# The Transformation of Manufacturing and the Decline in U.S. Employment*

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**Abstract**

Using data from a variety of sources, this paper comprehensively documents the dramatic changes in the manufacturing sector and the large decline in employment rates and hours worked among prime-aged Americans since 2000. We use cross-region variation to explore the link between declining manufacturing employment and labor market outcomes. We find that manufacturing decline in a local area in the 2000s had large and persistent negative effects on local employment rates, hours worked and wages. We also show that declining local manufacturing employment is related to rising local opioid use and deaths. These results suggest that some of the recent opioid epidemic is driven by demand factors in addition to increased opioid supply. We conclude the paper with a discussion of potential mediating factors associated with declining manufacturing labor demand including public and private transfer receipt, sectoral switching, and inter-region mobility. Overall, we conclude that the decline in manufacturing employment was a substantial cause of the decline in employment rates during the 2000s particularly for less educated prime age workers. Given the trends in both capital and skill deepening within this sector, we further conclude that many policies currently being discussed to promote the manufacturing sector will have only a modest labor market impact for less educated individuals.

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# 1 Introduction

The period since 2000 has witnessed two profound changes in the U.S. economy. One of these has been the dramatic transformation of the manufacturing sector along several dimensions. Manufacturing employment fell by about 5.5 million jobs between 2000 and 2017, with much of these losses occurring even before the start of the Great Recession. While manufacturing employment has been in decline since the 1970, this fall far surpasses the already substantial loss of 2 million jobs between 1980 and 2000. Despite employing less labor, however, the manufacturing sector has seen no persistent decline in its output. Instead, in spite of a decline during the recession, real manufacturing output is at least 5 percent higher today than it was in 2000. During this time, the manufacturing sector has become much more capital intensive. Both the capital to labor ratio of the manufacturing sector increased sharply and the labor share of manufacturing fell sharply during the 2000s relative to other sectors. Finally, workers employed in manufacturing are now less likely to be drawn from those with less education.

Contemporaneous with these changes in the manufacturing sector has been a large and sustained decline in employment and hours worked for prime age workers. Between 2000 and 2017, employment rates for men aged 21-55 fell by 4.6 percentage points and hours worked fell by over 180 hours per year. The declines in employment started prior to the Great Recession, accelerated during the Great Recession, and have only rebounded partially as of 2017. For comparison, the secular decline in annual hours worked for prime age men from 2000 to 2017 is as large as the cyclical decline in their annual hours worked during the 1982 recession. The declines are even larger for prime age workers with lower levels of accumulated schooling. Notably, less educated women also saw a pronounced decline in hours worked during the 2000s, reversing a century long trend.

While other sectors in the economy have undoubtedly changed in significant ways over the past few decades, the transformation of manufacturing is of particular interest to economists for several reasons.[1] The massive historical size of the manufacturing sector in the economy, accounting in 1980 for nearly one-fifth of all jobs, is one reason to be especially interested in the effect of changes in manufacturing. Another reason is that manufacturing tends to be highly spatially concentrated compared to other sectors. Consequently, shocks to manufacturing may have larger labor market effects given both local spillovers and the fact that cross-region mobility is costly. Additionally, compared to other sectors, manufacturing has traditionally occupied a disproportionate role in policy debates. This has been evident

[1]Manufacturing decline has also attracted considerable recent popular attention. For example, see Quinones (2015) and Goldstein (2017).

recently in the US with discussions of how both trade and environment policies interact with the manufacturing sector. Finally, for many decades the manufacturing sector has been one where relatively less-educated Americans, and especially less-educated men, have enjoyed labor market success. As of 1980, over one-third of employed men between the ages of 21 and 55 with a high school degree or less worked in the manufacturing sector.

In this paper, we examine how much, and by what mechanisms, changes in manufacturing since 2000 have affected the employment rates of prime age men and women. We use a variety of data sources and empirical approaches to answer these questions. We document that the persistent long run decline in employment and hours for prime age workers did not occur evenly across the United States. Furthermore, exploiting cross-region variation, we estimate a strong cross-commuting zone correlation between declining manufacturing employment and declining employment rates of prime age workers. Using a shift share instrument, we find that a 10 percentage point decline in the local manufacturing share reduced local employment rates by 3.7 percentage points for prime age men and 2.7 percentage points for prime age women. To put the magnitude in perspective, naively extrapolating the local estimates suggests that between one-third and one-half of the decline in employment rates and annual hours for prime age workers during the 2000s can be attributed to the decline in the manufacturing sector. This naive estimate ignores many important general equilibrium effects that will certainly alter the exact quantitative magnitude, but it suggests that the decline of the manufacturing sector is a first order factor explaining the declining participation rate of prime age workers in the U.S. during the last two decades. Our results are even larger for prime age men with lower levels of accumulated schooling.

Because it is based, in part, on the national trend in manufacturing, the shift share instrument captures the combined effect of all shocks that affected national manufacturing activity. One of these shocks, which has received considerable attention in the literature, is increased import competition because of rising trade with China. Yet, estimates in the literature suggest that import competition from China accounted for only about one-quarter of the decline in manufacturing during the 2000s.[2] The manufacturing sector has simultaneously experienced other dramatic changes over the past two decades most notably in automation and the rise of robotics.[3] We extend our shift-share IV analysis to examine how the effect of manufacturing decline from Chinese import-competition compares to the effect of other shocks in manufacturing that are orthogonal to trade-related factors. First, we show that manufacturing employment declined substantially over the 2000s even in markets where there was essentially no manufacturing loss because of Chinese imports. Further, we show

[2]See, for example, Autor et al. (2013).

