast and Rust Belt have lower upward mobility outcomes than regions such as the Northeast, the Great Plains, and the West Coast. There is also substantial within-state, and even within-commuting zone, variation in most states, but particularly states such as Texas, Missouri, and Ohio. Yet, no study has sought to rigorously investigate whether there is any statistical relationship between these two geographic trends.

Finally, the ongoing economic restructuring might not be uniformly impacting population subgroups. While now popularly viewed as a labor market issue that predominantly impacts working-class white men in small Midwestern factory towns, the loss of production jobs in the manufacturing sector has and continues to impact a much broader segment of American society. As documented by William Julius Wilson (1996), blue collar jobs in goods-producing industries rapidly disappeared from cities during the second half of the 20th century and were often relocated to white suburban areas. This labor market shift precipitously reduced the amount of middle-wage occupational opportunities available to Black workers, thereby cutting off prospects for upward economic mobility at a quicker pace than for white workers.

Nationally, the share of Black workers employed in manufacturing industries (versus other industries) exceeded the share of white workers employed in manufacturing industries until the 1990s, the time period when the 1980-1988 birth cohorts chronicled in the present study began to enter the labor force (Figure 1). Recent findings by Wrigley-field and Seltzer (2020) likewise document how Black workers have become increasingly more likely to be involuntary laid off from jobs in the manufacturing industry since the late 1990s, a trend that cannot be explained by differences in the occupational composition of Black and white workers, among other explanations. Simply put, the process of deindustrialization has not occurred evenly across geographic areas and population subgroups in the U.S., and as a result, might be exacerbating racial/ethnic inequalities in upward economic mobility.

TRENDS IN INTERGENERATIONAL MOBILITY

This analysis is motivated by recent temporal, geographic, and population subgroup trends in intergenerational income mobility for birth cohorts born in the second half of the 20th century. Stratification researchers rely on indicators of intergenerational income mobility, such as the intergenerational elasticity (IGE) and rank-rank slope, because they provide a straightforward description of change in the opportunity structure of societies over time as well as a comparison in economic opportunity across and within societal and geographic contexts (Bloome 2015; Cheng and Song 2019; Hout 2015). Higher levels of income mobility imply that social origins do not necessarily portend social destinations, while lower levels of income mobility indicate a deterministic social structure where early life circumstances of advantage or disadvantage predict later life outcomes (Black and Devereux 2010; Bloome and Dyer 2018; Hout 2015).

The majority of studies on long-term trends in relative intergenerational mobility suggest little if any change in intergenerational income mobility for birth cohorts born during the several decades following World War II (Lee and Solon 2009), but a minimal decline in mobility for cohorts born after the 1980s (Mazumder 2012).[19] Findings by Bloome and Western (2011) and Davis and Mazumder (2020) suggest more heterogeneity in mobility trends for birth cohorts born prior to the 1980s. Davis and Mazumder's (2020) results, for instance, demonstrate that birth cohorts who entered the labor market in the 1980s – a period that coincided with rapid increases in income inequality, among other dimensions of economic inequality – experienced higher intergenerational persistence than birth cohorts who entered the labor market in the 1970s.

As briefly noted in the prior section, Chetty et al. (2014) documented substantial heterogeneity in relative income mobility across and within U.S. regions and states for birth cohorts born in the 1980s. For children of these birth cohorts with parents at the 25th percentile of the national income distribution, the range of upward mobility in adulthood spans from reaching the 27th income percentile to the 64th income percentile depending on the labor market one grew up in.

Researchers have also documented temporal trends in racial differences in income mobility. Looking at intergenerational income elasticities for Black and white men from cohorts born in 1966 and 1979, Bloome and Western (2011) find that income mobility decreased for both groups over time, although the decline in mobility over this time period was larger for Blacks. Examining male birth cohorts born in the late 1950s and early 1960s, Bhattacharya and Mazumder (2011) find similar results indicating that intergenerational persistence is much higher

[19] In contrast to trends in relative mobility, absolute mobility has declined considerably for birth cohorts born since the 1940s (Chetty, Grusky, et al. 2016; Davis and Mazumder 2020).

for Black men than white men. Recent findings by Chetty et al. (2018), focusing on birth cohorts born between 1978-1983, find that the Black-white disparities persist for children born during these years, but also find little difference in upward mobility outcomes between whites and Hispanics and whites and Asians. These results remain even when accounting for different compositional rates of marriage across racial/ethnic groups, which creates mechanical differences in household income between single- and dual-earner families. However, Chetty et al. (2018) also find heterogeneity across gender within racial/ethnic groups, finding, for instance, that Black women have slightly higher rates of relative upward mobility than white women.

In a similar manner to the theorized association between labor market changes and intergenerational income mobility outcomes made by Davis and Mazumder (2020), noted above, the present study seeks to assess how relative declines in manufacturing employment during the turn of the millennium impacted intergenerational mobility. I primarily leverage variation in labor market experiences and intergenerational mobility outcomes across birth cohorts and geographic areas, but also across race and gender.

LIFE COURSE PERSPECTIVES

The convergence of life course trajectories with historical events – such as economic downturns and armed conflicts – and the implementation of new policy regimes can impact the life chances of birth cohorts (Elder 1974; Hout 2015). The experiences of birth cohorts throughout the life course are particularly influenced by the sequential nature of life transitions as well as the idiosyncratic deviations in timing of life transitions for specific cohorts as a result of historical time and place (Elder 1998). Elder’s research (e.g. 1998), for instance, demonstrates how the socioeconomic outcomes of cohorts are influenced by the age at which they experience economic adversity. In the Children of the Great Depression, Elder (1974) finds that cohorts in their teenage years during the Great Depression (born in the early 1920s) experienced less economic difficulty in adulthood than cohorts in early adolescence (born the late 1920s) because they experienced less material deprivation and duress during their formative childhood years. Variation in age across these two cohorts during the Great Depression also impacted the sequence and timing of life events, including moving away from parental households, marriage, and childbearing.

A broader literature in the social sciences has sought to document how timing of entry into the labor force – whether prior to, during, or after economic recessions – alters the job opportunities, entry salaries, lifetime pay, and educational attainment of cohorts (Kahn 2010; Oreopoulos, Wachter, and Heisz 2012; Rinz 2019). Recent findings by Rinz (2019) on the impacts of the Great Recession on employment and earnings finds that younger birth cohorts faced more substantial earnings losses than older birth cohorts. This so-called "failure to launch" initiated by labor market entry during an economic recession can have a cascading set of consequences for life transitions, economic attainment, and autonomy (e.g. Mykyta 2012; Qian 2012).

This literature on economic shocks concentrates primarily on the presence or absence of employment opportunities in local labor markets, but less so on the attributes of those jobs. The research conducted here re-conceptualizes economic shocks as fluctuations to the industrial composition of employment opportunities in the manufacturing sector, and the resultant decline in middle-wage, middle-skill jobs. Accordingly, I adjust for the unemployment rate in the statistical analyses to hold constant whether job opportunities are present or not.

I consider two types of measures of compositional change to labor markets: first, continuous measures of the relative share of employment, annual earnings, and business establishments in a local labor market that are concentrated in manufacturing sector; and second, an absolute measure of the number of large manufacturing establishments (primarily factories or plants) that are present in a local labor market. Leveraging the alignment of 9 consecutive birth cohorts, I implement a generalized difference-in-difference modeling strategy that estimates the relationship between labor market transitions and income mobility through two-way fixed effects. This modeling strategy, described in the next section, allows for an examination of how different experiences of labor market change might set birth cohorts onto very different intergenerational economic attainment paths.

EMPIRICAL APPROACH

This study takes a macro-level approach towards the analysis of intergenerational mobility processes. The units of analysis are birth cohorts nested within county labor markets. This innovative panel design provides analytical leverage to examine how places produce people over time – how the outcomes of birth cohorts can vary according to annual fluctuations in time-varying economic experiences in the labor market. By conceptualizing mobility processes as the aggregate outcomes of birth cohorts, rather than the outcomes of individuals, the present analysis emphasizes how opportunity structures are shaped by the combination of geographic and temporal contexts. To demonstrate the structure of the data, Figure 2 depicts a schematic of the dataset for birth cohorts born in Kenosha county, Wisconsin between 1980-1988.

A central aim of this study is to examine how labor market conditions upon labor force entry are associated with upward income mobility later in adulthood; therefore, the industrial composition of local labor markets are measured at age 18, when most individuals in birth cohorts complete secondary schooling and either enter the labor force immediately or pursue higher education.[20,21] The guiding assumptions of selecting this age for when covariates are measured is that (a) manufacturing jobs have historically only required a high school degree, and (b) age 18 is when the majority of individuals in these cohorts entered the labor force (Fernandes-Alcantara 2018; U.S. Bureau of Labor Statistics 2020; author's calculations of BLS data). Critically, this point in the life course coincides with the end of secondary education and the decision to either directly enter the labor force or acquire additional schooling (i.e. vocational training or higher education). As the manufacturing sector has declined in recent decades, the amount of well-paying jobs that only require a high school degree have diminished, and most earnings growth in the sector has occurred for college-educated workers rather than those without a college degree (Levinson 2017).[22] The intuition of this empirical approach, therefore, is to evaluate how declines manufacturing employment opportunities in labor markets are associated with reductions in upward mobility.

DATA and METHODS

To study the relationship between market structure and economic opportunity, I combine cohort measures of intergenerational income mobility estimated by Chetty et al. (2014) with subnational business register data from the Census Bureau's County Business Patterns (CBP) to estimate county-level associations between manufacturing decline and intergenerational income mobility. I augment this constructed dataset with county- and cohort-specific social, economic, and compositional covariates to adjust for potential sources of confounding.

---

[20] To assess the sensitivity of age 18, I additionally estimate models that instead set labor market entry for covariates at ages 17-20. The results are approximately the same. What is most relevant is that each birth cohort has a different experience based on annual changes in labor market conditions.
[21] In a recent study on intergenerational income mobility, Davis and Mazumder (2020) make a similar argument that age of labor market entry is between ages 18-22.
[22] Using data from the CPS, (Levinson 2017) shows that there was a 31.5% decline in workers with high school degrees in the manufacturing sector between 2000 and 2016.

Intergenerational Income Mobility

I access county- and cohort-specific estimates of rank-rank intergenerational income mobility for birth cohorts between 1980 to 1988 generated by Chetty et al. (2014) using linked parent-child federal tax records. These estimates of intergenerational income mobility comprise nearly 95% of all U.S. citizens born to each of these nine cohorts. For each birth cohort, Chetty et al. (2014) generated parent income rank by arranging parents according to their mean family income in the national income distribution when the children were between the ages 15-19. Child income rank was generated by arranging children by their family income in the national income distribution at ages 24 and 26. With these two measures of parent and child income from a population-based sample, Chetty et al. (2014) produced measures of "absolute upward mobility" which summarize the mean rank achieved by children at age 24 and 26 conditional on the rank of their parents. The analysis by Chetty et al. (2014) indicates a linear relationship for the rank-rank measures of intergenerational income mobility, which suggests little variation in mobility across parent origin percentiles. To capture the upward mobility of those at the bottom of the national income distribution, the present analysis uses a measure of this absolute upward mobility conditional on the parents at the 25th income percentile.

Because age 24 and age 26 measures of upward mobility might be influenced by life-cycle bias (discussed in more depth later in this section), I also use several mobility measures from Chetty et al. (2018) that consist of estimates of income mobility (i) at age 30 for the aggregated 1980-1982 birth cohorts and (ii) at ages 31-37 for the aggregated 1978-1983 birth cohorts. These measures from Chetty et al. (2018) come from the same dataset of linked parent-child tax records discussed above and were constructed by Opportunity Insights using the same methodology. This aggregate cohort data unfortunately precludes the analysis of within-county birth cohort comparisons, but does help validate the cross-county results.

Manufacturing Employment

I operationalize manufacturing levels as the relative share of jobs in a county labor market that are located in the manufacturing sector. I represent this share in percentage terms to facilitate the interpretation of coefficient tables. To assess the sensitivity of this employment measure, I also use two additional relative measures of manufacturing: (a) the percentage of overall, annual county-level earnings that are concentrated in the manufacturing sector, and (b) the percentage of manufacturing business establishments in a labor market.

For each of the three operationalizations of manufacturing – employment, annual payroll, and business establishments – I calculate two cohort- and county-specific measures: (1) the percentage of manufacturing at the approximate timing of labor force entry, here defined as age 18,[23] and (2) the change in the percentage of manufacturing in a county labor market throughout a birth cohorts adolescent years (i.e. $\Delta M_c = M_{c,0} - M_{c,18}$, c = county). The first measure is used to test for variation in the share of manufacturing across county labor markets; the second measure is used to test for change in the share of manufacturing throughout adolescence. The intuition of these two parameters is discussed in further detail in the methods section.

I additionally use an absolute measure of manufacturing change: the number of manufacturing plants in a county labor market that employ over 500 or over 1000 workers. These measures are calculated from full business register data between 1980-2006 accessed from the Census Bureau's County Business Patterns Program (CBP). Prior to 1998, business

[23] Only about 15% of the manufacturing workforce had less than high school educational attainment in 2000. The plurality (about 40%) had a high school diploma as their highest level of educational attainment.

establishments are classified according to 4-digit Standard Industrial Classification (SIC) codes; starting in 1998 and afterwards, business establishments are classified according to 6-digit North American Industry Classification System (NAICS) codes. Business establishments in manufacturing industries are determined based on the 2-digit classification codes 20-39 for SIC-designated years and the 2-digit classification codes 31-33 for NAICS-designated years.

Covariates

The upward mobility prospects of cohorts might be influenced by a bevy of social, economic, and compositional features of local communities and birth cohorts. The models adjust for several of these important cohort- and labor market-specific contextual features. The covariates included in the present models are specific to the year of labor market entry for each cohort, primarily set at age 18 (e.g. covariates for the 1980 cohort are calculated in 1998; for the 1981 cohort, 1999; etc.).

I use annual county-level population data from the National Center of Health Statistics to calculate the (a) population size and (b) percentage black, for each cohort at age 18, as well as the percentage of the county population of working-age (15-64) and (d) old age (65+). I access data on county-level poverty rates from the Census Bureau's Small Area Income and Poverty Estimates and county-level unemployment rates from the Census Bureau's Local Area Unemployment Statistics. Data on per capita income are drawn from the Bureau of Economic Analysis and are adjusted to 2000 dollars and logged to adjust for nonormality. To account for differences in educational attainment across counties over time, I retrieve county-level statistics on the percentage of the population with a high school degree or less from the 1990, 2000, and 2010 Decennial Censuses and use linear interpolation to estimate values for the intervening intercensal years. Finally, since state economic policy regimes and the presence of labor unions are associated with manufacturing decline, I adjust for the percentage of workers in each state in each year who are represented by a labor union.[24] These data originated from the Current Population Survey and are calculated and compiled via the Union Membership and Coverage Database (Hirsh, Macpherson, and Vroman 2019).

METHODOLOGY and MODEL SPECIFICATION

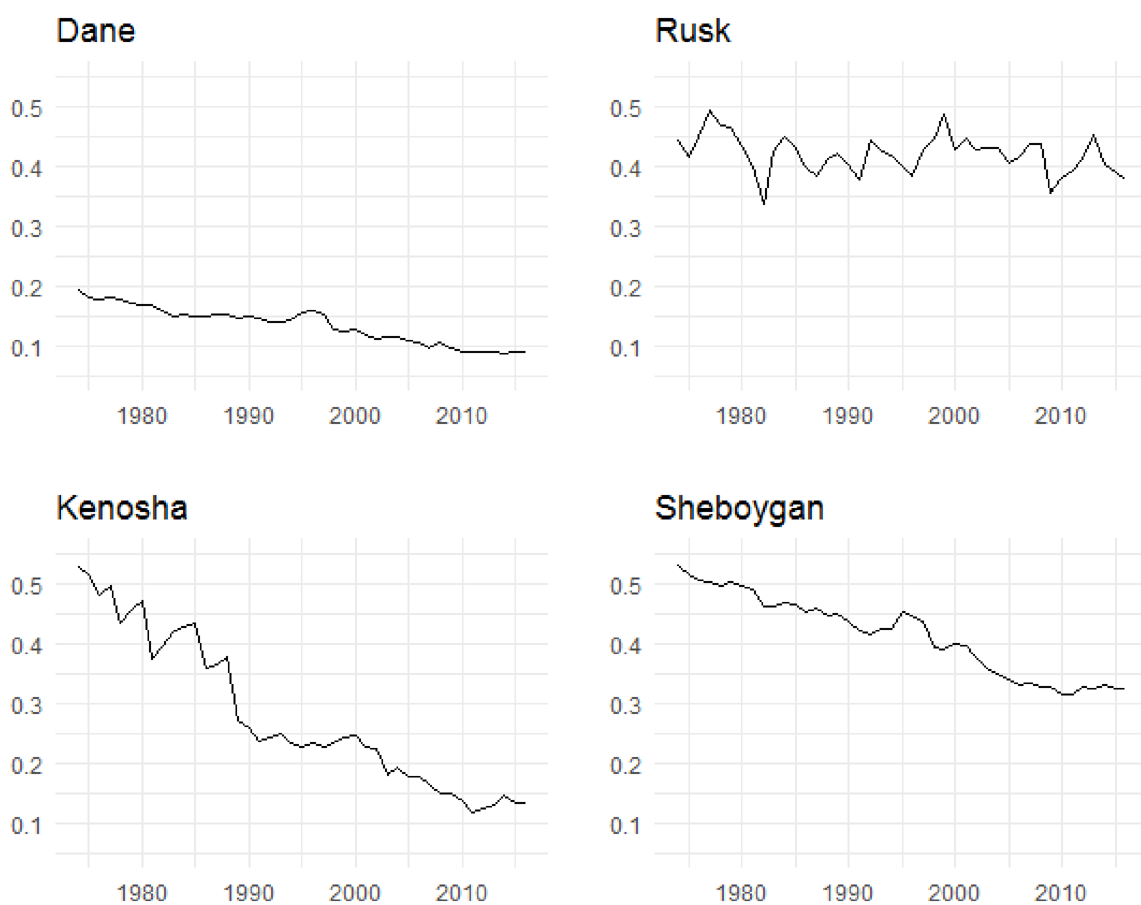
There are two important parameters that are estimated in this analysis: (1) the share of manufacturing at age of labor force entry (here defined as age 18), and (2) the change in the share of manufacturing between birth and entry into the labor force. The first parameter is important because it quantifies how variation in the relative share of manufacturing jobs across geographic areas might predict income mobility. This parameter also gives an indication about how initial employment opportunities upon labor force entry might set cohorts of workers onto different work trajectories with different economic outcomes. The second parameter is important because it contains information about the history of labor market change in communities, but also the history of labor market change in communities that is *specific* to each birth cohort. For instance, for the 1980 cohort in county *c*, the change in manufacturing ($\Delta M_{c,1980}$) would be $M_{c,1980}-M_{c,1998}$, while the change in manufacturing for the 1981 cohort ($\Delta M_{c,1981}$) would be $M_{c,1981}-M_{c,1999}$. We might conceptualize the relationship between both parameters as a 2x2 table:

	Low %M	High %M
Low ΔM	A	B
High ΔM	C	D

[24] I alternatively test a measure of union membership rather than union coverage which yields approximately the same results.