[3]See, for example, Acemoglu and Restrepo (2017).

that shocks to manufacturing that were unrelated to China or trade (including presumably, things like rising automation) had very similar effects on local labor markets to the Chinese import shock. An implication of these results is that policy efforts to address the adverse labor market effects of trade will not reverse the broader trend in manufacturing employment that has significantly weakened labor market options, particularly for less educated workers.

We find that local employment losses from manufacturing decline were accompanied by reductions in wages. This suggests that the negative employment effects were not due to shifts in labor supply but were instead the result of falling labor demand, which likely adversely affected worker wellbeing. Consistent with this interpretation, we use data from a variety of sources to show that local manufacturing decline was associated with increased prescription opioid drug use and overdose deaths at the local level. We also show that manufacturing decline resulted in more failed drug tests among workers tested by their firms, confirming that much of this local increased drug use occurred among the affected workers themselves. Besides providing evidence about the adverse effect of negative manufacturing shocks on worker well-being, the drug results highlight how, by virtue of the effect on opioid use that they stimulate, negative local labor market shocks may have interacted with factors like changes in physician prescription behavior to drive the ongoing opioid epidemic in the U.S. More generally, our findings contribute to an emerging consensus that labor market conditions may drive different dimensions of health.[4]

One natural question is why the decline in the manufacturing sector has led to such persistent declines in employment rates. The U.S. economy has experienced sector declines throughout its history, and the manufacturing sector itself has, at other periods, shed large numbers of jobs. Yet, rarely have the negative employment rate effects of these changes been as large or persistent - presumably because of various mediating mechanisms that have eased employment transitions. To highlight the differences with earlier periods, we use our shift share methodology to show that local manufacturing employment declines during the 1980s had little effect on local employment rates during that time period. To help explain this difference, we present evidence on the role of three mediating mechanisms: transfer receipt from public and private sources; skill-mismatch within the manufacturing sector; and regional migration.

We find some evidence that declining manufacturing labor demand is associated with increased disability take up. However, the effects are quantitatively small and are not likely to explain why employment rates have remained so persistently low in the wake of declining manufacturing employment for most individuals. Additionally, we find no evidence of altered cohabitation patterns - a measure of private transfers - in response to declining local man-

[4]See, for example, Charles and DeCicca (2008).

ufacturing shares. We provide further evidence of increasing skill mismatch even within the manufacturing sector. Manufacturing is becoming an increasingly skilled sector, particularly relative to other industries that have historically employed lower educated workers such as retail and construction. We show that relative to other industries, the manufacturing sector has experienced the largest increase in the the job opening rate during the 2000s. Finally, we document that the reduced propensity of workers to move across regions in response to a local manufacturing shock is a striking feature of the data during recent periods relative to prior periods.

Our work complements the growing literature exploring the declining employment to population ratio during the 2000s. Moffitt (2012) was one of the early contributors to this literature documenting that employment rates for younger and less educated men were declining sharply prior to the Great Recession. Krueger (2017) documents the change in labor force participation rates for different demographic groups based on age and sex. He finds that both the aging of the population and an increase in school enrollment explains some of the declining labor force participation rate. Aguiar et al. (2017) documents declining employment rates and hours worked for individuals aged 21-30 and 31-55 by sex and education. They find that employment rates and hours worked fell most for young less-educated men. Abraham and Kearney (2018) survey the literature on declining employment rates during the 2000s.

Others have made the link between declining manufacturing employment and labor market outcomes during the 2000s. For example, Charles et al. (2016) and Charles et al. (Forthcoming) show that manufacturing employment has declined sharply during the early 2000s and that local declines in the share of workers employed in manufacturing are strongly correlated with increased rates of non-employment during the 2000-2007 period. Acemoglu et al. (2016), Autor et al. (2013), and Pierce and Schott (2016) all highlight the role of increased competition from China in declining manufacturing employment during the 2000s. Acemoglu et al. (2016) and Autor et al. (2013) use local labor market variation to show that increased Chinese import competition in the manufacturing sector led to declining local employment rates. In a separate line of work, Acemoglu and Restrepo (2017) show that increased automation via the use of robots has led to a decline in manufacturing employment and a decline in employment. Our work complements both of these extensive literatures by providing a broad overview of the link between declining manufacturing employment and labor market outcomes of prime wage workers during the 2000-2017 period. We also discuss potential reasons why the decline in manufacturing demand may result in lower employment rates.

# 2 Aggregate Trends in Labor Markets and Manufacturing During the 2000s

Two changes in the economy of historically massive size and significance occurred during the 2000s. One of these was a massive transformation in the manufacturing sector. The other was a sharp secular decline in work propensity among prime age persons with few, if any, historical precedents. The bulk of our analysis in this paper examines whether and how much these two phenomena are causally related, and evaluates alternative mechanisms that might account for the link between them. Before turning to this work, this section summarizes the magnitude and key features of national changes in manufacturing and employment rates over the 2000s.

## 2.1 Declining Work During the 2000s

We use two main data sources to study employment changes during the 2000s: several years of March Supplement of the Current Population Survey (CPS) plus the 1980, 1990, and 2000 U.S. Census, which we combine with the 2001-2016 American Community Surveys (ACS).[5] The CPS allows us to study long time series while the large samples in the Census/ACS facilitate cross region analysis. For both datasets, we restrict the samples to persons aged 21 to 55 (inclusive), who are living outside of group quarters and who are not in the military. The data are weighted using survey weights provided by the CPS and Census/ACS.

Figure 1 plots the trends in annual hours worked for men aged 21-55 using the CPS sample. The figure shows that from 1976 through 2000, prime age men worked slightly more than 1,950 hours per year on average at the peak of business cycles. Annual hours began falling before the Great Recession, declining throughout most of the period from 2000 to 2007. Hours plummeted during the Great Recession and have only rebounded modestly after its end. By 2016, men aged 21-55 worked, on average, only 1,785 per year. These primed-aged men thus work, on average, 185 *fewer* hours per year than they did in 2000, which represents a massive decline in work activity by historical standards. Figure 1 shows that the secular decline in annual hours worked for prime age men between 2000 and 2016 is larger than the drop in hours this group experienced during the severe 1982 recession.

A striking feature of the hours reduction between 2000 and 2016 is that almost all of the decline was the result of changes along the extensive margin of labor supply. While unemployment rates have returned to pre-recessionary levels, the employment rate for prime

[5]We downloaded all the CPS and the Census/ACS data directly from http://cps.ipums.org/cps/ and https://usa.ipums.org/usa/, respectively.

Figure 1: Annual Hours Worked, Males 21-55, CPS




Note: Figure shows the annual hours worked by year of men 21 to 55 using the CPS sample. Annual hours worked are recorded by multiplying weeks worked during the prior calendar year by the number of hours per week the individual usually works. Year $t$ measures of annual hours worked were reported by year $t+1$ respondents.

age men as of 2016 is still 4.6 percentage points below its 2000 level. In 2016, only 82.2 percent of prime age men were working, compared to 86.8 percent of men aged 21-55 worked in 2000. About half of this decline occurred prior to the Great Recession.

Figure 2 shows the annual decline in hours worked for men aged 21 to 55 relative to year 2000 for different education groups: persons with a bachelor's degree or more (accumulated education $\geq$ 16 years), persons with some college but no bachelor's degree (accumulated education = 13, 14, or 15 years), and persons with only a high school degree or less (accumulated educated $\leq$ 12 years). The declines in annual hours worked during the 2000s was largest for those with the least completed schooling. By 2016, prime age men with a bachelor's degree experienced a decline in annual work hours of roughly 150 hours, or about 7%, whereas those with less than a bachelor's degree saw their annual hours of work fall by over 200 hours relative to levels in 2000, a decrease of nearly 12%.[6]

Figure 3 plots the change over time in the share of 21 to 55 year old men who report not working during the year, separately by their level of education. In the mid-1980s, only about 9 percent of males aged 21-55 with education $\leq$ 12 worked zero weeks during the year. This number has increased with each successive recession and has generally not fallen back to its original level when the recession is over. By 2016, fully one-fifth of all men who had only a high school education or less worked zero weeks during the year. Among men with some college training but no Bachelors' degree, the fraction working zero hours over the entire year rose from about 6 percent to about 15 percent. Long-term detachment from the labor market appears to be becoming a defining feature of the labor market experience of men who are not college graduates.[7]

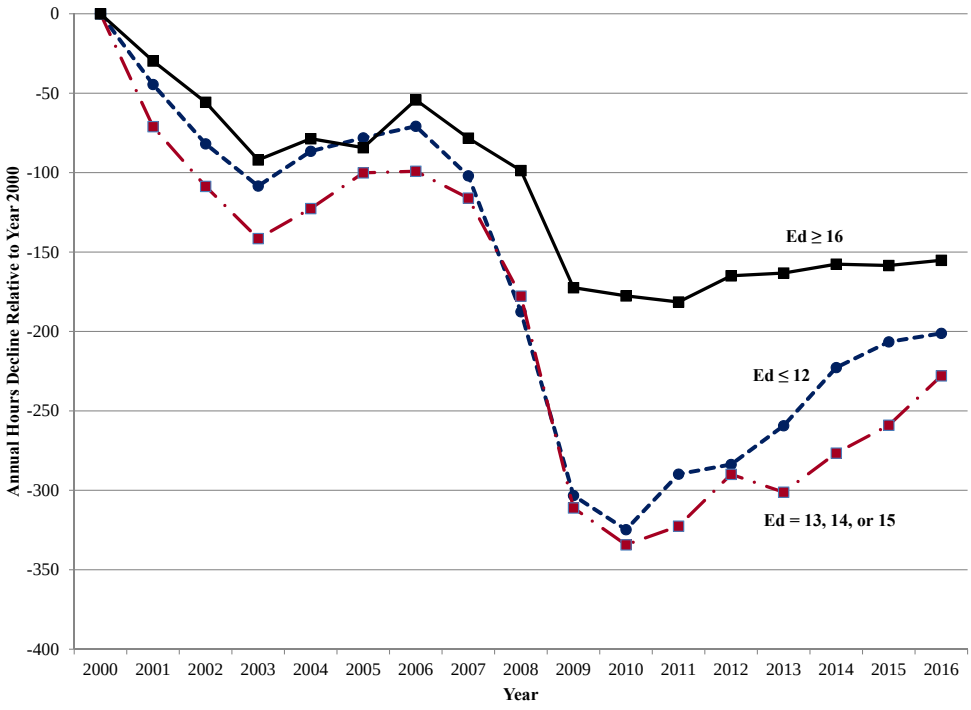
Table 1 shows that the decline in annual work hours for men with less than a bachelor's degree spanned different races and locations. The first two columns of the table show results for native born white and black men of prime age. While white men worked more than black men in all years during the 2000s, the decline in annual hours worked was slightly larger for white men (233 vs 201 hours per year). The latter three columns examine patterns for prime age men with less than a bachelor's degree who live in city centers, those in the suburbs (within a metro area but outside the city center), and those living in rural areas (outside of a metro area). While hours of work fell substantially for men everywhere, those living outside of city centers experienced the largest reductions.