Counties that had little manufacturing change over time and little manufacturing at the year of labor market entry are in cell A; counties with high manufacturing change yet still have high manufacturing are in cell D. Cell B represents counties that maintained robust manufacturing industries over a cohort's adolescence and into the years in which they entered the labor market. Cell C, on the other hand, represents counties that once had strong manufacturing but experienced large declines by the time a cohort had entered the labor force. Each of these cells represent vastly different county-/cohort-specific trajectories and experiences.

Simplifying this 2x2 table to display overall county-level trajectories of manufacturing employment, the following figure gives examples for each cell from Wisconsin counties:



Model Specification

I begin by estimating cross-sectional models predicting intergenerational income mobility for birth cohorts born between 1980-1988. The baseline model is estimated as follows:

(Eq. 1) $$Y_{pctile} = \beta_1 M_{18,c} + \beta_2 x + \alpha_g + \mu_c$$

where Y_{pctile} refers to the absolute upward mobility for those in the 25th percentile, $\beta_1 M_{18,c}$ refers to a coefficient and vector of variables for share of manufacturing at age 18 for county c (e.g. for the 1980 cohort, age 18 coincides with the year 1998); $\beta_2 x$ refers to a vector of coefficients and binary coded year variables of year-specific birth cohorts as well as additional covariates; α_g refers to a vector of geography-specific intercepts (set to the commuting zone), and μ_c refers to county-specific error terms. To account for non-independence of cohort observations within counties (i.e. nine birth year cohorts within each county) and states, I cluster standard errors at the state-level. Moreover, I include a set of population weights when estimating the models – the average cohort size for each county.

Next, to estimate the impact of overall change in the share of manufacturing throughout each birth cohort's childhood/adolescence, I estimate the following model which incorporates $\beta_2 \Delta M_c$, the percentage point change in the share of manufacturing between birth and entry into the workforce (e.g. for the 1980 cohort, $\Delta M_c = M_{1980} - M_{1998}$):

(Eq. 2) $$Y_{pctile} = \beta_1 M_{18,c} + \beta_2 \Delta M_c + \beta_3 x + \alpha_g + \mu_c$$

In the final analysis (Eq. 3), I swap out commuting zone fixed effects for county fixed effects:

(Eq. 3) $$Y_{pctile} = \beta_1 M_{18,c} + \beta_2 x + \alpha_c + \mu_c$$

This equation now estimates within-county variation in birth cohort mobility outcomes rather than across-county variation. This identification strategy provides important conceptual and empirical leverage in understanding processes of intergenerational mobility since the estimation is now based on intra-cohort variation in county-level labor market experiences and mobility outcomes. Similar to multivariate models in which individuals have multiple observations over time, this model tracks counties with multiple observations of cohorts over time.

Life-Cycle Bias

The data used in this analysis measures children's intergenerational income mobility in early adulthood at ages 24 and 26. Although prior literature on earnings trajectories over the life course suggests that rank-based measures solidify around these ages for cohorts born prior to the 1980s (Chetty, Hendren, Kline, Saez, et al. 2014; Topel and Ward 1992),[25] it is unknown whether the 1980s cohorts will experience similar patterns of earnings attainment as they continue to age. Life-cycle bias – whether point-in-time income is an accurate representation of average lifetime income (Cheng and Song 2019; Haider and Solon 2006) – might be an issue for this analysis if (a) earnings trajectories change drastically between the 1980 to 1988 cohorts, and (b) the "head start" for individuals who directly enter the labor force after high school is not surpassed by those who complete a higher education degree and enter the labor market sometime in their early 20s.

In the latter case, anticipated lifetime earnings for those with a college degree are on average higher than those with only a high school degree; but a measure of intergenerational income mobility will not represent this average lifetime rank distribution if it is measured when

[25] Topel and Ward (1992) estimate that approximately 2/3rds of lifetime wage growth for individuals occurs during their first decade in the labor market.

those with a college degree are only beginning their careers and have lower job tenure and earnings attainment than those without a college degree who have had more time for career advancement. Moreover, life-cycle bias can also be the result from the inconsistency between point-in-time vs. lifetime measurement of the *parent's* income. Since the current analysis compares 9 successive cohorts, life-cycle bias on the parents' side of the rank-rank measurement should not be an issue when comparing across birth cohorts because the average parents age for these cohorts did not change substantially over this time period (Appendix Figure 1).

I address the broader issue of life-cycle bias by estimating a separate set of models using data from another Opportunity Insights dataset that measures income mobility over a longer period of time, at age 30 (1980-1982 cohorts) and age 31-37 (1978-1983 cohorts). These models, presented in the results section, indicate that the same cross-sectional estimates hold when estimated at a later point in the life course, which provide evidence that life-cycle bias is not driving the results.

The Impact of Manufacturing Decline on Parents Income

Deindustrialization has not only impacted the occupational opportunities of new entrants into the labor force, but also the opportunities of mid- and late-career workers as well. The parents of the children from the 1980-1988 cohort might also experience job displacement and/or income loss as the result of the changing industrial structure of U.S. labor markets. The extent to which this is the case will downwardly bias the estimates of upward mobility (as well as the coefficient estimates in the models) because the parents' income will be lower as the result of deindustrialization induced income loss. The data used in this study do not provide the ability to sidestep this methodological concern entirely, but it does allow for insight into the extent to which this is an issue.

Figure 3 presents a heat map of the share of employment in manufacturing industries by binned age groups (on the y-axis) and year (on x-axis). This figure illustrates that between the 1998-2006 period, the rate of change in manufacturing employment decreased more rapidly for younger workers than older workers. The decline in manufacturing employment for those in the 35-44 and 45-54 age groups decreased much more gradually than those in the late teens and 20s age groups. This graphical representation of manufacturing decline demonstrates that for this 1998-2006 period, we should expect the association to be driven by manufacturing employment decline for the children and not the parents. I directly test whether this is the case by running a set of sensitivity models that separately swap out the overall manufacturing employment parameter for each age group specific manufacturing employment parameter. The results provide strong evidence that the decline of manufacturing employment for older age workers is not overly influencing the findings of the main analysis.

RESULTS

Descriptives

Figure 4 displays the changing distribution of the percentage of jobs in manufacturing between 1980-2016. The average county share of manufacturing employment in 1980 was 28%; in 1990, 23.5%; in 2000, 20.1%; and in 2016, 16.3%. Over this nearly four-decade period, the distribution of manufacturing employment becomes increasingly positively skewed.

Table 1 displays key descriptive statistics for the entire sample. The average share of county-level manufacturing employment during labor market entry (i.e. 1998-2006) for the 1980-1988 cohorts was 14.5% (SD = 9.6). From birth until labor force entry at age 18, these cohorts witnessed an average 10.2 (SD = 7.9) percentage point decline in county-level manufacturing employment.

Variation across Labor Markets

Table 2 displays the coefficients for models estimating rank in the national household income distribution at age 24 (Panel A), age 26 (Panel B), age 30 (Panel C), and ages 31-37 (Panel D) for children whose parents' were located at the 25th percentile of the income distribution. All models presented in this table include commuting zone fixed effects which adjust for unobserved time-varying social, economic, and contextual characteristics shared by counties within the same local labor markets, even for those that span state borders. This level of fixed effects is a more robust adjustment than state fixed effects, although state-level economic and other public policies might be as salient in shaping opportunity structures (e.g. Montez, Hayward, & Zajacova 2019). I address this theoretical concern about the importance of state-level policies in shaping the economic outcomes of cohorts by including a full set of state-by-cohort fixed effects dummies in the final model, Model 3.

I operationalize the industrial composition of labor markets primarily as (a) the share of jobs in a labor market located within the manufacturing sector, expressed as a percentage, and (b) the percentage point change in this share of manufacturing employment between birth and labor market entry. Although employment is the clearest indicator of occupational opportunities in the manufacturing sector, I assess the sensitivity of this measure with two additional operationalizations: (1) the relative percentage of total annual labor market earnings that are taken home by manufacturing workers, and (2) the relative percentage of manufacturing business establishments in a labor market. The number of county-cohort observations for the business establishment models is slightly larger than the employment and annual payroll models because some data on the latter two are suppressed by the Census Bureau to anonymize the business operations of individual companies.[26]

In Panel A and Panel B, Model 1 estimates the percentage of manufacturing coefficient along with commuting zone fixed effects, birth cohort fixed effects, and the full set of covariates previously described in the data section; while Model 2 additionally estimates the percentage point change in manufacturing employment coefficient. In Model 3, I adjust for all state-by-cohort specific trends.

Focusing on the full model, Model 3, for the percentage of manufacturing employment coefficient, the results indicate that a one percentage point increment in manufacturing employment in a county labor market is associated with a significant .079 (S.E. = .015) increase in national household income rank at age 24 (Panel A, Model 3) and a significant .067 (S.E. = .016) increase in national household income rank at age 26 (Panel B, Model 3). For the change in manufacturing employment between birth and labor force entry coefficient, a one percentage point decline in manufacturing employment between birth and labor market entry is associated with a significant -.055 (S.E. = .014) decrease in national household income rank at age 24 (Panel A, Model 3) and a significant -.052 (S.E. = .015) decrease in national household income rank age 26 (Panel B, Model 3). Using the two other operationalizations of the manufacturing composition of labor markets, the results are approximately the same, with mostly equivalent effect sizes and precision of estimates for both the age 24 and age 26 income mobility outcomes.

[26] A dataset by Eckert et al. (2020) was recently released which includes values for these suppressed/missing cells based on an algorithm that accounts for suppression flags in the original CBP data. In the next version of this study, I intend to conduct a sensitivity check which re-estimates models using these imputed values. That said, there are only about 200 missing values for manufacturing employment, so I would not expect the results to change much.

To account for the possibility of life-cycle bias – that is, to determine whether age 24 and age 26 are too early in the life course to accurately evaluate average lifetime rank distributions in income – I present models estimating rank in the national household income distribution at age 30 in Panel C and ages 31-37 in Panel D. Although data are only available here for the combined 1980-1982 cohort and 1978-1983 cohort, respectively, the estimates are similar, albeit half the size, to those that include separate observations for the 9 cohorts in Panels A and B.[27] The results from these models provide evidence that life-cycle bias should not be a concern when interpreting the age 24 and age 26 models.

Overall, what do the results from this table mean? For the percentage manufacturing employment parameter at age 26 (Panel B, Model 3), the difference between counties at the 10th percentile (5.4% of employment in manufacturing) and 90th percentile (27.1% of employment in manufacturing) of the distribution is roughly equivalent to a difference of 1.5 income rank percentiles at age 26. Between the 1st percentile (2% of employment in manufacturing) and the 99th percentile (48.3% of employment in manufacturing) of the distribution, this is equivalent to a 3.1 percentile difference in income mobility.

In terms of the change in manufacturing employment (ΔM) parameter, county-cohorts experienced an average decline of 10.5 percentage points in manufacturing employment between birth and labor market entry, which means that the average decline in intergenerational mobility associated with decline of manufacturing employment is about 0.55 income percentiles. At the 99th percentile (28.9 percentage point loss in manufacturing), ΔM predicts a decline of 1.5 income percentiles.

---

[27] Note, however, that the distribution of variables is different for the models in these final two panels since they are based on aggregate values of the 1980-1982 and 1978-1983 cohorts.

If we return to the conceptual 2x2 table displayed earlier, Kenosha county, Wisconsin has suffered large declines in manufacturing employment over the past four decades. Yet, this experience of decline varies markedly based on *when* cohorts were born. Birth cohort matters not just in terms of the opportunities that are available upon labor market entry at age 18, but also in terms of the shifting 18-year window of history for which each cohort lives through. For Kenosha, the table below calculates the predicted decline in income percentile for each cohort at age 24 and age 26 based on the history of manufacturing decline over adolescence, ages 0-18.

Kenosha			
Cohort	Percentage Point Decline in Manufacturing	Predicted Decline in Income Percentile from ΔM coef (Age 24)	Predicted Decline in Income Percentile from ΔM coef (Age 26)
1980	23.8	-1.4	-1.2
1981	13.0	-0.7	-0.7
1982	14.9	-0.8	-0.8
1983	19.3	-1.1	-1.0
1984	20.5	-1.2	-1.1
1985	25.2	-1.4	-1.3
1986	16.5	-0.9	-0.9
1987	18.8	-1.1	-1.0
1988	20.2	-1.2	-1.1

We see that the $\Delta M_{Kenosha}$ varies by cohort, which meaningfully impacts intergenerational income mobility prospects. The difference between being born in Kenosha in 1980 and 1981 in terms of the ΔM parameter is .7 income percentiles (age 24) and .5 income percentiles (age 26). Meanwhile, differences between other cohorts, such as the 1987 and 1988 cohorts are less substantial.

Variation within Labor Markets

The previous models leverage geographic and temporal (birth cohort) variation to evaluate how different ecological economic contexts produce diverging intergenerational mobility outcomes. These models demonstrate how the geography of deindustrialization has played an important role in shaping the economic fortunes of birth cohorts born throughout the 1980s. Yet, an important question that follows from this analysis is how changing labor market contexts *within* the same community might change the opportunity structure for successive birth cohorts. That is, do annual changes in deindustrialization regulate upward economic movement for birth cohorts as they enter shifting labor market contexts? The nested structure of the income mobility data – nine successive birth cohorts within each county – facilitates an innovative within-county methodological approach that capitalizes on yearly fluctuations in labor market conditions. In this analysis, critically, the interpretation of the estimated parameters differs from the previous across labor market analysis once county fixed effects are incorporated into the regression equation. For the percentage of manufacturing employment coefficient, rather than the cross-sectional interpretation which informs us about the difference in mobility outcomes across places with low- and high-levels of manufacturing, the panel interpretation now informs us about how change across birth cohorts in manufacturing employment upon labor market entry is associated with mobility outcomes.

Table 3 presents the results of the county fixed effects models predicting rank in the national household income distribution at age 24 (Panel A) and age 26 (Panel B).[28] Model 1 and Model 2 separately estimate the percentage of manufacturing employment coefficient and change in manufacturing employment coefficient, respectively, along with relevant covariates; Model 3 simultaneously estimates both coefficients. For Model 1, the coefficient for the percentage of manufacturing employment, $\beta = .066$ (S.E. = .021) is sizeable and statistically

[28] The age 30 and ages 31-37 measures include only one observation per county (i.e. the aggregate 1980-1982 and 1978-1983 cohorts, respectively), so cannot be analyzed through this within-county fixed effects framework.

significant below the $p < .01$ level for the age 24 measure of income mobility (Panel A), but diminishes in magnitude and significance for the age 26 measure of income mobility, $\beta = .030$ (S.E. = .024) (Panel B). Since manufacturing employment declined on average in counties between 1998 to 2006 from 17.1% to 12.6%, a drop of 4.5 percentage points, this 9-year change in county-level manufacturing reduced absolute upward mobility on average by about 0.3 percentiles in the national income distribution between the 1980 and 1988 cohort.[29]

This pattern of results holds when swapping out the measure of manufacturing employment for the measure of manufacturing earnings; but for the business establishment measure, the effect size remains sizeable and statistically significant when predicting both income mobility at age 24 and age 26. Manufacturing business establishments decreased on average by 0.9 percentage points between 1998-2006 (from 5.4% to 4.5%), indicating that on average, counties experienced a reduction in absolute upward mobility by 0.54 percentiles at age 24 and 0.63 percentiles at age 26.

Manufacturing Plants

Table 4 presents the results of equations that swap out the relative measures of manufacturing employment, annual payroll, and business establishments with an absolute measure of the number of manufacturing business establishments that employ over 500 or 1000 workers. These models are equivalent to those estimated in Eq. 3 in the previous section, leveraging variation within counties. For manufacturing business establishments with greater than 500 workers, the results show sizeable and statistically significant results for both age 24

[29] 4.5 * 0.066 = .297

and age 26 measures of income mobility. The results are similar in magnitude for the 1000+ workers measure, but are not statistically significant.

Looking at the 500+ measure for the full model and age 26 income mobility (Panel B, Model 3) the loss of one manufacturing business establishment between is associated with a decrease in income mobility of .047 income percentiles in the national income distribution (S.E. =.011). The average member of the 1980-1988 birth cohorts lived in a county that experienced a drop from 12.64 manufacturing business establishments with 500+ workers in 1998 to 9.07 manufacturing business establishments with 500+ workers in 2006; this average decline of 3.57 businesses of 500+ workers is equivalent to an average decline of .17 income percentiles. The 90th percentile of the 500+ business establishment distribution experienced a decrease from 36 establishments to 27 establishments between 1998-2006, equivalent to a decline of .423 income percentiles in the national income distribution. The 95th percentile experienced a decrease from 89 to 51 business establishments, a decline of 1.8 income percentiles in the national income distribution.

For the long-term change coefficient, one additional lost manufacturing business establishment with 500 or more workers throughout adolescence is associated with a decline of -.018 (S.E.=.004) income percentiles. At the 75th percentile (8 lost establishments), 90th percentile (22 lost establishments), and 95th percentile (73 lost establishments), this is equivalent to a reduction in income rank of 0.14, 0.4, and 1.3 income percentiles in the national income distribution.

It is unclear why the results are only significant when using the 500+ business establishment measure. Perhaps communities with business establishments of such a large size were also more likely to have other employment opportunities available.[30] Overall, however, the results from this section provide further evidence that declines in manufacturing employment are associated with reduced upward mobility outcomes, disadvantaging birth cohorts who were raised in areas that larger declines in manufacturing.

Manufacturing Decline by Age Group

An important assumption of the previously estimated equations is that the structural declines in manufacturing employment are primarily impacting the economic opportunities of the children from these birth cohorts rather than their parents. If the parents of these birth cohorts are experiencing job displacement from the manufacturing sector, and consequently, experiencing substantial reductions in household income, then the estimates from Eq. 1 – Eq. 3 will be biased downwards. That is, the parents' income, measured when the birth cohort is ages 15-19, might be impacted by the same process that is constraining the upward income attainment of the children. I evaluate whether this concern of endogeneity is substantially biasing the results by estimating separate models that use county-level age group specific measures of manufacturing employment to predict upward income mobility. These data are drawn from the Census Bureau's Quarterly Workforce Indicators database and the age groups vary in bin size across the age distribution (e.g. 14-18, 19-21, 22-24, 25-34). If the theoretical model posited throughout this study is correct, then we should expect that the effect size should be largest at the younger end of the age distribution. After all, the decline of manufacturing employment opportunities for new entrants into the labor force is what should be most predictive of reductions in income mobility for these birth cohorts. Conversely, a uniform effect size across

[30] In the next iteration of this analysis, I intend to look at subsets of counties based on urbanicity/rurality to see whether this might explain the discrepancy across the 500+ and 1000+ measure.

the age distribution might suggest that the previous models are underestimating the true effect size, since manufacturing decline for those in mid-life, for instance, are as predictive of changes in intergenerational mobility as manufacturing decline for the 1980s birth cohorts studied in this analysis.

Table 5 and Figure 5 both present the summary results of these models for both the commuting zone and county-fixed effects equations. I estimate these models using the full Model 3 specification used in the prior analyses, adjusting for the ΔM parameter with overall county-level manufacturing because data on age group specific measures from the QWI dataset are only available starting from 1990. For this set of models, I set labor market entry age at 19 – i.e. all covariates are measured for each cohort when they are age 19 – because the QWI data age-group that most aligns with labor market entry is the 19-21 category.

The results show that the magnitude and level of statistical precision are highest for the manufacturing employment coefficients at the younger end of the age distribution. With exception to Panel D (Age 26 income mobility with county fixed effects), there is generally a monotonic decrease in effect size and significance level as the coefficient estimated goes up the age distribution. This suggests that older age manufacturing employment levels do not predict intergenerational income mobility as strongly as younger age manufacturing employment levels. For the ages 19-21 manufacturing employment coefficient in Panel B, a one percentage point increment is associated with a .161 increase in rank in upward mobility at age 26 in the national household income distribution, which is equivalent to a difference between the 10th percentile (3.2% of 19-21 year old's in manufacturing) and 90th percentile (18.5% of 19-21 year old's in manufacturing) of about 3 income percentile ranks. Across the 1st percentile (1.4%) and 99th percentile (40.5%), this represents a difference in upward movement of 6.5 income percentile ranks. The findings from this analysis therefore (a) demonstrate that the potential endogeneity between manufacturing and income should not be impacting the estimation of the previous models too much, but also, (b) the magnitude of the effect size of declining manufacturing on upward mobility is even larger when swapping out the overall county measure of manufacturing for an age-specific measure of manufacturing.

Out-Migration

People are not confined to the geographic community in which they were raised. In a community with poor economic opportunities – either lacking in the availability of jobs or the quality of jobs – workers might seek employment elsewhere either by commuting on a daily basis or out-migrating entirely. The county-cohort specific estimates of intergenerational income mobility used in this study link the income rank of the parents of the birth cohort in a particular county to the income rank of the children regardless of whether they remain or move out of their county of origin. Literature on residential migration indicates that rates of cross-region, cross-state, and cross-county moves have been decreasing in recent decades; in 2000, the 5-year cross-state migration rate was 8.9% while the cross-county migration rate was 18.6% (Molloy, Smith, and Wozniak 2011).[31] This secular decline in short- and long-distance residential moves coincides with reductions in the wage returns to changing employers, suggesting that people are now less likely to move across state boundaries for labor market reasons (Molloy, Smith, and Wozniak 2013). Children of the 1980s birth cohorts have also been more likely to live in their parental home through their 30s (Mykyta 2012; U.S. Census Bureau 2020).

[31] Lifetime rates of cross-state migration for all U.S. citizens in 2000 was 32% (Molloy et al. 2011).

Given these empirical trends that document that younger workers are less likely to move away from their origin communities, out-migration is unlikely to be driving these findings. Nevertheless, to assess whether selective out-migration affects the results, I estimated models that partitioned counties according to whether they had positive or negative net migration rates. Since data on annual county- and age-specific estimates of net migration rates are unavailable, I relied on decadal county data of net-migration rates for 20-24 year old's estimated by the Applied Population Laboratory at UW-Madison (Winkler et al. 2013).

The results, presented in Appendix Table 1, suggest that the coefficient for the percentage of manufacturing employment is statistically significant only for counties with positive net migration rates. The coefficient is about three times larger for areas with positive net migration than negative net migration, although the difference between the two are not statistically significant. For the manufacturing change between birth and labor force entry coefficient, the effect is sizeable and negative for both subsets of counties, but less precisely estimated for areas with positive net migration. In sum, the results from these models demonstrate how the downward influence of local labor market opportunities in the community of origin persists irrespective of whether counties experienced positive or negative net migration; at the same time, historical decline of manufacturing opportunities is more salient in reducing upward mobility for counties with negative net migration patterns.

Subgroup Analyses

The aim of the preceding analyses was to determine whether and to what extent manufacturing decline has contributed to geographic and temporal disparities in intergenerational income mobility. But labor market inequalities often result in disparate social and economic outcomes across population subgroups, such as race, ethnicity, gender, and class. In this section, I test whether deindustrialization has occurred evenly across population subgroups to determine whether the postindustrial transition from a goods-producing economy to a service-providing economy might be contributing to growing disparities in upward economic mobility.

I draw on a separate Opportunity Insights dataset (Chetty et al. 2018) to access county-level race/ethnicity- and gender-specific estimates of upward income mobility for the aggregate 1978-1983 birth cohort. I combine these measures of intergenerational mobility with equivalent covariates that average the county-cohort experiences of these four birth cohorts. Unlike the previously estimated models that measure income mobility at age 24, 26, 30, or 31-37, the income mobility measures used in this analysis were accessed from tax records when these birth cohorts were only between the ages of 31-37. To ensure that the mobility outcomes of men and women are not biased by the income of their partners or spouses (i.e. total household income), I use mobility estimates that are based on where men and women end up in the national *individual* income distribution.

The results presented in Table 6A and 6B, show that the change in manufacturing employment coefficient is approximately three times larger and more precisely estimated for non-Hispanic Black men than non-Hispanic white, but the coefficient is small and non-significant for Hispanic men.[32] In contrast, the effect size is small and non-significant above the $p < .05$ threshold for Black, white, and Hispanic women. For the change in manufacturing coefficient, the effect is large and significant for white and Hispanic men, but not for any of the female racial/ethnic groups. These results provide evidence that deindustrialization is not a uniform process across these race/ethnicity and gender stratified groups, but rather a contributor

[32] These results roughly hold if I limit the white male sample to only the sample of counties available for the Black male sample.

to differential economic outcomes which constrain upward mobility for certain groups more severely than others. They also indicate two separate pathways through which deindustrialization differentially impacts groups of workers: (1) the direct availability of manufacturing sector jobs upon labor market entry, which impacts Black male workers the most, and (2) the long-term decline manufacturing from local labor markets, which impacts Hispanic and white male workers the most.

Extended Analysis: 1960-1980 Cohorts

The results presented here, rather than being evidence an ongoing trend, might just be a period effect: the labor market entry conditions experienced by the 1980-1988 cohorts were specific to social and economic events between 1998-2006, such as the dot-com bubble, 9/11, and the beginning of the Afghanistan and Iraq wars. The 1983 and later cohorts experienced the Great Recession early in their work-life, economic events that would impact their financial fortunes and occupational opportunities prior to the age 24 measure of intergenerational income mobility. A related issue is that these nine cohorts entered the labor force sometime between the middle to tail-end of the overall manufacturing decline that has occurred since the 1970s. It would be informative to gauge whether we can extrapolate the experiences of these cohorts to a broader range of cohorts.

To further evaluate and contextualize the findings in the broader scale of the process of contemporary deindustrialization in the U.S., I draw on an analogous set of state-level measures of intergenerational income inequality estimated by Chetty, Grusky, et al. (2017) using linked cross-sections of CPS and Census data spanning eight decades, focusing on birth cohorts born in 1960, 1970, and 1980. The measure of mobility here is slightly different and not directly comparable to the results previously estimated – the *state*-level mean probability that a child's earnings will surpass their parents between ages 25-35; this is an absolute measure of intergenerational mobility – but the goal of this analysis is to assess whether the results presented throughout this study are the continuation of an ongoing process of structural economic change.

Table 7 presents the results from this analysis, which only has 146 observations from 50 states plus the District of Columbia. There are no covariates with exception to adjusting for cohort/year of labor market entry. These models are estimated using variation within states (similar to Eq. 3), and the manufacturing levels are estimated at entry into the labor market at age 18.[33] A one-point increase in share of manufacturing employment in a state is associated with an increase of .18 (SD=.086) in the probability of surpassing parent's earnings. Over this 20-year time span, from 1978 to 1998, the share of state-level manufacturing employment declined from 26.2% to 15.2%, a drop of 11 percentage points which would account for an average decline of about 2 percentage points in the probability of a child surpassing parent's earnings. For states that experienced sharp declines such as Michigan and Ohio which witnessed drops of about 20 percentage points in the share of manufacturing employment, this calculates to a 3.6 percentage point drop in the probability of surpassing parent's earnings between ages 25-35. Although less weight should be given to these results given the limitations of the small model, they are one final indication that the main findings presented in this study fit into a broader structural process that has been ongoing in the U.S. since about the second half of the 20th century.

DISCUSSION

The aim of this study was twofold: first, to examine whether the changing industrial composition of U.S. labor markets – and consequently, the availability of middle wage job

[33] Over this broad timeframe, there might be differences across cohorts in the share going onto college versus ending educational attainment with a college degree (Kahn 2010), as well as differences in the average age at high school completion. This might make the age 18 of labor market entry assumption less stable.

opportunities – has suppressed upward intergenerational mobility; and second, to test whether this structural transformation might be exacerbating inequalities in upward intergenerational mobility across population subgroups. I constructed a detailed county-level dataset that consisted of cohort-varying measures of labor market characteristics and intergenerational income mobility. The unique panel structure and modeling strategy of this analysis demonstrates the analytical utility of conceptualizing how variation across and within ecological economic contexts can produce economic disparities in economic attainment across generations. Rather than examining individual-level intergenerational mobility, the present study contributes to the literature on stratification processes by giving precedence to the compositional role of labor markets on aggregate population processes. As deindustrialization transforms the nature of work in the U.S. and globally, this macro-level approach clarifies the population-level consequences. The findings illustrate how the geography of economic mobility is appreciably determined by ecological features of local labor markets.

The results provide four new important findings and contributions to the literature on social stratification, labor market inequality, and life course trajectories. First, for birth cohorts born between 1980-1988, entering a labor market with a high relative share of manufacturing jobs was associated with increased upward income mobility in adulthood in comparison to entering a labor market with fewer manufacturing jobs. This finding is perhaps the most robust association estimated in this study, showing durability regardless of whether the child's income attainment was measured at age 24, 26, 30, or 31-37, and irrespective of cohort. For the age 26 measure, for instance, the difference between being raised in the bottom 1st percentile and top 99th percentile of areas with manufacturing employment translates into a gap of 3.1 income percentile ranks of upward mobility.

The second primary finding of this study is that industrial composition doesn't only matter in terms of the immediate availability of job opportunities, but also in terms of how industrial change has impacted communities over time. The social and economic contexts of communities can change drastically over time; the opportunities that parents expect will be available to their children when they reach adulthood can dissipate by the time the children's birth cohort enters the labor force almost two decades after birth. As demonstrated in this analysis, the amount and pace of labor market change varies considerably across U.S. counties. How might this industrial change manifest itself and contribute to reductions in upward mobility? Possibilities might include deterioration of the built environment (e.g. idled or shuttered factories) as a reminder of vanished opportunity (Goldstein 2017), economic "despair" initiated by the lack of economic opportunities (Case and Deaton 2017; Shanahan et al. 2019), and demographic changes such as economic out-migration and shifting age distributions. The findings accentuate the importance of this change over time: larger long-term losses in relative manufacturing employment were associated with reduced upward mobility. Long-term manufacturing decline was associated with an average reduction of half of an income percentile in upward movement in the national income rank distribution, with areas that experienced the sharpest reductions in manufacturing employment experiencing a reduction of 1.5 income rank percentiles in upward mobility.

Third, the findings provide partial evidence that annual shifts in manufacturing employment *within* community labor markets suppress upward intergenerational income mobility. Between 1980-1988, manufacturing employment predicts a decrease in upward mobility by about a third of an income percentile. While this effect size seems modest over this brief 9-year period, the effect is much larger if we place these cohorts into the broader context of

U.S. deindustrialization, a process that began in the 1970s and continues today. And in fact, in a sensitivity analysis that examined state-level manufacturing decline and intergenerational mobility for cohorts born in 1960, 1970, and 1980 (entering the labor market in 1978, 1988, and 1998), the results provide support that this process of industrial change has been occurring over a broader span of time than the lifetimes of the 1980 birth cohorts. The present study therefore contributes to literature on life course transitions, demonstrating how the fortunes of birth cohorts vary according to historical time and place (Elder 1998).

The final finding of this study is perhaps the most alarming: the decline of middle-wage manufacturing employment has been more severe for some population subgroups than others. Manufacturing decline is associated with larger reductions in upward income mobility for black male workers than white male workers. This finding provides evidence that the transition to a post-industrial society is exacerbating present day inequalities and aligns with other recent findings on rising labor market inequality associated with the decline of the manufacturing sector (Wrigley-field and Seltzer 2020).

Limitations

An important limitation of this analysis is that the manufacturing and mobility measures are aggregate and ecological, which means that the models estimated here should only be used to describe macro-level cohort and county processes. Yet, this macro-level approach is informative because it charts out meaningful variation in opportunity structures across and within birth cohorts and geographic areas. Rather than a constraint, this population-level emphasis provides novel insight into how ecological economic contexts can meaningfully shape social mobility across generations. That said, readers should take caution when using this research to describe individual-level social mobility. While I attempt to address several issues that might bias the results of aggregate analysis (i.e. geographic out-migration), this analysis cannot fully account for variation across individuals. Future research should link data on individual-level work histories with contextual, community-specific labor market characteristics in order to evaluate how structural economic changes have impacted upward economic mobility. The Conclusion Chapter of this dissertation presents portions of a recently submitted grant proposal for using data from the National Longitudinal Study of Adolescent to Adult Health (Add Health) to explore how both the individual-level experiences and aggregate-level processes of deindustrialization have hampered intergenerational income mobility.

As noted throughout this study, three other important concerns/limitations of this analysis include (a) life-cycle bias, (b) the impacts of deindustrialization on parental income rank, and (c) geographic out-migration. Through robustness models that swapped out the age 24 and age 26 measures of income mobility for age 30 and ages 31-37 measures of income mobility, the results generally remained the same; this suggests that life-cycle bias should not be overly influencing the findings, although the effect size does diminish slightly as these cohorts age. This might suggest that later birth cohorts were able, to some extent, surmount the economic penalties they faced from declining opportunities in the manufacturing sector. Regardless if life-cycle bias were a larger concern, the results would still demonstrate how early adult trajectories of income rank are impacted by changes to the industrial composition of labor markets.

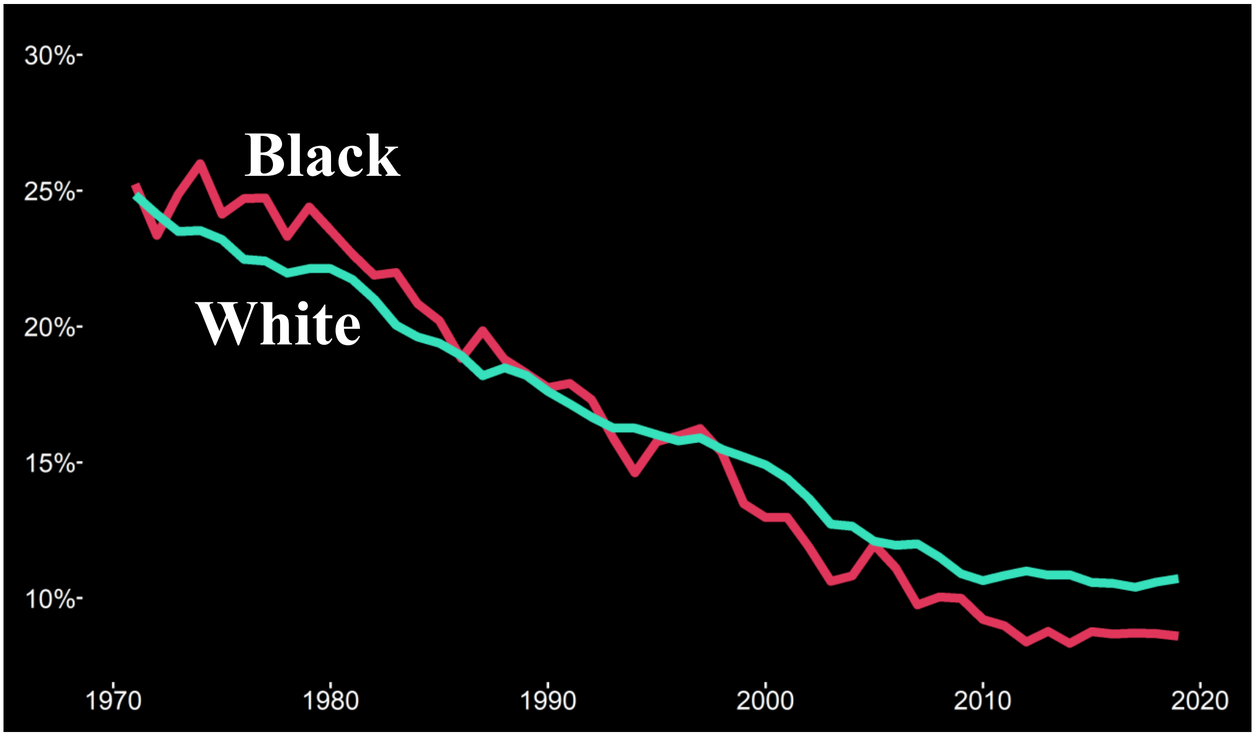
I address the potential endogeneity issue of manufacturing decline downwardly biasing the estimates of upward intergenerational mobility by estimating a set of separate models that swap out overall county- and cohort-/year-specific measures of manufacturing employment for *age group*-, county-, and cohort-/year-specific measures of manufacturing employment. These sensitivity models document a larger and more highly significant relationship between manufacturing employment and intergenerational mobility at the younger end of the age distribution. This implies that the main models are not unduly impacted by this endogeneity concern; yet, the data and modeling strategy are unable to entirely quantify the extent to which this might downwardly bias the estimates. Finally, I address the impact of selective out-migration by estimating stratified models according to positive or negative rates of net migration. There is no significant difference in the effect size of the manufacturing employment parameter across these two categories of counties, which provides some evidence that the results are not driven by geographic mobility.