We have thus far presented annual hours results only for prime-aged men. Figure 4 presents trends in hours worked for prime age women during the 2000s, separately by their

[6] In 2000, prime age men with at least a bachelor's degree worked 2,190 hours per year. The corresponding annual hours worked in 2000 for those with some college and those with a high school degree or less were 1,950 and 1,830 hours per year, respectively.

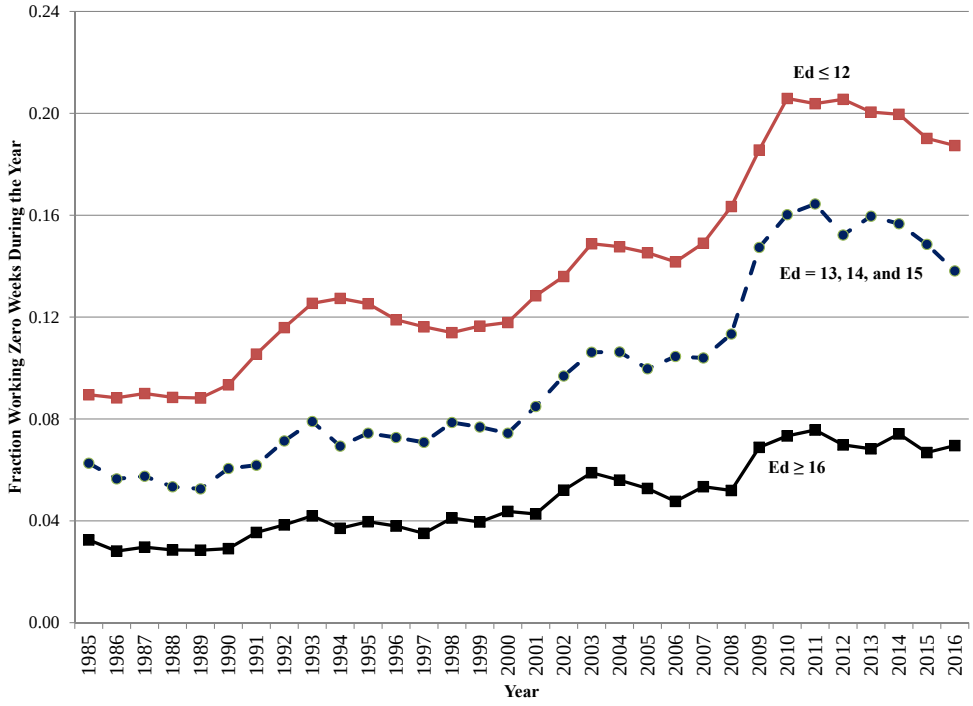
[7] Excluding individuals enrolled full time in school has little effect on these time series patterns.

Figure 2: Annual Hours Worked, Males 21-55, By Education, CPS




Note: Figure shows the annual hours worked by year of men 21 to 55 by education using the CPS sample. Annual hours worked are recorded by multiplying weeks worked during the prior calendar year by the number of hours per week the individual usually works. Year $t$ measures of annual hours worked were reported by year $t+1$ respondents. Education groups include having a bachelor's degree or more (Ed $\geq$ 16), some college but no bachelor's degree (Ed = 13, 14, or 15), or no post high school training (Ed $\leq$ 12).

Figure 3: Fraction Working Zero Weeks During the Year, Males 21-55, By Education, CPS




Note: Figure shows the fraction of males aged 21-55 working zero hours during the year. The dashed line measures those with these than a bachelor's degree while the solid measures those with a bachelor's degree or more. Annual hours worked are recorded by multiplying weeks worked during the prior calendar year by the number of hours per week the individual usually works. Year $t$ measures of annual hours worked were reported by year $t+1$ respondents.

Table 1: Annual Hours Worked for Men Aged 21-55 With Less Than A Bachelor's Degree, March CPS

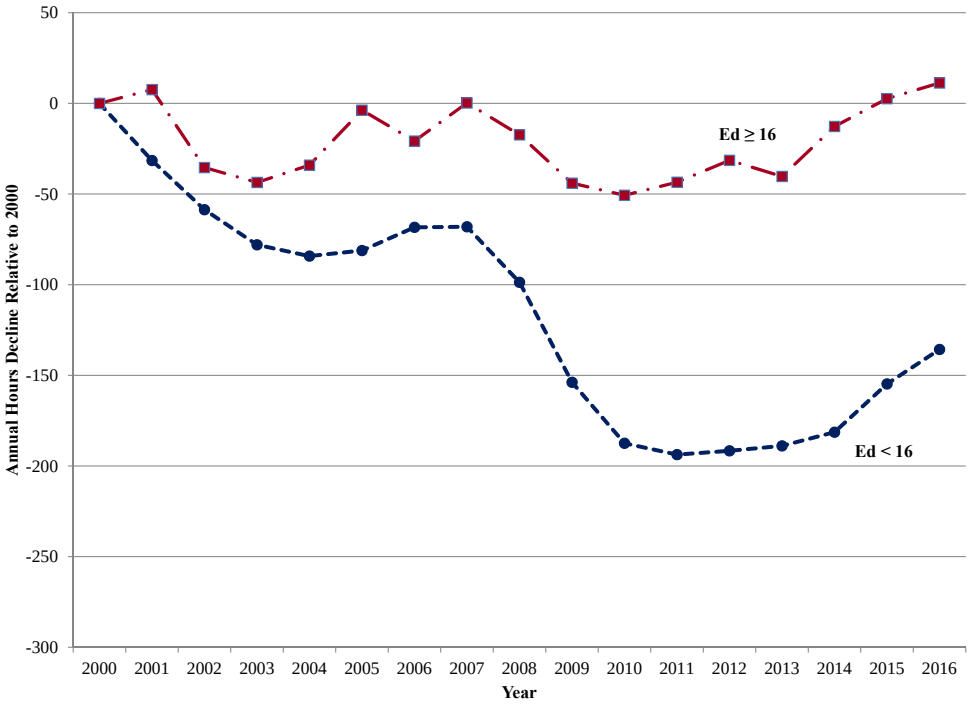
| | Native White | Native Black | City Center | Suburb | Rural |
|---|---|---|---|---|---|
| 2000 | 1,947 | 1,556 | 1,748 | 1,938 | 1,920 |
| 2016 | 1,714 | 1,355 | 1,569 | 1,714 | 1,697 |
| $\Delta$ 2000-2016 | -233 | -201 | -179 | -224 | -223 |
| % Decline | -12.0% | -12.9% | -10.2% | -11.6% | -11.6% |

Note: Table shows the annual hours worked for men aged 21-55 with less than a bachelor's degree in 2000 and 2016. Columns 1 and 2 further restricts the sample include whites and blacks born in the U.S. The latter three columns restricts the sample to those of all races living in center cities, suburbs, or rural areas. See text for additional details.

level of education. We show results separately by gender chiefly because of the massive secular increase in women's hours worked over the past century. Showing results for the full population runs the risk of having this well-understood secular change for women be the dominant feature of the series, swamping the key features of men's annual hours patterns that we have shown. Figure 4 shows that while annual hours worked for college-graduate women were relatively constant over the 2000s, women with less than a bachelor's degree experienced a decline of about 140 hours per year between 2000 and 2016. The pattern of hours changes for these prime-age, less educated women was very similar to that of their male counterparts: declines pre-dated the start of the Great Recession, accelerated over the course of the recession, and have only modestly recovered since. Also like less educated men, the decline in annual hours worked for less educated women was chiefly driven by falling employment propensities. Whereas 71 percent of women aged 21-55 with less than a bachelor's degree were employed in 2000, the shared was only 66 percent in 2017.

To summarize, during the 2000s, there were large reductions in annual hours worked for both prime age men and women, with the declines concentrated among those with less than a bachelor's degree. Further, nearly all of the hours reduction was the result of falling employment rates. Although the U.S. unemployment rate has returned to its pre-recession level, employment rates for prime age workers still lag behind where they were before the recession. What reconciles these seemings conflicting two facts is the decision of many of those not working to cease searching for work.

Figure 4: Annual Hours Worked, Females 21-55, By Education, CPS




Note: Figure shows the annual hours worked by year of women 21 to 55 by education using the CPS sample. Annual hours worked are recorded by multiplying weeks worked during the prior calendar year by the number of hours per week the individual usually works. Year $t$ measures of annual hours worked were reported by year $t+1$ respondents. Education groups include having a bachelor's degree or more (Ed $\geq$ 16) or less than a bachelor's degree (Ed $<$ 16).

## 2.2 The Transformation of the Manufacturing Sector During the 2000s

Although, as shown below, the manufacturing sector has been undergoing large evolution since at least the mid-1970s, the changes the sector has experienced since 2000 have been particularly profound. We highlight key features of these dramatic changes.

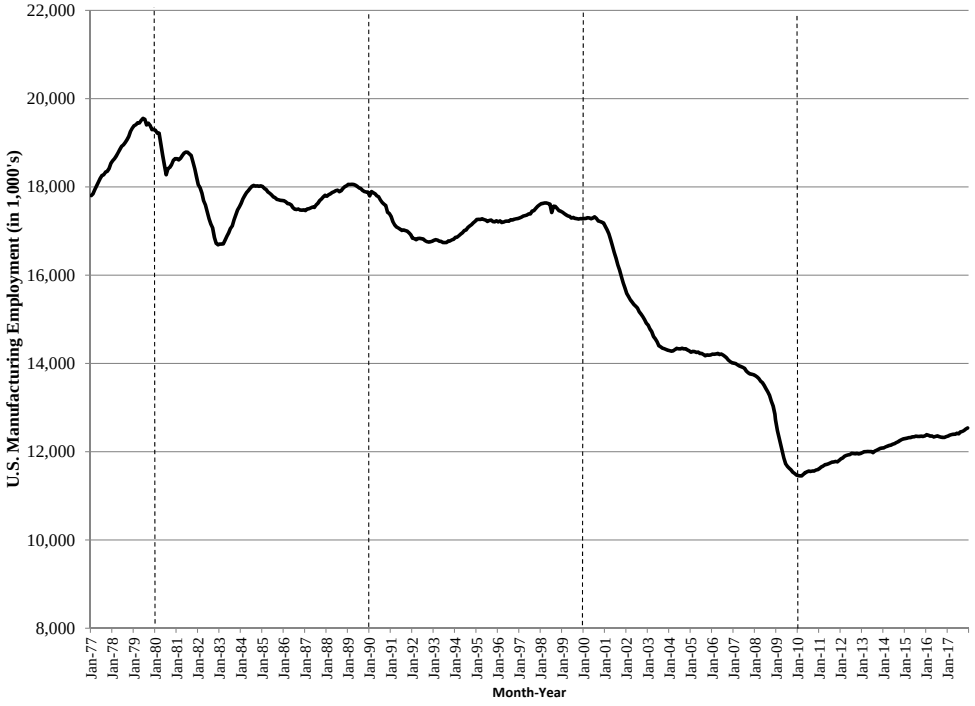
Perhaps the most stunning transformation in the sector has been the massive national decline in the number of manufacturing jobs. Figure 5 shows the trend in monthly employment in the U.S. manufacturing industry from January 1977 through December 2017. These data come from the BLS's Current Employment Statistic's establishment survey. Continuing a pattern that dates to the mid-1970s, the U.S. lost about 2 million manufacturing jobs between 1980 and 2000. After 2000, the trend decline in manufacturing employment accelerated dramatically. Six million manufacturing jobs disappeared between 2000 and 2010, with much of the job loss occurring prior to the start of the Great Recession. In the years after the Great Recession, U.S. manufacturing employment has remained depressed, rebounding only slightly through 2017. On net, 5.5 million U.S. manufacturing jobs were lost between 2000 and 2017. These large recent declines dwarf those of the 1980s and 1990s.