CONCLUSIONS

In short, the results suggest four new important findings and contributions. First, children from the 1980-1988 cohorts who lived in counties with a higher share of manufacturing – operationalized as either business establishments, employment, or annual payroll – experienced increased income mobility outcomes in comparison to those who lived in counties with a lower share of manufacturing. Second, children from these cohorts who lived in counties that experienced larger contractions in manufacturing throughout their adolescence faced larger economic penalties in adulthood via reduced levels of upward intergenerational mobility. Third, the specific experiences of birth cohorts within counties upon entry into the labor market impacted their prospects for upward mobility, although only when income mobility was measured at age 24 and not age 26. Fourth, there are substantial differences in the effect size of manufacturing employment across population subgroups, which indicate that the process of deindustrialization might be exacerbating present day and historical inequalities in movement up the income distribution. This research therefore charts a new direction in the literature on social stratification being the first study to directly examine how variation in the loss of manufacturing jobs across labor markets has contributed to growing disparities in upward mobility across geographic areas, birth cohorts, racial/ethnic groups, and gender. It also refocuses the discussion about *who* is impacted by deindustrialization since the research design emphasizes comparisons across race/ethnicity and gender.

FIGURES

Figure 1. Percentage of Black and White Workers Employed in Manufacturing Jobs between 1970-2019



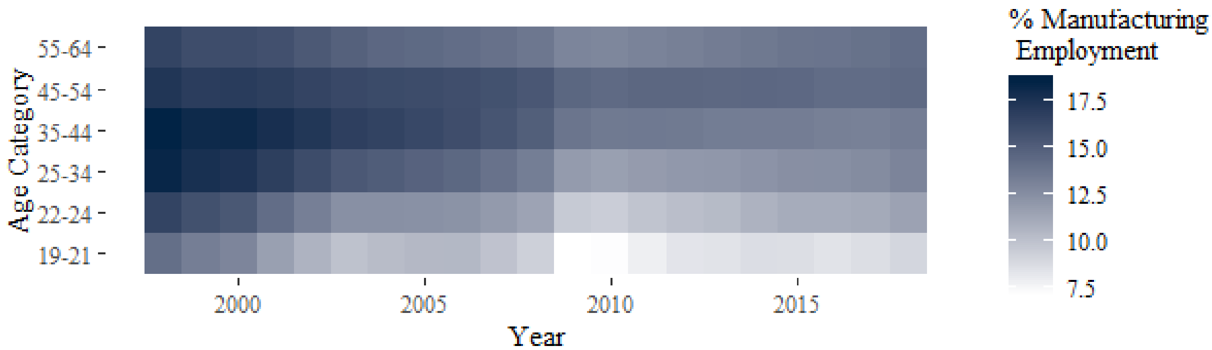
Black workers (red), white workers (green). Data: Current Population Survey.

Figure 2. Example Schematic of Dataset for Birth Cohort Observations from Kenosha County, Wisconsin

County	Cohort	Year	Age 24 Mobility	Age 26 Mobility[1]	% Manufacturing	Δ Manufacturing
Kenosha, WI	1980	1998	44.4	41.1	23.3	23.8
Kenosha, WI	1981	1999	46.7	43.1	24.3	13.0
Kenosha, WI	1982	2000	44.5	40.7	24.7	14.9
…	…	…	…	…	…	…
Kenosha, WI	1988	2006	42.8	NA	17.6	20.2

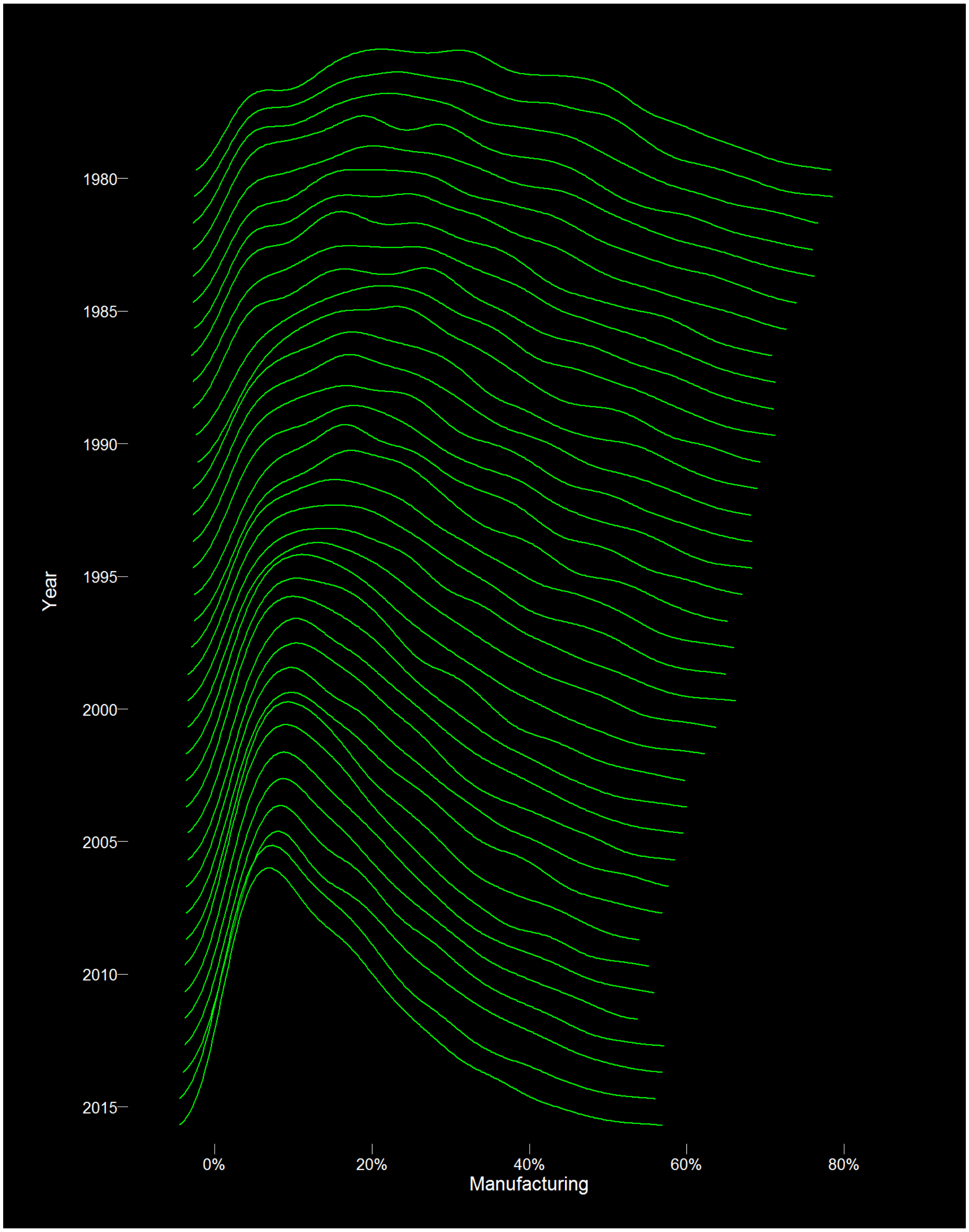
Notes: [1]Estimates of income distribution rank at age 26 are only available for the 1980-1986 birth cohorts.

Figure 3. Heat Map of the Average Share of Manufacturing Employment by Age Group



Data: Census Bureau, Quarterly Workforce Indicators Dataset

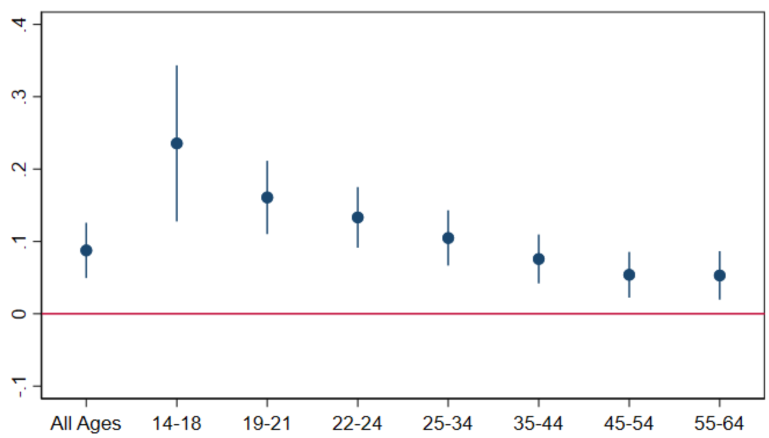
Figure 4. Annual County-Level Distribution of Manufacturing Employment, 1980-2016



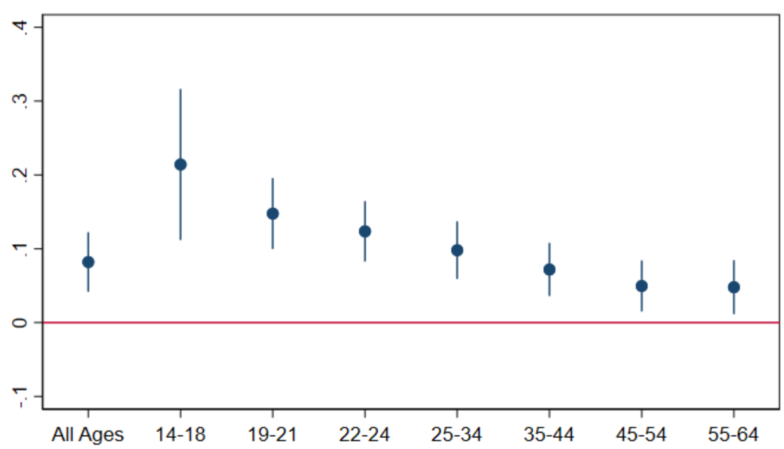
Notes: The average county share of manufacturing employment in 1980 was 28%; in 1990, 23.5%; in 2000, 20.1%; and in 2016, 16.3%.

Figure 5. Models Predicting Intergenerational Income Mobility using Age Category Specific Measures of Manufacturing Employment

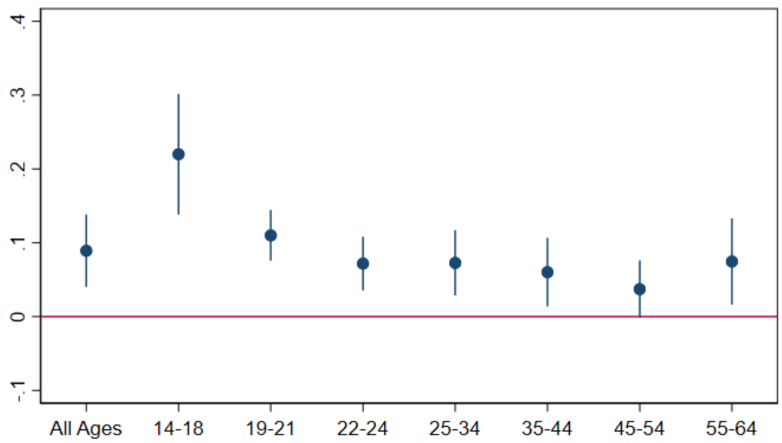
A. Rank in national household income distribution at age 24 – Commuting Zone Fixed Effects



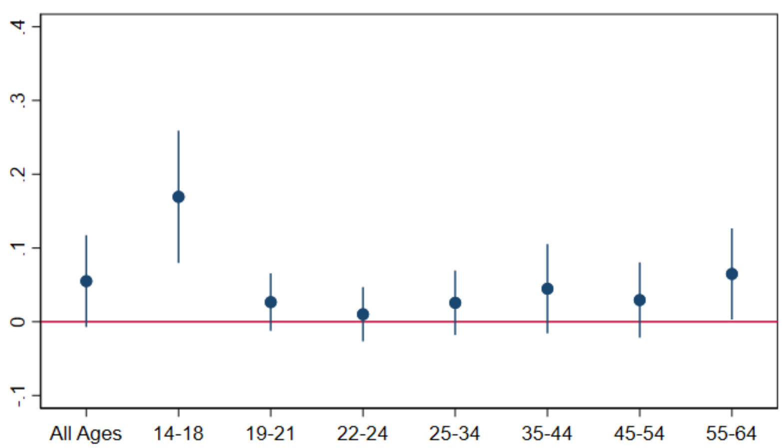
B. Rank in national household income distribution at age 26 – Commuting Zone Fixed Effects



C. Rank in national household income distribution at age 24 – County Fixed Effects



D. Rank in national household income distribution at age 26 – County Fixed Effects



TABLES

Table 1. Descriptive Statistics

Variable	Mean	Std. Dev.
25^{th} percentile origin at age 24	46	4.4
25^{th} percentile origin at age 26	44.3	4.4
Employment		
% Manufacturing	14.4	9.6
Δ Manufacturing	10.2	7.9
Annual Payroll		
% Manufacturing	18.3	12.7
Δ Manufacturing	12.0	10
Establishments		
% Manufacturing	5.0	1.9
Δ Manufacturing	1.9	1.8

Table 2. Parameter Estimates of Manufacturing Measures from Commuting Zone Fixed Effects Models Predicting Intergenerational Income Mobility at Age 24 (Panel A) and Age 26 (Panel B) for 1980-1988 Cohorts, Age 30 (Panel C) for Combined 1980-1982 Cohorts, and Age 31-37 (Panel D) for Combined 1978-1983 Cohorts

A. Rank in national household income distribution at age 24

	Employment			Annual Payroll			Business Establishments		
	M1	M2	M3	M1	M2	M3	M1	M2	M3
% Manufacturing	0.085***	0.088***	0.079***	0.053***	0.052***	0.044***	0.342***	0.346***	0.241***
	(0.016)	(0.016)	(0.015)	(0.011)	(0.011)	(0.010)	(0.058)	(0.060)	(0.068)
Δ Manufacturing		-0.057***	-0.055***		-0.044***	-0.046***		-0.038	0.043
(cohort: age 0-18)		(0.015)	(0.014)		(0.011)	(0.010)		(0.072)	(0.070)
Commuting Zone FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE X Cohort FE	No	No	Yes	No	No	Yes	No	No	Yes
Observations	11666	11666	11666	11666	11666	11666	11855	11855	11855
R2	0.782	0.785	0.833	0.781	0.784	0.832	0.781	0.781	0.828

B. Rank in national household income distribution at age 26

	Employment			Annual Payroll			Business Establishments		
	M1	M2	M3	M1	M2	M3	M1	M2	M3
% Manufacturing	0.069***	0.071***	0.067***	0.039**	0.038**	0.033**	0.259***	0.252***	0.177**
	(0.016)	(0.016)	(0.016)	(0.011)	(0.011)	(0.011)	(0.055)	(0.057)	(0.063)
Δ Manufacturing		-0.054***	-0.052***		-0.044***	-0.046***		0.060	0.125
(cohort: age 0-18)		(0.014)	(0.015)		(0.010)	(0.011)		(0.063)	(0.071)
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE X Cohort FE	No	No	Yes	No	No	Yes	No	No	Yes
Observations	9179	9179	9179	9179	9179	9179	9325	9325	9325
R2	0.801	0.804	0.837	0.799	0.803	0.836	0.800	0.800	0.832

C. Rank in national household income distribution at age 30									
	Employment			Annual Payroll			Business Establishments		
	M1	M2	M3	M1	M2	M3	M1	M2	M3
% Manufacturing	0.032**	0.030*	0.030*	0.012	0.010	0.009	0.175***	0.166***	0.157**
	(0.011)	(0.011)	(0.012)	(0.008)	(0.009)	(0.009)	(0.048)	(0.047)	(0.049)
Δ Manufacturing		-0.043**	-0.045***		-0.039***	-0.041***		0.101*	0.109*
(cohort: age 0-18)		(0.013)	(0.013)		(0.010)	(0.010)		(0.049)	(0.050)
Commuting Zone FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	No	Yes	No	No	Yes	No	No	Yes
Observations	2511	2511	2511	2511	2511	2511	2709	2709	2709
R2	0.870	0.873	0.879	0.869	0.872	0.878	0.868	0.869	0.875

D. Rank in national household income distribution at age 31-37									
	Employment			Annual Payroll			Business Establishments		
	M1	M2	M3	M1	M2	M3	M1	M2	M3
% Manufacturing	0.030*	0.030*	0.029*	0.011	0.011	0.010	0.204***	0.168**	0.155**
	(0.013)	(0.014)	(0.014)	(0.010)	(0.010)	(0.011)	(0.056)	(0.052)	(0.055)
Δ Manufacturing		-0.034*	-0.032*		-0.035**	-0.033**		0.159**	0.157**
(cohort: age 0-18)		(0.014)	(0.014)		(0.011)	(0.011)		(0.052)	(0.053)
Commuting Zone FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	No	Yes	No	No	Yes	No	No	Yes
Observations	2642	2642	2642	2642	2642	2642	3008	3008	3008
R2	0.876	0.878	0.886	0.875	0.878	0.885	0.873	0.875	0.883

* p<.05, ** p<.01, *** p<.001 (two tailed tests)

Notes: (a) Age 24 (Panel A) and age 26 (Panel B) models include 9 separate cohorts born between 1980-1988 nested within each county; Age 30 (Panel C) models include only a combined 1980-1982 cohort, Age 31-37 (Panel D) models include only a combined 1978-1983 cohort. (b) Models are weighted by average within-county cohort size at age 18, (c) Standard errors clustered at the state-level, (d) covariates include birth cohort FE (for the age 24 and age 26 models), cohort population at age 18, % of cohort black, county poverty rate, county logged per capita income adjusted to year 2000 dollars, county unemployment rate, county-level % with high school or less educational attainment, state-level % of workers represented by labor unions, and county % working age population and % old age dependent population, (e) All covariates are time-varying for when cohort is age 18.