Figure 6 shows that declining manufacturing employment corresponded with a sharp decline in the number of manufacturing establishments. After a steady rise in the number of manufacturing establishments between the late 1970s and late 1990s, the U.S. lost over 75,000 manufacturing establishments between 2000 and 2014. Like the decline in manufacturing employment, much of the decline in establishments occurred prior to the Great Recession. Since the end of the Great Recession, the number of establishments in the manufacturing industry has not rebounded. As of 2014, the number of U.S. manufacturing establishments were 50,000 lower than in 1977. The decline in the manufacturing employment during the 2000s is distinct in modern U.S. history. Not only did manufacturing employment fall by one-third since 2000, the declines were associated with a twenty percent reduction in the number of manufacturing establishments.

What has driven this decline in manufacturing employment and establishments? Figure 7 shows dramatically that manufacturers did not hire less labor because of falling demand for manufacturing output. The figure plots the percent deviations in real output for the U.S. manufacturing sector relative to 2000Q1, which is anchored at 100.[8] The figure shows that, in spite of some reduction in manufacturing output during the Great Recession, a 27% decline in manufacturing employment and a 21% decline in manufacturing establishments, U.S. total manufacturing output is today seven percent higher than its 2000 level. Thus,

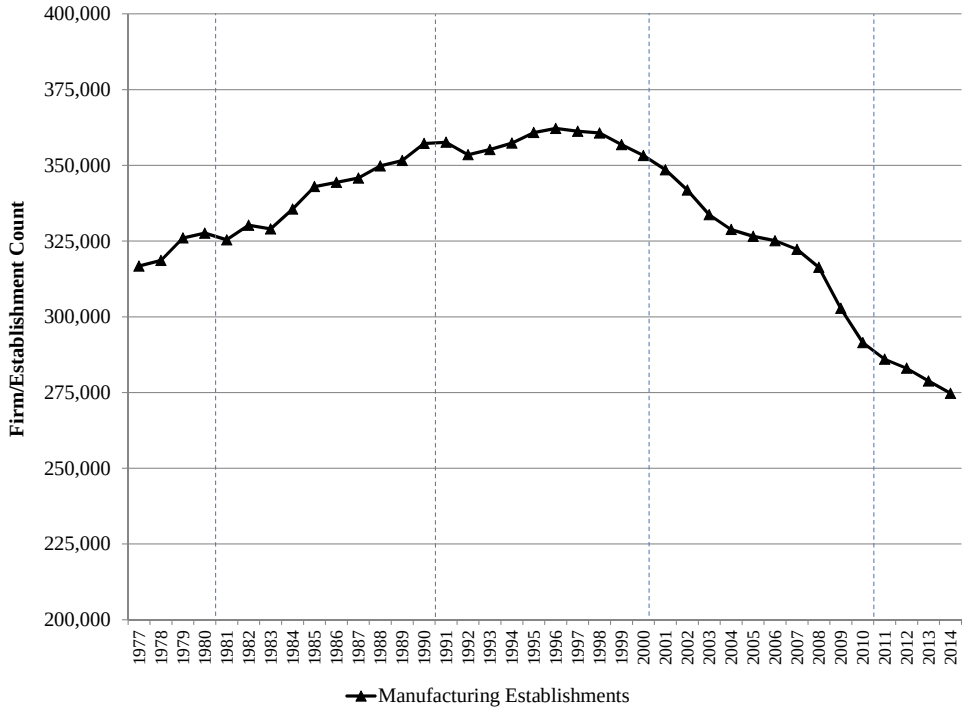
[8]Data from the U.S. Bureau of Labor Statistics.