Table 3. Parameter Estimates of Manufacturing Measures from County Fixed Effects Models Predicting Intergenerational Income Mobility at Age 24 (Panel A) and Age 26 (Panel B)

	Employment			Annual Payroll			Business Establishments		
A. Rank in national household income distribution at age 24									
	M1	M2	M3	M1	M2	M3	M1	M2	M3
% Manufacturing	0.066**		0.038	0.040*		0.030	0.649***		0.589**
	(0.021)		(0.029)	(0.015)		(0.022)	(0.177)		(0.188)
Δ Manufacturing		-0.043**	-0.030		-0.022*	-0.011		-0.243*	-0.109
(cohort: age 0-18)		(0.012)	(0.017)		(0.009)	(0.013)		(0.107)	(0.110)
Commuting Zone FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE X Cohort FE	No	No	Yes	No	No	Yes	No	No	Yes
Observations	11666	11666	11666	11666	11666	11666	11855	11855	11855
R2	0.081	0.081	0.082	0.080	0.079	0.080	0.087	0.080	0.088
B. Rank in national household income distribution at age 26									
	Employment			Annual Payroll			Business Establishments		
	M1	M2	M3	M1	M2	M3	M1	M2	M3
% Manufacturing	0.030		0.005	0.012		0.002	0.700***		0.695***
	(0.024)		(0.031)	(0.017)		(0.024)	(0.143)		(0.155)
Δ Manufacturing		-0.027*	-0.025		-0.011	-0.010		-0.192**	-0.008
(cohort: age 0-18)		(0.013)	(0.016)		(0.009)	(0.013)		(0.071)	(0.074)
Commuting Zone FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE X Cohort FE	No	No	Yes	No	No	Yes	No	No	Yes
Observations	9179	9179	9179	9179	9179	9179	9325	9325	9325
R2	0.054	0.055	0.055	0.054	0.054	0.054	0.067	0.055	0.067

* p<.05, ** p<.01, *** p<.001 (two tailed tests)

Notes: (a) Age 24 (Panel A) and age 26 (Panel B) models include 9 separate cohorts born between 1980-1988 nested within each county; (b) Models are weighted by average within-county cohort size at age 18, (c) Standard errors clustered at the state-level, (d) covariates include birth cohort FE (for the age 24 and age 26 models), cohort population at age 18, % of cohort black, county poverty rate, county logged per capita income adjusted to year 2000 dollars, county unemployment rate, county-level % with high school or less educational attainment, state-level % of workers represented by labor unions, and county % working age population and % old age dependent population, (e) All covariates are time-varying for when cohort is age 18.

Table 4. Parameter Estimates of Manufacturing Measures from County Fixed Effects Models Predicting Intergenerational Income Mobility at Age 24 (Panel A) and Age 26 (Panel B) Using Absolute Measures of Manufacturing Decline

A. Rank in national household income distribution at age 24						
	500+ Employees			1000+ Employees		
	M1	M2	M3	M1	M2	M3
# Manufacturing	0.040***		0.036**	0.060*		0.045
Establishments	(0.009)		(0.011)	(0.028)		(0.038)
Δ Manufacturing		-0.040**	-0.038***		-0.029	-0.023
(cohort: age 0-18)		(0.014)	(0.010)		(0.032)	(0.030)
Commuting Zone FE	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
State FE X Cohort FE	No	No	Yes	No	No	Yes
Observations	11860	11855	11855	11860	11855	11855
R2	0.084	0.090	0.095	0.079	0.078	0.079

B. Rank in national household income distribution at age 26						
	500+ Employees			1000+ Employees		
	M1	M2	M3	M1	M2	M3
# Manufacturing	0.051**		0.047***	0.060		0.047
Establishments	(0.015)		(0.011)	(0.033)		(0.035)
Δ Manufacturing		-0.022**	-0.018***		-0.021	-0.014
(cohort: age 0-18)		(0.007)	(0.004)		(0.018)	(0.015)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
State FE X Cohort FE	No	No	Yes	No	No	Yes
Observations	9328	9325	9325	9328	9325	9325
R2	0.066	0.058	0.068	0.056	0.054	0.056

* p<.05, ** p<.01, *** p<.001 (two tailed tests)

Notes: (a) Age 24 (Panel A) and age 26 (Panel B) models include 9 separate cohorts born between 1980-1988 nested within each county; (b) Models are weighted by average within-county cohort size at age 18, (c) Standard errors clustered at the state-level, (d) covariates include birth cohort FE (for the age 24 and age 26 models), cohort population at age 18, % of cohort black, county poverty rate, county logged per capita income adjusted to year 2000 dollars, county unemployment rate, county-level % with high school or less educational attainment, state-level % of workers represented by labor unions, and county % working age population and % old age dependent population, (e) All covariates are time-varying for when cohort is age 18.

Table 5. Models Predicting Intergenerational Income Mobility using Age Category Specific Measures of Manufacturing Employment

A. Rank in national household income distribution at age 24 – Commuting Zone Fixed Effects								
	All Ages	14-18	19-21	22-24	25-34	35-44	45-54	55-64
% Manufacturing	0.088***	0.235***	0.161***	0.133***	0.105***	0.076***	0.054**	0.053**
	(0.019)	(0.054)	(0.025)	(0.021)	(0.019)	(0.017)	(0.016)	(0.017)
Δ Manufacturing	-0.062***	-0.047**	-0.041**	-0.046***	-0.055***	-0.061***	-0.063***	-0.063***
(cohort: age 0-19)	(0.016)	(0.015)	(0.013)	(0.013)	(0.014)	(0.015)	(0.017)	(0.017)
Observations	8372	8365	8372	8372	8372	8372	8372	8372
R2	0.839	0.839	0.844	0.844	0.843	0.839	0.836	0.836
B. Rank in national household income distribution at age 26 – Commuting Zone Fixed Effects								
	All Ages	14-18	19-21	22-24	25-34	35-44	45-54	55-64
% Manufacturing	0.082***	0.214***	0.148***	0.124***	0.098***	0.072***	0.050**	0.048*
	(0.020)	(0.051)	(0.024)	(0.020)	(0.019)	(0.018)	(0.017)	(0.018)
Δ Manufacturing	-0.056**	-0.043*	-0.036*	-0.041**	-0.050**	-0.055**	-0.057**	-0.057**
(cohort: age 0-19)	(0.017)	(0.017)	(0.014)	(0.014)	(0.015)	(0.017)	(0.018)	(0.019)
Observations	7140	7134	7140	7140	7140	7140	7140	7140
R2	0.840	0.839	0.844	0.844	0.843	0.840	0.837	0.837
C. Rank in national household income distribution at age 24 – County Fixed Effects								
	All Ages	14-18	19-21	22-24	25-34	35-44	45-54	55-64
% Manufacturing	0.089***	0.220***	0.110***	0.072***	0.073**	0.060*	0.037	0.075*
	(0.024)	(0.041)	(0.017)	(0.018)	(0.022)	(0.023)	(0.019)	(0.029)
Δ Manufacturing	-0.042***	-0.041***	-0.034**	-0.038**	-0.040**	-0.044***	-0.048***	-0.046***
(cohort: age 0-19)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.012)	(0.011)	(0.011)
Observations	8372	8365	8372	8372	8372	8372	8372	8372
R2	0.116	0.120	0.121	0.117	0.116	0.115	0.114	0.116
D. Rank in national household income distribution at age 26 – County Fixed Effects								
	All Ages	14-18	19-21	22-24	25-34	35-44	45-54	55-64
% Manufacturing	0.055	0.169***	0.027	0.010	0.026	0.045	0.029	0.065*
	(0.031)	(0.045)	(0.019)	(0.018)	(0.022)	(0.030)	(0.025)	(0.031)
Δ Manufacturing	-0.011	-0.010	-0.013	-0.015	-0.013	-0.013	-0.015	-0.013
(cohort: age 0-19)	(0.010)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Observations	7140	7134	7140	7140	7140	7140	7140	7140
R2	0.084	0.088	0.083	0.083	0.083	0.084	0.083	0.085

* p<.05, ** p<.01, *** p<.001 (two tailed tests)

Notes: (a) all models include 9 separate cohorts born between 1980-1988 nested within each county; (b) Models are weighted by average within-county cohort size at age 18, (c) Standard errors clustered at the state-level, (d) covariates include birth cohort FE (for the age 24 and age 26 models), cohort population at age 18, % of cohort black, county poverty rate, county logged per capita income adjusted to year 2000 dollars, county unemployment rate, county-level % with high school or less educational attainment, state-level % of workers represented by labor unions, and county % working age population and % old age dependent population, (e) All covariates are time-varying for when cohort is age 18.

Table 6A. Male – Race-Specific Regression Models

A. Black Male						
	Employment		Annual Payroll		Business Establishments	
	M1	M2	M1	M2	M1	M2
% Manufacturing	0.066***	0.068***	0.047***	0.048***	0.111	0.121
	(0.016)	(0.016)	(0.013)	(0.013)	(0.066)	(0.066)
Δ Manufacturing	0.001	0.005	-0.010	-0.008	0.238***	0.248***
(cohort: age 0-19)	(0.016)	(0.017)	(0.012)	(0.014)	(0.060)	(0.058)
Observations	13530	13530	13530	13530	14487	14487
R2	0.625	0.653	0.625	0.653	0.620	0.648
B. White Male						
	Employment		Annual Payroll		Business Establishments	
	M1	M2	M1	M2	M1	M2
% Manufacturing	0.017	0.018	0.008	0.009	0.054	0.045
	(0.010)	(0.010)	(0.008)	(0.008)	(0.067)	(0.068)
Δ Manufacturing	-0.029***	-0.031***	-0.025***	-0.028***	0.095*	0.088*
(cohort: age 0-19)	(0.009)	(0.009)	(0.006)	(0.007)	(0.037)	(0.038)
Observations	22067	22067	22067	22067	26806	26806
R2	0.867	0.873	0.867	0.873	0.854	0.860
C. Hispanic Male						
	Employment		Annual Payroll		Business Establishments	
	M1	M2	M1	M2	M1	M2
% Manufacturing	0.004	0.006	-0.004	-0.002	0.045	0.020
	(0.018)	(0.018)	(0.013)	(0.014)	(0.081)	(0.084)
Δ Manufacturing	-0.047***	-0.046**	-0.034**	-0.035**	0.070	0.085
(cohort: age 0-19)	(0.014)	(0.015)	(0.011)	(0.012)	(0.074)	(0.075)
Observations	14549	14549	14549	14549	15857	15857
R2	0.644	0.656	0.644	0.656	0.638	0.651

* p<.05, ** p<.01, *** p<.001 (two tailed tests)

Notes: (a) all models include 9 separate cohorts born between 1980-1988 nested within each county; (b) Models are weighted by average within-county cohort size at age 18, (c) Standard errors clustered at the state-level, (d) covariates include birth cohort FE (for the age 24 and age 26 models), cohort population at age 18, % of cohort black, county poverty rate, county logged per capita income adjusted to year 2000 dollars, county unemployment rate, county-level % with high school or less educational attainment, state-level % of workers represented by labor unions, and county % working age population and % old age dependent population, (e) All covariates are time-varying for when cohort is age 18.

Table 6B. Female – Race-Specific Regression Models

A. Black Female						
	Employment		Annual Payroll		Business Establishments	
	M1	M2	M1	M2	M1	M2
% Manufacturing	0.022	0.020	0.016	0.015	-0.024	-0.059
	(0.012)	(0.013)	(0.009)	(0.010)	(0.057)	(0.061)
Δ Manufacturing	0.020	0.020	0.011	0.011	0.149**	0.154**
(cohort: age 0-19)	(0.013)	(0.014)	(0.010)	(0.010)	(0.046)	(0.049)
Observations	13449	13449	13449	13449	14415	14415
R2	0.682	0.692	0.682	0.692	0.680	0.690
B. White Female						
	Employment		Annual Payroll		Business Establishments	
	M1	M2	M1	M2	M1	M2
% Manufacturing	0.019	0.019	0.005	0.005	0.072	0.063
	(0.011)	(0.011)	(0.009)	(0.009)	(0.083)	(0.086)
Δ Manufacturing	-0.015	-0.016	-0.016**	-0.017**	0.079	0.087
(cohort: age 0-19)	(0.009)	(0.010)	(0.006)	(0.007)	(0.049)	(0.049)
Observations	22068	22068	22068	22068	26754	26754
R2	0.913	0.916	0.913	0.916	0.906	0.909
C. Hispanic Female						
	Employment		Annual Payroll		Business Establishments	
	M1	M2	M1	M2	M1	M2
% Manufacturing	0.006	0.004	0.004	0.003	-0.010	-0.027
	(0.013)	(0.014)	(0.010)	(0.010)	(0.071)	(0.072)
Δ Manufacturing	-0.008	-0.006	-0.008	-0.007	0.083	0.094
(cohort: age 0-19)	(0.011)	(0.012)	(0.009)	(0.010)	(0.066)	(0.070)
Observations	14869	14869	14869	14869	16195	16195
R2	0.731	0.740	0.731	0.740	0.719	0.728

* p<.05, ** p<.01, *** p<.001 (two tailed tests)

Notes: (a) all models include 9 separate cohorts born between 1980-1988 nested within each county; (b) Models are weighted by average within-county cohort size at age 18, (c) Standard errors clustered at the state-level, (d) covariates include birth cohort FE (for the age 24 and age 26 models), cohort population at age 18, % of cohort black, county poverty rate, county logged per capita income adjusted to year 2000 dollars, county unemployment rate, county-level % with high school or less educational attainment, state-level % of workers represented by labor unions, and county % working age population and % old age dependent population, (e) All covariates are time-varying for when cohort is age 18.

Table 7. Regression models predicting state-level mean probability that a child's earnings will surpass their parents between ages 25-35

	State Fixed Effects		
	Employment	Annual Payroll	Establishments
% Manufacturing	0.18*	0.12	1.05*
	(0.09)	(0.07)	(0.47)
1970 Cohort	-0.77	-1.14	-0.89
	(-0.76)	(-0.70)	(-0.70)
1980 Cohort	-11.06***	-11.45***	-11.03***
	(-1.09)	(-1.08)	(-1.04)
Intercept	59.08***	60.01***	56.59***
	(2.32)	(2.29)	(3.26)
Observations	146	146	146
R2	0.922	0.920	0.922

* p<.05, ** p<.01, *** p<.001 (two tailed tests)

Notes: (a) Models consist of 3 cohorts (1960,1970,1980), (b) Standard errors are clustered at the state-level.

APPENDIX

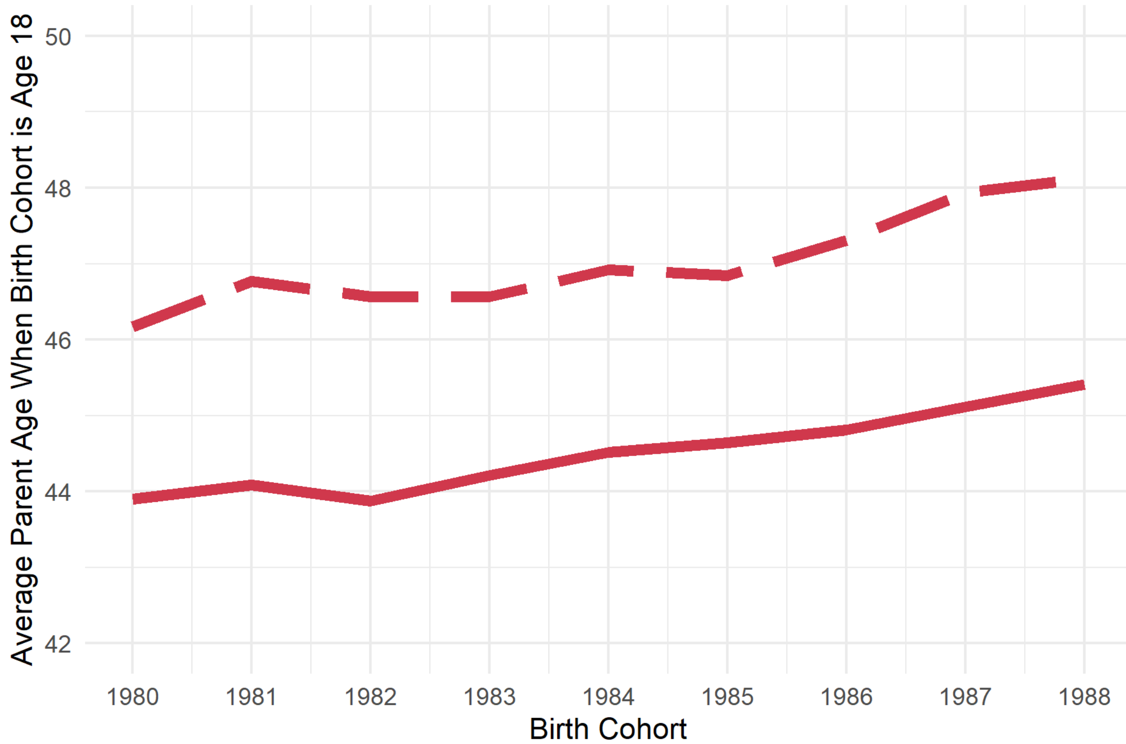
Appendix Table 1. Subset Models Predicting Age 26 Upward Income Mobility by Positive and Negative Net Migration Rates

	Negative NMR	Positive NMR	Negative NMR	Positive NMR
% Manufacturing	0.039	0.118***	0.020	0.062
	(0.022)	(0.029)	(0.022)	(0.052)
Δ Manufacturing	-0.054*	-0.031	-0.059**	-0.031
(cohort: age 0-19)	(0.021)	(0.019)	(0.021)	(0.021)
Fixed Effects	Commuting Zone		County	
Covariates	Yes		Yes	
N	5717	3358	4902	3358
R-sq	0.823	0.858	0.844	0.099

* p<.05, ** p<.01, *** p<.001 (two tailed tests)

Notes: (a) all models include 9 separate cohorts born between 1980-1988 nested within each county; (b) Models are weighted by average within-county cohort size at age 18, (c) Standard errors clustered at the state-level, (d) covariates include birth cohort FE (for the age 24 and age 26 models), cohort population at age 18, % of cohort black, county poverty rate, county logged per capita income adjusted to year 2000 dollars, county unemployment rate, county-level % with high school or less educational attainment, state-level % of workers represented by labor unions, and county % working age population and % old age dependent population, (e) All covariates are time-varying for when cohort is age 18.