Figure 5: Monthly U.S. Manufacturing Employment 1977-2014



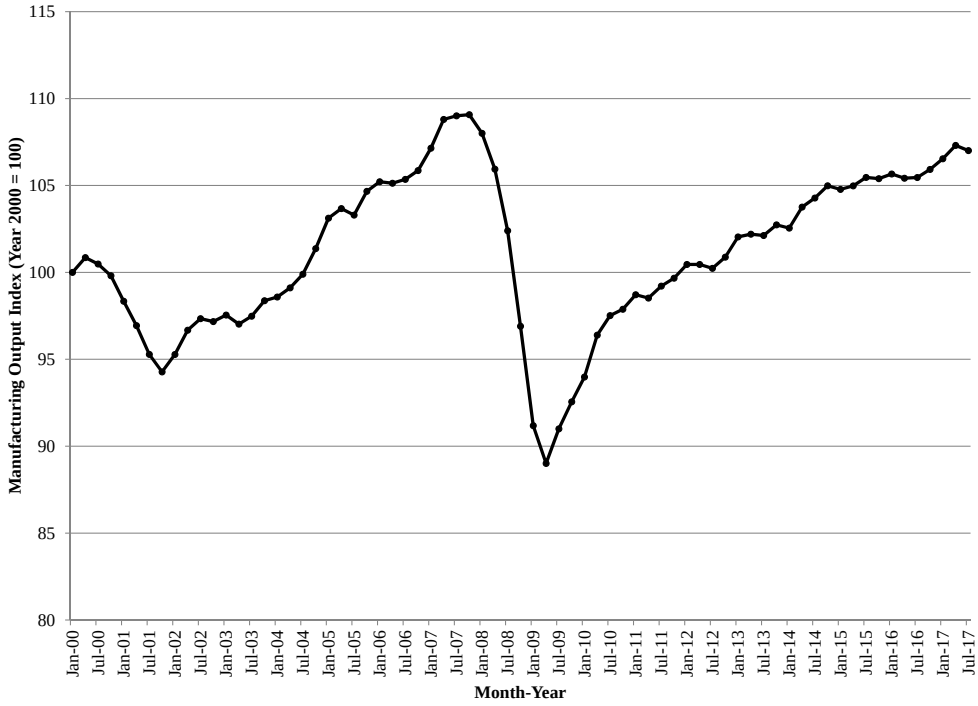

Note: Figure shows total employment in the manufacturing industry within the U.S. over time. Data comes for the Bureau of Labor Statistic's (BLS) Current Employment Statistics and was downloaded directly from the St. Louis Federal Reserve's economic data website. Vertical lines represent January of 1980, 1990, 2000, and 2010, respectively.

Figure 6: Total Manufacturing Establishments 1977-2017 (in 1,000s)




Note: Figure shows total number of establishments in the manufacturing industry within the U.S. over time. Data comes for the Longitudinal Business Database (LBD). Vertical lines represent 1980, 1990, 2000, and 2010, respectively.

Figure 7: U.S. Quarterly Real Output Index for the Manufacturing Sector (2000Q1 = 100)




Note: Figure shows an index for real output in the manufacturing sector over time. Data from 2000Q1 is set to 100. All subsequent quarter-year pairs are percent changes relative to 2000Q1. Data comes for the U.S. Bureau of Labor Statistics and was downloaded directly from the St. Louis Federal Reserve's economic data website.

demand for manufacturing labor has not been accompanied by a commensurate decline in the demand for the goods made by manufacturers.[9]

The adoption of production techniques that use less labor in favor of technology and other inputs is a potential explanation for manufacturing's falling labor demand. Various pieces of evidence suggest that there has been greater technology adoption and capital deepening

[9]There is a fair bit of heterogeneity across manufacturing sub-industries with respect to output growth during the 2000s. Using data from the Bureau of Economic Analysis, we measure annualized growth rates in real value added between 2000 and 2016 for each three-digit manufacturing sub-industry. During this period, seven manufacturing sub-industries had growth rates larger than 10 percent, another six had growth rates between -10 percent and 10 percent, and six had growth rates less than -10 percent. The largest positive growth rate was in "computer and electronic products" (over 200 percent increase) while the largest contraction was in "apparel and leather and allied products" (over 50 percent decline). Houseman et al. (2015) emphasize the importance of computer and electronic products in driving U.S. manufacturing output growth during the 2000s.

in the sector over the past two decades.

Figure 8 plots the evolution of the labor share for the manufacturing sector and for the total non-farm business sector from 1987 through 2015. Consistent with the findings of Karabarbounis and Neiman (2014), the labor share fell broadly in the U.S. economy, with the declines concentrated in the post-2000 period. The labor share in the manufacturing sector fell by about 20 percent between 2000 and 2015. By comparison, the labor share in the broad non-farm business sector (which includes the manufacturing sector) fell by only about 10 percent over the same period. Figure 9 shows the capital intensity of the manufacturing sector and the non-farm business sector during the 1987 to 2015 period. The figure shows clearly that manufacturing became substantially more capital intensive during the 2000s, both absolutely and relative to other non-farm sectors in the economy. The manufacturing sector has not dramatically shrunk since 2000. Rather, the sector has grown and done so while sharply substituting capital for workers in production.