Appendix Figure 1. Average Ages of Mothers (solid line) and Fathers (dashed line) for 1980-1988 Birth Cohorts when Cohort is 18 Years Old



Notes: (1) Data are calculated from CPS ASEC; (2) Data are weighted using ASEC person weights.

Conclusion

Deindustrialization is not a completed, historical event, but an ongoing process that continues to transform the occupational structure of U.S. labor markets and polarize the income distribution. For those from advantaged backgrounds, who are able to pursue and complete a college degree, opportunity abounds. For those with fewer resources, pathways to upward mobility have diminished in recent decades. In this dissertation, I have documented how this bifurcation of economic opportunity – prompted mainly by the decline of middle-wage occupational opportunities – has altered population processes, including fertility, cause-specific mortality, and social mobility.

I began the Introduction chapter of this dissertation by calling attention to the apparent discrepancy between demographic trends and economic conditions in recent years. Social scientists have spent decades documenting the relationship between population processes and the business cycle, but have mostly adhered to analyzing conventional economic indicators. The findings from these three studies demonstrate that rather than becoming unmoored, demographic conditions remain responsive to economic conditions vis-à-vis long-term structural economic changes.

This finding should prompt sociologists, demographers, and other social scientists to think more deeply about how we conceptualize cyclical and secular shifts in economic conditions, and their attendant impacts on demographic processes. The very idea of the "business cycle" creates a false impression that society is static over the long-term. Even during extended periods of relative stability when consistent pro-cyclical or counter-cyclical trends are identifiable, societies are constantly in a process of transition. The research presented here emphasizes the importance of understanding the role of changing temporal contexts in determining underlying distributions of social and economic resources across and within populations.

Looking ahead, the research presented here motivates several new research directions. First, the large-scale economic uncertainty initiated by structural economic changes over the past several decades might be influencing other population dynamics, such as external and internal migration, other types of cause-specific mortality besides drug mortality, and family demography processes. That is, this dissertation only scratches the surface on the far-ranging demographic implications of deindustrialization.

Second, future research should continue to investigate how this economic restructuring has contributed to inequities across population subgroups. As the U.S. labor market inevitably shifts towards service-dominated industries, researchers should evaluate how this transition might be independently contributing to racial/ethnic, gender, and class, among other subpopulation disparities in outcomes. Documenting this process might help researchers and policymakers identify areas of intervention to ensure that the transition to a postindustrial economy does not disadvantage certain groups.

Third, although the studies in this dissertation sought to accentuate the role of aggregate, macro-level demographic processes, future research should try to simultaneously model both the individual-level and aggregate-level. This type of methodological approach will provide insight into how individual-level outcomes vary as a function of aggregate-level contexts.

My ongoing research seeks to directly address the latter two research directions, specifically, subgroup heterogeneity and multi-level processes. Building off of findings from Chapter 3 of this dissertation, I recently submitted a grant proposal for a project that will use data from the National Longitudinal Study of Adolescent to Adult Health (Add Health) to examine how contexts of economic opportunity during the transition into adulthood shape trajectories of economic attainment and upward intergenerational income mobility. A primary innovation of this proposed project is that it will link data on individual-level work histories with contextual, community-specific labor market characteristics in order to evaluate how structural economic changes have impacted upward economic mobility. Critically, the research methodology of this new study will test whether and to what extent ecological economic conditions can explain diverging trends in intergenerational mobility across racial groups. Overall, the aim of this research is to generate policy discussions amongst researchers, policymakers, lawmakers, and the general public about how deindustrialization might be exacerbating pre-existing inequalities in upward economic mobility.

References

Abel, Jaison R. and Richard Deitz. 2012. "Job Polarization and Rising Inequality in the Nation and the New York-Northern New Jersey Region." *SSRN Electronic Journal, (Social Science Research Network)* 18(7):1–7.

Acemoglu, Daron and David Autor. 2011. "Skills, Tasks and Technologies: Implications for Employment and Earnings." Pp. 1043–1171 in *Handbook of Labor Economics, Vol 4B*. Vol. 4.

Adda, Jerome and Yarine Fawaz. 2019. *The Health Toll of Import Competition*.

Alexander, Monica J., Mathew V. Kiang, and Magali Barbieri. 2018. "Trends in Black and White Opioid Mortality in the United States, 1979-2015." *Epidemiology* 29(5):707–15.

Allison, Paul D. 2009. *Fixed Effects Regression Models*. Vol. 168. SAGE Publications.

Anderson, RN and HM Rosenberg. 1998. "Age Standardization of Death Rates: Implementation of the Year 2000 Standard." *National Vital Statistics Reports* 47(3).

Arai, Lisa. 2007. "Peer and Neighbourhood Influences on Teenage Pregnancy and Fertility: Qualitative Findings from Research in English Communities." *Health and Place* 13(1):87–98.

Arias, Elizabeth and Jiaquan Xu. 2019. "United States Life Tables, 2017." *National Vital Statistics Reports* 68(7).

Atkinson, Robert D., Luke A. Stewart, Scott M. Andes, and Stephen J. Ezell. 2012. "Worse than the Great Depression: What Experts Are Missing About American Manufacturing Decline." *The Information Technology & Innovation Foundation* (May):Atkinson, R. D., Stewart, L. A., Andes, S. M., E.

Autor, David. 2010. "The Polarization of Job Opportunities in the U . S . Labor Market." *Community Investments* 23(April):360–61.

Autor, David. 2011. "The Polarization of Job Opportunities in the U.S. Labor Market:" 23(2).

Autor, David H. and David Dorn. 2013. "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market." *American Economic Review* 103(5):1553–97.

Autor, David H., David Dorn, and Gordon H. Hanson. 2017. "When Work Disappears: Manufacturing Decline and the Falling Marriage-Market Value of Men." (July):1–55.

Autor, David H., Lawrence F. Katz, and Melissa S. Kearney. 2006. "The Polarization of the U.S. Labor Market." *American Economic Review* 96(2):189–94.

Balbo, Nicoletta and Nicola Barban. 2014. "Does Fertility Behavior Spread among Friends?" *American Sociological Review* 79(3):412–31.

Balbo, Nicoletta, Francesco C. Billari, and Melinda Mills. 2013. "Fertility in Advanced Societies: A Review of Research." *European Journal of Population / Revue Européenne de Démographie* 29(1):1–38.

Bao, Yuhua, Yijun Pan, Aryn Taylor, Sharmini Radakrishnan, Feijun Luo, Harold Alan Pincus, and Bruce R. Schackman. 2017. "Prescription Drug Monitoring Programs Are Associated

With Sustained Reductions in Opioid Prescribing By Physicians." *Health Affairs* 35(6):1045–51.

Becker, Gary S. 1960. "An Economic Analysis of Fertility." Pp. 209–40 in *Demographic and Economic Change in Developed Countries*. National Bureau of Economic Research, Inc.

Bernardi, Laura and Andreas Klärner. 2014. "Social Networks and Fertility." *Demographic Research*.

Betz, Michael R. and Lauren E. Jones. 2018. "Wage and Employment Growth in America's Drug Epidemic: Is All Growth Created Equal." *American Journal of Agricultural Economics* 100(5):1357–74.

Bhattacharya, Debopam and Bhashkar Mazumder. 2011. "A Nonparametric Analysis of Black – White Differences in Intergenerational Income Mobility in the United States." *Quantitative Economics* 2:335–79.

Black, Sandra E. and Paul J. Devereux. 2010. *Recent Developments in Intergenerational Mobility*. Working Paper 15889. Cambridge, MA.

Black, Sandra E., Paul J. Devereux, and Kjell G. Salvanes. 2015. "Losing Heart? The Effect of Job Displacement on Health." *Industrial and Labor Relations Review* 68(4):833–61.

Bloome, Deirdre. 2015. "Racial Inequality Trends and the Intergenerational Persistence of Income and Family Structure." *American Sociological Review* 79(6):1196–1225.

Bloome, Deirdre and Shauna Dyer. 2018. "Educational Inequality , Educational Expansion , and Intergenerational Income Persistence in the United States."

Bloome, Deirdre and Bruce Western. 2011. "Cohort Change and Racial Differences in Educational and Income Mobility." *Social Forces* 90(2):375–95.

Bongaarts, J. 1978. "A Framework for Analyzing the Proximate Determinants of Fertility." *Population and Development Review* 4(1):105–32.

Bongaarts, John and Griffith Feeney. 1998. "On the Quantum and Tempo of Fertility." *Population and Development Review* 24(2):271.

Boonstra, Heather D. 2014. "What Is behind the Declines in Teen Pregnancy Rates?" *Guttmacher Policy Review* 17(3):15–21.

Bound, John, Laura Dresser, and Irene Browne. 1999. "The Erosion of the Relative Earnings of African American Women During the 1980s." Pp. 61–104 in *Latinas and African American Women at Work, Race, Gender, and Economic Inequality*. Russell Sage Foundation.

Bradley, Elizabeth H., Maureen Canavan, Erika Rogan, Kristina Talbert-slagle, Chima Ndumele, Lauren Taylor, and Leslie A. Curry. 2016. "Variation In Health Outcomes: The Role Of Spending On Social Services, Public Health, And Health Care, 2000 – 09." *Health Affairs* 35(5):760–68.

Brand, Jennie E. 2015. "The Far-Reaching Impact of Job Loss and Unemployment." *Annual Review of Sociology* 41:359–75.

Brand, Jennie E. and Dwight Davis. 2012. "The Impact of College Education on Fertility: Evidence for Heterogeneous Effects." *Demography* 48(3):863–87.

Branum, Amy M. and Jo Jones. 2015. "Trends in Long-Acting Reversible Contraception Use Among U.S. Women Aged 15-44." *NCHS Data Brief* (188):1–8.

Brauner-Otto, Sarah R. and Claudia Geist. 2018. "Uncertainty, Doubts, and Delays: Economic Circumstances and Childbearing Expectations Among Emerging Adults." *Journal of Family and Economic Issues* 39(1):88–102.

Broman, Clifford L., V. Lee Hamilton, and William S. Hoffman. 1990. "Unemployment and Its Effects on Families : Evidence from a Plant Closing Study 1." *American Journal of Community Psychology* 18(5):643–59.

Browne, I. 2000. "Opportunities Lost? Race, Industrial Restructuring, and Employment among Young Women Heading Households." *Social Forces* 78(3):907–29.

Browning, Martin and Eskil Heinesen. 2012. *Effect of Job Loss Due to Plant Closure on Mortality and Hospitalization*. Vol. 31.

Buckles, Kasey, Daniel Hungerman, and Steven Lugauer. 2018. *Is Fertility a Leading Economic Indicator?* Working Paper 24355. Cambridge, MA.

Bureau of Labor Statistics. 2012. *The Recession of 2007–2009: BLS Spotlight on Statistics*.

Bureau of Labor Statistics. 2017. "Bureau of Labor Statistics Data Series: LNS14000000; Labor Force Statistics from the Current Population Survey."

Bureau of Labor Statistics. 2018. "Local Area Unemployment Statistics, State File [Dataset]." 1999–2016.

Bureau of Labor Statistics and U.S. Department of Labor. 2016. "Number of People Working Part Time for Economic Reasons Falls in June 2016." *The Economics Daily*. Retrieved December 25, 2017 (https://www.bls.gov/opub/ted/2016/number-of-people-working-part-time-for-economic-reasons-falls-in-june-2016.htm).

Burgard, Sarah A., Jennie E. Brand, and James S. House. 2009. "Perceived Job Insecurity and Worker Health in the United States." *Social Science and Medicine* 69(5):777–85.

Butz, William P. and Michael P. Ward. 1979. "The Emergence of Countercyclical U.S. Fertility." *The American Economic Review* 69:318–28.

Cadena, Brian C. and Brian K. Kovak. 2016. "Immigrants Equilibrate Local Labor Markets: Evidence from the Great Recession." *American Economic Journal. Applied Economics* 8(1):257–90.

Calnan, Ray and Gary Painter. 2017. "The Response of Latino Immigrants to the Great Recession: Occupational and Residential (Im)Mobility." *Urban Studies* 54(11):2561–91.

Carrington, William J. and Bruce C. Fallick. 2015. *Do We Know Why Earnings Fall with Job Displacement ? Do We Know Why Earnings Fall with Job Displacement ?* Working Paper 2015-01. Washington, D.C.

Case, Anne and Angus Deaton. 2015. "Rising Morbidity and Mortality in Midlife among White Non-Hispanic Americans in the 21st Century." *Proceedings of the National Academy of Sciences* 112(49):15078–83.

Case, Anne and Angus Deaton. 2017. "Mortality and Morbidity in the 21st Century." *Brookings Papers on Economic Activity* 397–476.

Case, Anne and Angus Deaton. 2018. "Deaths of Despair Redux: A Response to Christopher Ruhm." 1–4.

Catalano, R. 1991. "The Health Effects of Economic Insecurity." *American Journal of Public Health* 81(9):1148–52.

Catanzarite, Lisa and Michael Bernabé Aguilera. 2002. "Working with Co-Ethnics: Earnings Penalties for Latino Immigrants at Latino Jobsites." *Social Problems* 49(1):101–27.

Center for Behavioral Health Statistics and Quality. 2018. *2017 National Survey on Drug Use and Health: Detailed Tables*. Rockville, MD.

Centers for Disease Control and Prevention. 2019. "U.S. Opioid Prescribing Rate Maps." Retrieved (https://www.cdc.gov/drugoverdose/maps/rxrate-maps.html).

Cerdá, Magdalena, William R. Ponicki, Nathan Smith, Ariadne Rivera-aguirre, Corey S. Davis, Brandon D. L. Marshall, David S. Fink, Stephen G. Henry, Alvaro Castillo-carniglia, Garen J. Wintemute, Andrew Gaidus, Paul J. Gruenewald, and Silvia S. Martins. 2020. "State-Level Prescription Drug Monitoring Programs and County-Level Fatal Prescription Opioid Overdoses." *Epidemiology* 31(1).

Cha, Youngjoo and Stephen L. Morgan. 2010. "Structural Earnings Losses and Between-Industry Mobility of Displaced Workers , 2003 – 2008." *Social Science Research* 39(6):1137–52.

Charles, Kerwin Kofi and Philip DeCicca. 2008. "Local Labor Market Fluctuations and Health: Is There a Connection and for Whom?" *Journal of Health Economics* 27(6):1532–50.

Charles, Kerwin Kofi, Erik Hurst, and Matthew J. Notowidigdo. 2017. "HOUSING BOOMS, MANUFACTURING DECLINE, AND LABOR MARKET OUTCOMES." (July).

Cheng, Siwei and Xi Song. 2019. "Linked Lives, Linked Trajectories : Intergenerational Association of Intragenerational Income Mobility." *American Sociological Review* 84(6):1037–68.

Cherlin, Andrew, Erin Cumberworth, S. Philip Morgan, and Christopher Wimer. 2013. "The Effects of the Great Recession on Family Structure and Fertility" edited by S. Danziger. *The ANNALS of the American Academy of Political and Social Science* 650(1):214–31.

Chetty, By Raj, Nathaniel Hendren, Patrick Kline, Emmanuel Saez, and Nicholas Turner. 2014. "Is the United States Still a Land of Opportunity ? Recent Trends in Intergenerational Mobility." *American Economic Review: Papers & Proceedings 2014,* 104(5):141–47.

Chetty, Raj, David Grusky, Maximilian Hell, Nathaniel Hendren, Robert Manduca, and Jimmy Narang. 2016. *The Fading American Dream: Trends in Absolute Income Mobility Since 1940*. Working Paper 22910. Cambridge, MA.

Chetty, Raj, Nathaniel Hendren, Maggie R. Jones, and Sonya R. Poreter. 2018. "Race and Economic Opportunity in the United States: An Intergenerational Perspective."

Chetty, Raj, Nathaniel Hendren, Patrick Kline, and Emmanuel Saez. 2014. "Where Is the Land of Opportunity? The Geography of Intergenerational Mobility in the United States." *Quarterly Journal of Economics* 129(4):1553–1623.

Chetty, Raj, Nathaniel Hendren, Patrick Kline, Emmanuel Saez, and Nicholas Turner. 2014. "IS

THE UNITED STATES STILL A LAND OF OPPORTUNITY? RECENT TRENDS IN INTERGENERATIONAL MOBILITY.”

Chetty, Raj, Michael Stepner, Sarah Abraham, Shelby Lin, Benjamin Scuderi, Nicholas Turner, Augustin Bergeron, and David Cutler. 2016. “The Association between Income and Life Expectancy in the United States, 2001-2014.” *JAMA - Journal of the American Medical Association* 315(16):1750–66.

Choi, Kate H. 2014. “Fertility in the Context of Mexican Migration to the United States: A Case for Incorporating the Pre-Migration Fertility of Immigrants.” *Demographic Research* 30(1):703–38.

Cohen, Philip N. 2014. “Recession and Divorce in the United States, 2008–2011.” *Population Research and Policy Review* 33(5):615–28.

Cohen, Philip N. and Matt L. Huffman. 2007. “Black Under-Representation in Management across U.S. Labor Markets.” *The ANNALS of the American Academy of Political and Social Science* 609(1):181–99.

Colantone, Italo, Rosario Crinò, and Laura Ogliari. 2019. “Globalization and Mental Distress.” *Journal of International Development* 119:181–207.

Couch, Kenneth A. and Robert Fairlie. 2010. “Last Hired, First Fired? Black-White Unemployment and the Business Cycle.” *Demography* 47(1):227–47.

Couch, Kenneth A., Gayle L. Reznik, Howard M. Iams, and Christopher R. Tamborini. 2018. “The Incidence and Consequences of Private Sector Job Loss in the Great Recession.” *Social Security Bulletin* 78(1):31–46.

Cunningham, Evan. 2018. “Great Recession , Great Recovery ? Trends From.” (April):1–27.

Currie, Janet, Jonas Jin, and Molly Schnell. 2019. “U.S. Employment and Opioids: Is There a Connection?” Pp. 253–80 in *Health and Labor Markets (Research in Labor Economics, Volume 47)*.

Currie, Janet and Hannes Schwandt. 2014. “Short- and Long-Term Effects of Unemployment on Fertility.” *Proceedings of the National Academy of Sciences of the United States of America* 111(41):14734–39.

Cutcher-Gershenfeld, Joel, Dan Brooks, and Martin Mulloy. 2015. *The Decline and Resurgence of the U.S. Auto Industry*. #339.

Dahl, Molly and Thomas DeLeire. 2008. *The Association between Children’s Earnings and Fathers’ Lifetime Earnings: Estimates Using Administrative Data*. 1342–08.

Dasgupta, Nabarun, Leo Beletsky, and Daniel Ciccarone. 2018. “Opioid Crisis : No Easy Fix to Its Social and Economic Determinants.” *American Journal of Public Health* 108(2):182–86.

Davis, Jonathan M. V and Bhashkar Mazumder. 2020. *The Decline in Intergenerational Mobility After 1980*.

Department of the Treasury. 2012. *The Financial Crisis Response In Charts*.

DeShazo, Richard D., Mckenzie Johnson, Ike Eriator, and Kathryn Rodenmeyer. 2018. “Backstories on the US Opioid Epidemic . Good Intentions Gone Bad , an Industry Gone Rogue ,.” *The American Journal of Medicine* 131(6):595–601.

DiPrete, Thomas A. 1993. "Industrial Restructuring and the Mobility Response of American Workers in the 1980s." *American Sociological Review* 58(1):74–96.

Doleac, Jennifer L. and Anita Mukherjee. 2018. *The Moral Hazard of Lifesaving Innovations : Naloxone Access , Opioid Abuse , and Crime*.

Eckert, Fabian, Teresa C. Fort, Peter K. Schott, and Natalie J. Yang. 2020. *Imputing Missing Values in the US Census Bureau's County Business Patterns*.

Elder, Glen H. 1974. *Children of the Great Depression: Social Change in Life Experience*. 1st Editio. Chicago, IL: University of Chicago Press.

Elder, Glen H. 1998. "The Life Course as Developmental Theory." *Child Dev.* 69(1):1–12.

Ermisch, John. 1988. "Economic Influences On Birth Rates." *National Institute Economic Review* 126(1):71–92.

Ezzati, Majid, Ari B. Friedman, Sandeep C. Kulkarni, and Christopher J. L. Murray. 2008. "The Reversal of Fortunes : Trends in County Mortality and Cross-County Mortality Disparities in the United States." *PLoS Medicine* 5(4):557–68.

Fallick, Bruce C. 1996. "A REVIEW OF THE RECENT EMPIRICAL LITERATURE ON DISPLACED WORKERS." *Industrial and Labor Relations Review* 50(1):5–15.

Fernandes-Alcantara, Adrienne L. 2018. *Youth and the Labor Force : Background and Trends*.

Finer, Lawrence B., Jenna Jerman, and Megan L. Kavanaugh. 2012. "Changes in Use of Long-Acting Contraceptive Methods in the United States, 2007-2009." *Fertility and Sterility* 98(4):893–97.

Finer, Lawrence B. and Mia R. Zolna. 2016. "Declines in Unintended Pregnancy in the United States, 2008–2011." *New England Journal of Medicine* 374(9):843–52.

Fink, David S., Julia P. Schleimer, Aaron Sarvet, Kiran K. Grover, Chris Delcher, Alvaro Castillo-Carniglia, June H. Kim, Ariadne E. Rivera-Aguirre, Stephen G. Henry, Silvia S. Martins, and Magdalena Cerdá. 2018. "Association Between Prescription Drug Monitoring Programs and Nonfatal and Fatal Drug Overdoses: A Systematic ReviewPrescription Drug Monitoring Programs and Overdose." *Annals of Internal Medicine* 168(11):783–90.

Finley, Erin P., Ashley Garcia, Kristen Rosen, Don Mcgeary, Mary Jo Pugh, and Jennifer Sharpe Potter. 2017. "Evaluating the Impact of Prescription Drug Monitoring Program Implementation : A Scoping Review." *BMC Health Services Research* 17:1–8.

Flanagan, Christine and Ellen Wilson. 2013. *Amercian Community Survey Briefs: Home Value and Homeownership Rates: Recession and Post-Recession Comparisons From 2007-2009 to 2010-2012*. Washington, D.C.

Fletcher, Jason M. and Jessica Polos. 2017. "Nonmarital and Teen Fertility." (10833).

Flood, Sarah, Miriam King, Renae Rodgers, Steven Ruggles, and J. Robert Warren. 2018. "Integrated Public Use Microdata Series, Current Population Survey: Version 6.0 [Dataset]."

Fryer, Jr. Roland G., Devah Pager, and Jorg Spenkuch. 2013. "Racial Disparities in Job Finding and Offered Wages." *Journal of Law and Economics* 56(August).

Gallo, William T., Elizabeth H. Bradley, Michele Siegel, and Stanislav V Kasl. 2001. "The Impact of Involuntary Job Loss on Subsequent Alcohol Consumption by Older Workers : Findings From the Health and Retirement Survey." *Journal of Gerontology: Social Sciences* 56(1):3–9.

Gaydosh, Lauren, Robert A. Hummer, Taylor W. Hargrove, Carolyn T. Halpern, Jon M. Hussey, Eric A. Whitsel, Nancy Dole, and Kathleen Mullan Harris. 2019. "The Depths of Despair Among US Adults Entering Midlife." *American Journal of Public Health* 109(5):774–80.

Ghertner, Robin and Lincoln Groves. 2018. *The Opioid Crisis and Economic Opportunity: Geographic and Economic Trends*.

Glei, Dana A. and Samuel H. Preston. 2020. "Estimating the Impact of Drug Use on US Mortality, 1999-2016." *PLoS ONE* 1999–2016.

Goldstein, Amy. 2017. *Janesville: An American Story*. New York: Simon & Schuster.

Goodman-Bacon, Andrew. 2019a. *Difference-In-Difference with Variation in Treatment Timing*.

Goodman-Bacon, Andrew. 2019b. *So You've Been Told To Do My Difference-In-Difference Thing: A Guid*.

Goodman, Christopher J. and Steven M. Mance. 2011. "Monthly Labor Review: Employment Loss and the 2007–09 Recession: An Overview." *Monthly Labor Review* (April):3–12.

Granados, José A. Tapia, James S. House, Edward L. Ionides, Sarah Burgard, and Robert S. Schoeni. 2014. "Individual Joblessnes , Contextual Unemployment, and Mortality Risk." *American Journal of Epidemiology* 180(3):280–87.

Grant, Don Sherman II and Michael Wallace. 1994. "The Political Economy of Manufacturing Growth and Decline across the American States, 1970-1985." *Social Forces* 73(1):33–63.

Grecu, Anca M., Dhaval M. Dave, and Henry Saffer. 2019. "Prescription Drug Monitoring Programs and Prescription Drug Abuse." *Journal of Policy Analysis and Management* 38(1):181–209.

Guy, Gery P., Kun Zhang, Lyna Z. Schieber, Randall Young, and Deborah Dowell. 2020. "County-Level Opioid Prescribing in the United States , 2015 and 2017." *JAMA Internal Medicine* 179(4):1033–36.

Hadland, Scott E., Ariadne Rivera-aguirre, Brandon D. L. Marshall, and Magdalena Cerdá. 2019. "Association of Pharmaceutical Industry Marketing of Opioid Products With Mortality From Opioid-Related Overdoses." *JAMA Network Open* 2(1):1–12.

Haffajee, Rebecca L. and Michelle M. Mello. 2017. "Drug Companies' Liability for the Opioid Epidemic." *New England Journal of Medicine* 377(24):2301–5.

Haider, Steven and Gary Solon. 2006. "Life-Cycle Variation in the Association between Current and Lifetime Earnings." *American Economic Review* 96(4):1308–20.

Hall, Matthew, Kyle Crowder, and Amy Spring. 2015. "Neighborhood Foreclosures, Racial/Ethnic Transitions, and Residential Segregation." *American Sociological Review* 80(3):526–49.

Hamilton, Brady E. and Sharon E. Kirmeyer. 2017. "National Vital Statistics Reports Trends and Variations in Reproduction and Intrinsic Rates: United States, 1990–2014." 66(2).

Hamilton, Brady E., Joyce A. Martin, Michelle J. K. Osterman, Anne K. Driscoll, and Lauren M. Rossen. 2018. "Births: Provisional Data for 2017." *NVSS Vital Statistics Rapid Release* 2(002):1–21.

Hamilton, Brady E., Joyce A. Martin, Michelle J. K. S. Osterman, Anne K. Driscoll, and Lauren M. Rossen. 2017. "Vital Statistics Rapid Release Births: Provisional Data for 2016."

Hamilton, Brady E. and Paul D. Sutton. 2012. "Recent Trends in Births and Fertility Rates Through June 2012."

Hartmann, Heidi, Ashley English, and Jeffrey Hayes. 2010. "Women and Men's Employment and Unemployment in the Great Recession." (November 2009).

Hauser, Robert M., John N. Koffel, Harry P. Travis, and Pepter J. Dickinson. 1975. "Temporal Change in Occupational Mobility: Evidence for Men in the United States*." *American Sociological Review* 40(June):279–97.

Hedegaard, Holly, Arialdi M. Miniño, and Margaret Warner. 2020. "Drug Overdose Deaths in the United States , 1999 – 2018." *NCHS Data Brief* (356):1–8.

Hedegaard, Holly, Margaret Warner, and Arialdi M. Miniño. 2018. "Drug Overdose Deaths in the United States, 1999-2017." *NCHS Data Brief* (294):1–8.

Hederos, Karin, Markus Jantti, Lena Lindahl, and Jenny Torssander. 2017. "Trends in Life Expectancy by Income and the Role of Specific Causes of Death." *Economica*.

Helper, Susan, Timothy Krueger, and Howard Wial. 2012. *Locating American Manufacturing: Trends in the Geography of Production*.

Holder, Michelle. 2015. "The Impact of The Great Recession on the Occupational Segregation of Black Men in the U.S." (November).

Holder, Michelle. 2017. "African American Male Unemployment during the Great Recession in Comparison to Other Groups and Theoretical Considerations." Pp. 23–34 in *African American Men and the Labor Market during the Great Recession*. New York: Palgrave Macmillan US.

Hollingsworth, Alex, Christopher J. Ruhm, and Kosali Simon. 2017. "Macroeconomic Conditions and Opioid Abuse." *Journal of Health Economics* 56:222–33.

Horwitz, Jill, Corey S. Davis, Lynn S. McClelland, Rebecca S. Fordon, and Ellen Meara. 2018. "The Problem of Data Quality in Analyses of Opioid Regulation :" *NBER Working Paper*.

Hout, Michael. 2015. "A Summary of What We Know about Social Mobility." *The ANNALS of the American Academy of Political and Social Science* (January):27–36.

Hout, Michael and Erin Cumberworth. 2012. *The Labor Force and the Great Recession*.

Huijts, Tim, Aaron Reeves, Martin Mckee, and David Stuckler. 2015. "The Impacts of Job Loss and Job Recovery on Self-Rated Health: Testing the Mediating Role of Financial Strain and Income." *European Journal of Public Health* 25(5):801–6.

Jacobs, Ken, Zohar Perla, Ian Perry, and Dave Graham-squire. 2016. *Producing Poverty: The Public Cost of Low-Wage Production Jobs in Manufacturing*.

Janoski, Thomas., David (Research assistant) Luke, and Christopher (Lecturer in Sociology)

Oliver. 2014. *The Causes of Structural Unemployment : Four Factors That Keep People from the Jobs They Deserve*. Polity Press.

Jaret, Charles, Lesley Williams Reid, and Robert M. Adelman. 2003. "Black-White Income Inequality and Metropolitan Socioeconomic Structure." *Journal of Urban Affairs* 25(3):305–34.

Jolly, Nicholas A. and Brian J. Phelan. 2017. "The Long-Run Effects of Job Displacement on Sources of Health Insurance Coverage." *Journal of Labor Research* 38(2):187–205.

Jones, Jeff and Lydia Saad. 2020. *Gallup Poll Social Series: Mood of the Nation: Final Topline*.

Kahn, Lisa B. 2010. "The Long-Term Labor Market Consequences of Graduating from College in a Bad Economy." *Labour Economics* 17(2):303–16.

Kalleberg, Arne L. 2009. "Precarious Work , Insecure Workers : In Transition Employment Relations." *American Sociological Review* 74(1):1–22.

Kalleberg, Arne L. 2018. *Precarious Lives: Job Insecurity and Well-Being in Rich Democracies*. Wiley.

Kalleberg, Arne L. and Till M. von Wachter. 2017. "The U.S. Labor Market During and After the Great Recession: Continuities and Transformations." *RSF: The Russell Sage Foundation Journal of the Social Sciences* 3(3):1–19.

Kearney, Melissa S. and Riley Wilson. 2018. "Male Earnings, Marriageable Men, and Non-Marital Fertility: Evidence from the Fracking Boom." *The Review of Economics and Statistics*.

Kennedy, Sheela and Catherine A. Fitch. 2012. "Measuring Cohabitation and Family Structure in the United States: Assessing the Impact of New Data From the Current Population Survey." *Demography* 49(4):1479–98.

Kim, Ae-sook and Edward T. Jr Jennings. 2009. "Effects of U.S. States ' Social Welfare Systems on Population Health." *The Policy Studies Journal* 37(4).

Kirsch, Julie A. and Carol D. Ryff. 2016. "Hardships of the Great Recession and Health: Understanding Varieties of Vulnerability." *Health Psychology Open* 3(1).

Kmec, Julie A. 2003. "Minority Job Concentration and Wages." *Social Problems* 50(1):38–59.

Kolodny, Andrew, David Courtwright, Catherine S. Hwang, Peter Kreiner, John L. Eadie, Thomas Clark, and G. Alexander. 2015. "The Prescription Opioid and Heroin Crisis: A Public Health Approach to an Epidemic of Addiction." *Annual Review OfPublic Health Is* 36:559–74.

Kothari, Siddharth, Itay Saporta-Eksten, and Edison Yu. 2013. "The (Un)Importance of Geographical Mobility in the Great Recession." *Review of Economic Dynamics* 16(3):553–63.

Krueger, Alan B. 2017. *Where Have All the Workers Gone? An Inquiry into the Decline of the U.S. Labor Force Participation Rate*. Vol. 2.

Lang, Matthew, T. Clay McManus, and Georg Schaur. 2019. "The Effects of Import Competition on Health in the Local Economy." *Health Economics* (December 2017):44–56.

Lee, Chul-in and Gary Solon. 2009. "Trends in Intergenerational Income Mobility." 91(November):766–72.

Lee, Ronald. 2001. *Demography Abandons Its Core*.

Levine, Marc V. 2012. *Race and Male Employment in the Wake of the Great Recession: Black Male Employment Rates in Milwaukee And the Nation's Largest Metro Areas 2010*.

Levinson, Marc. 2017. *Job Creation in the Manufacturing Revival Job Creation in the Manufacturing Revival*. Washington, D.C.

Lim, Sojung. 2017. "'Bad Jobs' for Marriage: Precarious Work and the Transition to First Marriage." Pp. 399–427 in *Precarious Work (Research in the Sociology of Work, Volume 31)*, edited by A. L. Kalleberg and S. P. Vallas. Emerald Publishing Limited.

Lindberg, Laura, John Santelli, and Sheila Desai. 2016. "Understanding the Decline in Adolescent Fertility in the United States, 2007–2012." *J Adolesc Health* 59(5):577–83.

Long, Jason and Joseph Ferrie. 2013. "Intergenerational Occupational Mobility in Great Britain and the United States Since 1850." *The American Economic Review* 103(4):1109–37.

Low, Sarah. 2017. "Manufacturing Is Relatively More Important to the Rural Economy than the Urban Economy." *U.S. Department of Agriculture*. Retrieved (https://www.usda.gov/media/blog/2017/09/12/manufacturing-relatively-more-important-rural-economy-urban-economy).

Martin, J. A., B. E. Hamilton, and M. J. K. Osterman. 2018. "Births in the United States, 2016." *NCHS Data Brief* 67(1):1–8.

Martin, Joyce A., Brady E. Hamilton, Michelle J. K. Osterman, and Anne K. Driscoll. 2019. "National Vital Statistics Reports Births: Final Data for 2018." *National Vital Statistics Reports* 68(13):1980–2018.

Martin, Joyce A., Brady E. Hamilton, Michelle J. K. S. Osterman, Anne K. Driscoll, and T. J. Mathews. 2015. "National Vital Statistics Reports, Volume 66, Number 1, January 5, 2017." 66(1).

Martin, Steven P., Nan Marie Astone, and H. Elizabeth Peters. 2014. *Fewer Marriages, More Divergence: Marriage Projections for Millennials to Age 40*.

Massoglia, Michael and Brianna Remster. 2019. "Linkages Between Incarceration and Health." *Public Health Reports (Washington, D.C. : 1974)* 134(1):8S-14S.

Matysiak, Anna, Tomáš Sobotka, and Daniele Vignoli. 2014. "The Impact of the Great Recession on Age-Specific Fertility in Europe."

Mazumder, Bhashkar. 2012. "Is Intergenerational Economic Mobility Lower Now than in the Past?" *Chicago Fed Letter* (297).

McCall, Leslie, Derek Burk, Marie Laperrière, and Jennifer A. Richeson. 2017. "Exposure to Rising Inequality Shapes Americans' Opportunity Beliefs and Policy Support." *Proceedings of the National Academy of Sciences* 114(36):9593–98.

McConnell, Sheena, Kenneth Fortson, Dana Rotz, Peter Schochet, Paul Burkander, Linda Rosenberg, Annalisa Mastri, and Ronald D'Amico. 2016. "Providing Pubic Workforce Serivices to Job Seekers: 15-Month Impact Findings on the WIA Adult and Dislocated

Worker Programs." 162.

McKernan, Signe-Mary, Caroline Ratcliffe, Eugene Steuerle, and Sisi Zhang. 2014. "Disparities in Wealth Accumulation and Loss from the Great Recession and Beyond." *American Economic Review* 104(5):240–44.

Mclean, Katherine. 2018. """There's Nothing Here"': Deindustrialization as Risk Environment for Overdose." *International Journal of Drug Policy* 29(2016):19–26.

McLean, Katherine. 2016. ""There's Nothing Here": Deindustrialization as Risk Environment for Overdose." *International Journal of Drug Policy* 29:19–26.

Merline, Alicia C., Patrick M. O. Malley, John E. Schulenberg, Jerald G. Bachman, and Lloyd D. Johnston. 2004. "Substance Use Among Adults 35 Years of Age: Prevalence, Adulthood Predictors, and Impact of Adolescent Substance Use." *American Journal of Public Health* 94(1).

Miller, Sarah, Sean Altekruse, Norman Johnson, and Laura R. Wherry. 2019. *Medicaid and Mortality: New Evidence from Linked Survey and Administrative Data*.

Modena, Francesca and Fabio Sabatini. 2012. "I Would If I Could: Precarious Employment and Childbearing Intentions in Italy." *Review of Economics of the Household* 10(1):77–97.

Molloy, Raven, Christopher L. Smith, and Abigail Wozniak. 2011. "Internal Migration in the United States." *Journal of Economic Perspectives* 25(3):173–96.

Molloy, Raven, Christopher L. Smith, and Abigail Wozniak. 2013. *Declining Migration Within the US : The Role of the Labor Market*. 2013–27.

Monnat, Shannon M. 2018. "Factors Associated With County-Level Differences in U.S. Drug-Related Mortality Rates." *American Journal of Preventive Medicine* 1–10.

Monnat, Shannon M. 2019. "The Contributions of Socioeconomic and Opioid Supply Factors to U.S. Drug Mortality Rates: Urban-Rural and within-Rural Differences." *Journal of Rural Studies* 68(December 2018):319–35.

Montez, Jennifer Karas, Mark D. Hayward, and Anna Zajacova. 2019. "Educational Disparities in Adult Health : U.S . States as Institutional Actors on the Association." *Socius*.

Moore, Thomas S. 2010. "The Locus of Racial Disadvantage in the Labor Market." *American Journal of Sociology* 116(3):909–42.

Moretti, Enrico. 2012. *The New Geography of Jobs*. Houghton Mifflin Harcourt.

Morgan, S. Philip. 2003. "Is Low Fertility a Twenty-First-Century Demographic Crisis?" *Demography* 40(4):589–603.

Morgan, S. Philip, Erin Cumberworth, and Christopher Wimer. 2011. "The Great Recession's Influence on Fertility, Marriage, Divorce, and Cohabitation." Pp. 220–45 in *The Great Recession*, edited by B. Grusky, David B. Western and C. Wimer. New York: Russell Sage Foundation.

Morgan, S. Phillip., Erin. Cumberworth, and Christopher. Wimer. 2012. "Family, the Lifecourse, and the Great Recession." (October):5.

Murphy, Sherry L., Jiaquan Xu, Kenneth D. Kochanek, and Elizabeth Arias. 2018. *Mortality in* *the United States, 2017*.

Mykyta, Laryssa. 2012. "Economic Downturns and the Failure to Launch: The Living Arrangements of Young Adults in the U.S. 1995-2011." *U.S Census Bureau* 1–37.

Nagelhout, Gera E., Karin Hummel, Moniek C. M. de Goeij, Hein de Vries, Eileen Kaner, and Paul Lemmens. 2017. "How Economic Recessions and Unemployment Affect Illegal Drug Use: A Systematic Realist Literature Review." *International Journal of Drug Policy* 44:69–83.

NCHS. 2016. "Center for Disease Control and Prevention Natality Detail Data Set, 2000-2014. Restricted-Use Data File and Documentation."

Newman, Katherine S. and Hella Winston. 2016. *Reskilling America: Learning to Labor in the Twenty-First Century*. Metropolitan Books.

Nosrati, Elias, Michael Ash, Michael Marmot, Martin McKee, and Lawrence P. King. 2017. "The Association between Income and Life Expectancy Revisited: Deindustrialization, Incarceration and the Widening Health Gap." *International Journal of Epidemiology* (February 2018):1–11.

O'Hare, William P., Eric Jensen, and Barbara O'Hare. 2013. "Assessing the Undercount of Young Children in the U.S. Decennial Census: Implications for Survey Research and Potential Explanations." in *AAPOR*.

Office of Management and Budget. 2013. "OMB BULLETIN NO. 13-01: Revised Delineations of Metropolitan Statistical Areas, Micropolitan Statistical Areas, and Combined Statistical Areas, and Guidance on Uses of the Delineations of These Areas."

Okie, Susan. 2010. "A Flood of Opioids, a Rising Tide of Deaths." *New England Journal of Medicine* 363(21):1981–85.

Oreopoulos, Philip, Till Von Wachter, and Andrew Heisz. 2012. "The Short- and Long-Term Career Effects of Graduating in a Recession." *American Economic Journal: Applied Economics* 4(1):1–29.

Pager, Devah, Bart Bonikowski, and Bruce Western. 2009. "Discrimination in a Low-Wage Labor Market." *American Sociological Review* 74(5):777–99.

Pager, Devah and David S. Pedulla. 2015. "Race, Self-Selection, and the Job Search Process." *American Journal of Sociology* 120(4):1005–54.

Parrado, Emilio A. 2011. "How High Is Hispanic/Mexican Fertility in the United States? Immigration and Tempo Considerations." *Demography* 48(3):1059–80.

Parrado, Eric, Caner Asena, and Edward N. Wolff. 2007. "Occupational and Industrial Mobility in the United States." *Labour Economics* 14(3):435–55.

Pattillo, Mary E. 2013. *Black Picket Fences : Privilege and Peril among the Black Middle Class*. 2nd Editio.

Percheski, Christine and Rachel Kimbro. 2014. *How Did the Great Recession Affect Fertility? | Self-Sufficiency Research Clearinghouse*.

Pew Research Center. 2015. *The American Middle Class Is Losing Ground: No Longer the Majority and Falling behind Financially*. Washington, D.C.

Pfeffer, Fabian T., Robert F. Schoeni, Arthur Kennickell, and Patricia Andreski. 2016. "Measuring Wealth and Wealth Inequality: Comparing Two U.S. Surveys." *Journal of Economic and Social Measurement* 41(2):103–20.

Piotrowski, Martin, Arne Kalleberg, and Ronald R. Rindfuss. 2015. "Contingent Work Rising: Implications for the Timing of Marriage in Japan." *Journal of Marriage and Family* 77(5):1039–56.

Preston, Samuel H. 1975. "The Changing Relation between Mortality and Level of Economic Development." *Population Studies* 29(2):231–48.

Qian, Zhenchao. 2012. "During the Great Recession, More Young Adults Lived with Parents."

Rhodes, Tim. 2009. "Risk Environments and Drug Harms: A Social Science for Harm Reduction Approach." *International Journal of Drug Policy* 20(3):193–201.

Rindfuss, Ronald R., S. Philip Morgan, and Kate Offutt. 1996. "Education and the Changing Age Pattern of American Fertility: 1963-1989." *Demography* 33(3):277.

Rinz, Kevin. 2019. *Did Timing Matter? Life Cycle Differences in Effects of Exposure to the Great Recession*. Washington, D.C.

Riumallo-Herl, Carlos, Sanjay Basu, David Stuckler, Emilie Courtin, and Mauricio Avendano. 2014. "Job Loss, Wealth and Depression during the Great Recession in the USA and Europe." *International Journal of Epidemiology* 43(5):1508–17.

Rolfs, Robert T., Michael D. Friedrichs, Todd C. Grey, Kristina Russell, and Jonathan Anderson. 2012. "Risk Factors for Prescription Opioid-Related Death, Utah, 2008 – 2009." *Pain Medicine* 1580–89.

Royster, Deirdre A. 2003. *Race and the Invisible Hand : How White Networks Exclude Black Men from Blue-Collar Jobs*. University of California Press.

Ruggles, Steven, Katie Genadek, Ronald Goeken, Josiah Grover, and Matthew Sobke. 2017. "Integrated Public Use Microdata Series: Version 7.0 [Dataset."

Rugh, Jacob S. 2015. "Double Jeopardy: Why Latinos Were Hit Hardest by the US Foreclosure Crisis." *Social Forces* 93(3):1139–84.

Ruhm, Christopher J. 2003. "Good Times Make You Sick." *Journal of Health Economics* 22(4):637–58.

Ruhm, Christopher J. 2011. "Are Recessions Good for Your Health?" *Quarterly Journal of Economics* 115(2):617–50.

Ruhm, Christopher J. 2019. "Drivers of the Fatal Drug Epidemic." *Journal of Health Economics* 64:25–42.

Ryder, Norman B. 1980. "Components of Temporal Variations in American Fertility."

Sahin, Aysegul, Joseph Song, and Bart Hobijn. 2010. "The Unemployment Gender Gap During the 2007 Recession." *Current Issues in Economic and Finance* 16(2):1–7.

Sawhill, Isabel V. 1977. "Economic Perspectives on the Family." *Daedalus* 106:115–25.

Sawhill, Isabel and Joanna Venator. 2015. "Is There a Shortage of Marriage Able Men ?" (September).

Schaller, Jessamyn and Ann Huff Stevens. 2015. “Short-Run Effects of Job Loss on Health Conditions, Health Insurance, and Health Care Utilization.” *Journal of Health Economics* 43:190–203.

Schneider, Daniel. 2015. “The Great Recession, Fertility, and Uncertainty: Evidence From the United States.” *Journal of Marriage and Family* 77(5):1144–56.

Schneider, Daniel. 2017. “The Effects of the Great Recession on American Families.” *Sociology Compass* 11(4):1–11.

Schneider, Daniel and Alison Gemmill. 2016. “The Surprising Decline in the Non-Marital Fertility Rate in the United States.” *Population and Development Review* 42(4):627–49.

Schneider, Daniel and Kristen Harknett. 2019. “Consequences of Routine Work-Schedule Instability for Worker Health and Well-Being.” *American Sociological Review* 84(1):82–114.

Schneider, Daniel and Orestes P. Hastings. 2015. “Socioeconomic Variation in the Effect of Economic Conditions on Marriage and Nonmarital Fertility in the United States: Evidence From the Great Recession.” *Demography* 52(6):1893–1915.

Schoenfeld, Elinor R., George S. Leibowitz, Yu Wang, Xin Chen, Wei Hou, Sina Rashidian, Mary M. Saltz, Joel H. Saltz, and Fusheng Wang. 2019. “Geographic, Temporal, and Sociodemographic Differences in Opioid Poisoning.” *American Journal of Preventive Medicine* 57(2):153–64.

Seltzer, Nathan. 2019. “Beyond the Great Recession: Labor Market Polarization and Ongoing Fertility Decline in the United States.” *Demography* 56(4):1463–1493.

Semega, Jessica L., Kayla R. Fontenot, and Melissa A. Kollar. 2017. “Income and Poverty in the United States: 2016.”

Shanahan, Lilly, Sherika N. Hill, Lauren M. Gaydosh, Annekatrin Steinhoff, E. Jane Costello, Kenneth A. Dodge, Kathleen Mullan Harris, and William E. Copeland. 2019. “Does Despair Really Kill ? A Roadmap for an Evidence-Based Answer.” *American Journal of Public Health* 109(6):854–58.

Sobotka, Tomáš, Vegard Skirbekk, and Dimiter Philipov. 2011. “Economic Recession and Fertility in the Developed World.” *Population and Development Review* 37(2):267–306.

Song, Xi, Catherine G. Massey, Karen A. Rolf, Joseph P. Ferrie, Jonathan L. Rothbaum, and Yu Xie. 2019. “Long-Term Decline in Intergenerational Mobility in the United States since the 1850s.” *Proceedings of the National Academy of Sciences* 117(19).

Stevenson, Betsey and Justin Wolfers. 2007. “Marriage and Divorce: Changes and Their Driving Forces.” *Ssrn* 21(2):27–52.

Strully, Kate W. 2009. “Job Loss and Health in the u.s. Labor Market.” *Demography* 46(2):221–46.

Sullivan, D. and T. von Wachter. 2009. “Job Displacement and Mortality: An Analysis Using Administrative Data.” *The Quarterly Journal of Economics* 124(3):1265–1307.

Taylor, Paul, Rakesh Kochhar, Daniel Dockterman, and Seth Motel. 2011. “In Two Years of Economic Recovery, Women Lost Jobs, Men Found Them.” (202):1–25.

Thiede, Brian C. and Shannon M. Monnat. 2016. “The Great Recession and America’s Geography of Unemployment.” *Demographic Research* 35(1):891–928.

Topel, Robert H. and Michael P. Ward. 1992. “Job Mobility and the Careers of Young Men.” *The Quarterly Journal of Economics* 107(2):439–79.

van Tulder, Maurits, Antti Malmivaara, and Bart Koes. 2007. “Repetitive Strain Injury.” *The Lancet* 369:1815–22.

U.S. Bureau of Labor Statistics. 2008. *Labor Force Characteristics by Race and Ethnicity, 2007*.

U.S. Bureau of Labor Statistics. 2020. “Labor Force Participation Rate - 18-19 Yrs. [LNS11300088].”

U.S. Census Bureau. 2018. “County Business Patterns, State File [Dataset].” 1999–2016.

U.S. Census Bureau. 2020. “Historical Living Arrangements of Adults.” Retrieved (https://www.census.gov/data/tables/time-series/demo/families/adults.html).

U.S. Census Bureau, Decennial Statistical Studies Division. 2016. *2020 Census Research and Testing: Investigating the 2010 Undercount of Young Children - Examining the Coverage of Young Mothers*. Washington, D.C.

U.S. Department of Health and Human Services. 2008. *American Community Survey:New Survey Questions Enable Measurement of Marital Transitions*.

United States Department of Labor. 2012. *The African-American Labor Force in the Recovery*. Washington, D.C.

Valletta, Robert G., Catherine van der List, Robert Valletta, and Catherine van der List. 2015. “Involuntary Part-Time Work: Here to Stay?” *FRBSF Economic Letter*.

Venkataramani, Atheendar S., Elizabeth F. Bair, Rourke L. O’Brien, and Alexander C. Tsai. 2020. “Association Between Automotive Assembly Plant Closures and Opioid Overdose Mortality in the United States A Difference-in-Differences Analysis.” *JAMA Internal Medicine* 19104:1–9.

Villarreal, Andrés. 2014. “Explaining the Decline in Mexico-U.S. Migration: The Effect of the Great Recession.” *Demography* 51(6):2203–28.

Weiss, Audrey J., Anne Elixhauser, Marguerite L. Barrett, Claudia A. Steiner, Molly K. Bailey, and Lauren O. Malley. 2017. *Opioid-Related Inpatient Stays and Emergency Department Visits by State, 2009–2014*.

White, Lynn and Stacy J. Rogers. 2000. “Economic Circumstances and Family Outcomes : A Review of the 1990s Published by : National Council on Family Relations Linked References Are Available on JSTOR for This Article : Economic Circumstances and Family Outcomes : A Review of the 1990s.” 62(4):1035–51.

Winkler, Richelle, Kenneth M. Johnson, Cheng Cheng, Jim Beaudoin, Paul R. Voss, and Katherine J. Curtis. 2013. “Age-Specific Net Migration Estimates for US Counties, 1950-2010.” Retrieved (https://netmigration.wisc.edu/).

Wood, Catherine. 2014. “The Rise in Women’s Share of Nonfarm Employment During the 2007–2009 Recession: A Historical Perspective.” *Monthly Labor Review* (April):1–21.

Woolf, Steven H., Derek A. Chapman, Jeanine M. Buchanich, Kendra J. Bobby, Emily B. Zimmerman, and Sarah M. Blackburn. 2018. "Changes in Midlife Death Rates across Racial and Ethnic Groups in the United States : Systematic Analysis of Vital Statistics." *BMJ* 362(k3096):1–16.

Woolf, Steven H. and Heidi Schoomaker. 2020. "Life Expectancy and Mortality Rates in the United States, 1959-2017." *JAMA - Journal of the American Medical Association* 322(20):1996–2016.

Wrigley-Field, Elizabeth and Nathan Seltzer. 2020. *Unequally Insecure: Rising Black/White Disparities in Job Displacement, 1981-2017*. Washington Center for Equitable Growth Working Paper. Washington, D.C.

Xie, Yu and Alexandra Killewald. 2020. "Intergenerational Occupational Mobility in Great Britain and the United States Since 1850: Comment." *American Economic Review* 103(5):2003–20.

Yu, Wei Hsin and Shengwei Sun. 2018. "Fertility Responses to Individual and Contextual Unemployment: Differences by Socioeconomic Background." *Demographic Research* 39(1):927–62.

Zivin, K., M. Paczkowski, and S. Galea. 2011. "Economic Downturns and Population Mental Health: Research Findings, Gaps, Challenges and Priorities." *Psychological Medicine* 41(7):1343–48.

Zoorob, Michael J. and Jason L. Salemi. 2020. "Bowling Alone , Dying Together : The Role of Social Capital in Mitigating the Drug Overdose Epidemic in the United States." *Drug and Alcohol Dependence* 173(2017):1–9.