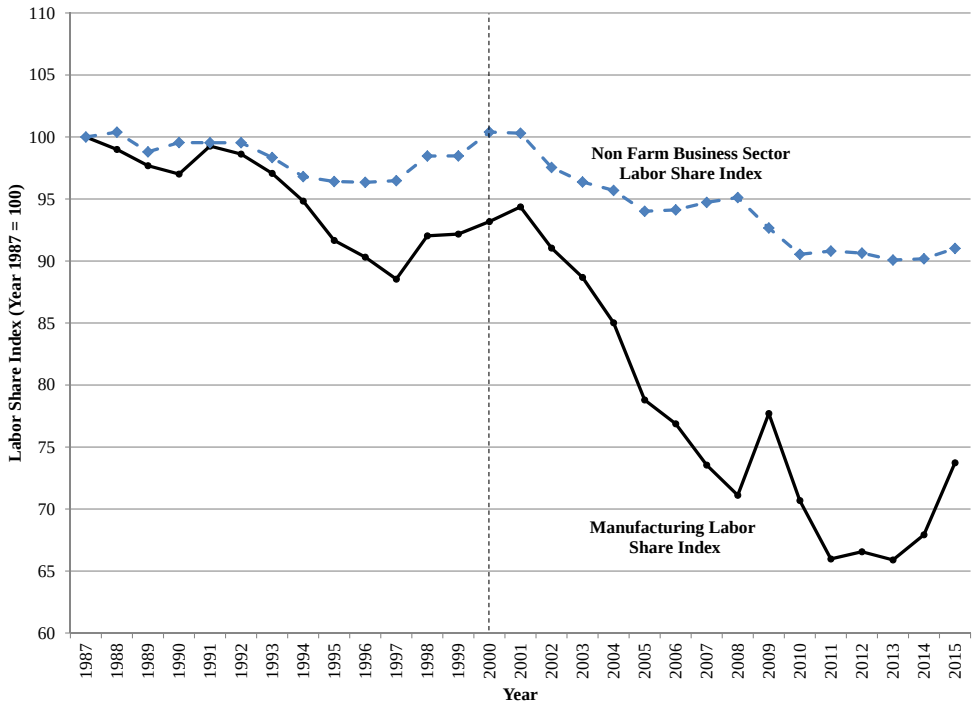
Another potential driver of decreased labor demand in manufacturing is the phenomenon of rising import competition from China during the 2000s. According to Autor et al. (2013), the real value of Chinese imports to the U.S.increased by 1,156% from early 1990s through 2007, with much of the growth occurring after 2000. This surge in Chinese imports to the U.S. relative to changes from other U.S. trading partners both in terms of levels and growth rates.[10]

Figure 10 shows the relationship between different 4-digit manufacturing industries' exposure to Chinese import competition and the percent decline in employment in the industry between 1999 and 2011 for the entire United States.[11] As highlighted by Autor et al. (2013), the figure shows that employment losses were larger in manufacturing industries that experienced larger Chinese import competition shocks. For example, during 1999 to 2011, industries where Chinese import competition grew by 30 percent experienced a 60 percent reduction in employment, compared to the 40 percent employment decline in industries that saw import competition grow by between 5 and 10 percent. This variation in industry employment loss by the amount of import competition underlies the regional analysis in Autor et al. (2013) and Acemoglu et al. (2016). Consistent with our earlier results on capital deepening and capital substitution, the figure also shows that industries that experienced little or no growth in import competition from China, represented in the first two bins, also had substantial declines in employment, with reductions of about 30-40 percent during the early 2000s. As Autor et al. (2013) note, import competition from China explains only about

[10]See Table 1 of Autor et al. (2013).

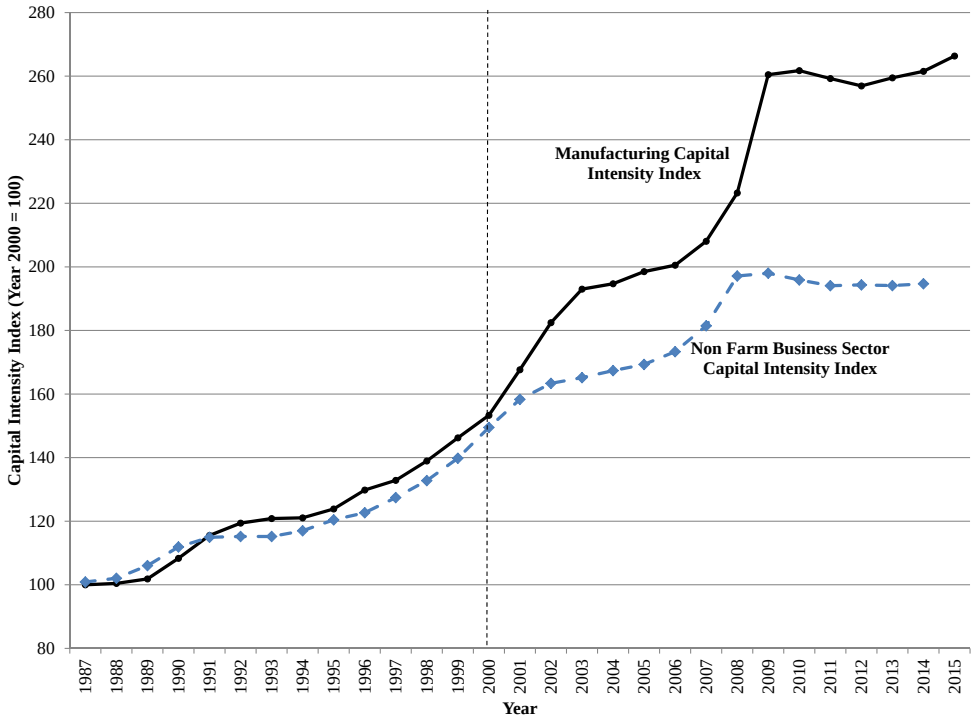
[11]For this analysis, we combine the Chinese import competition from Acemoglu et al. (2016) with data from NBER's CES Manufacturing Industry Database which tracks employment by detailed manufacturing industry through 2011. See http://www.nber.org/nberces/ for more details.

Figure 8: Labor Share Index for US Manufacturing and Private Non-Farm Business Sectors (Year 2000 = 100)



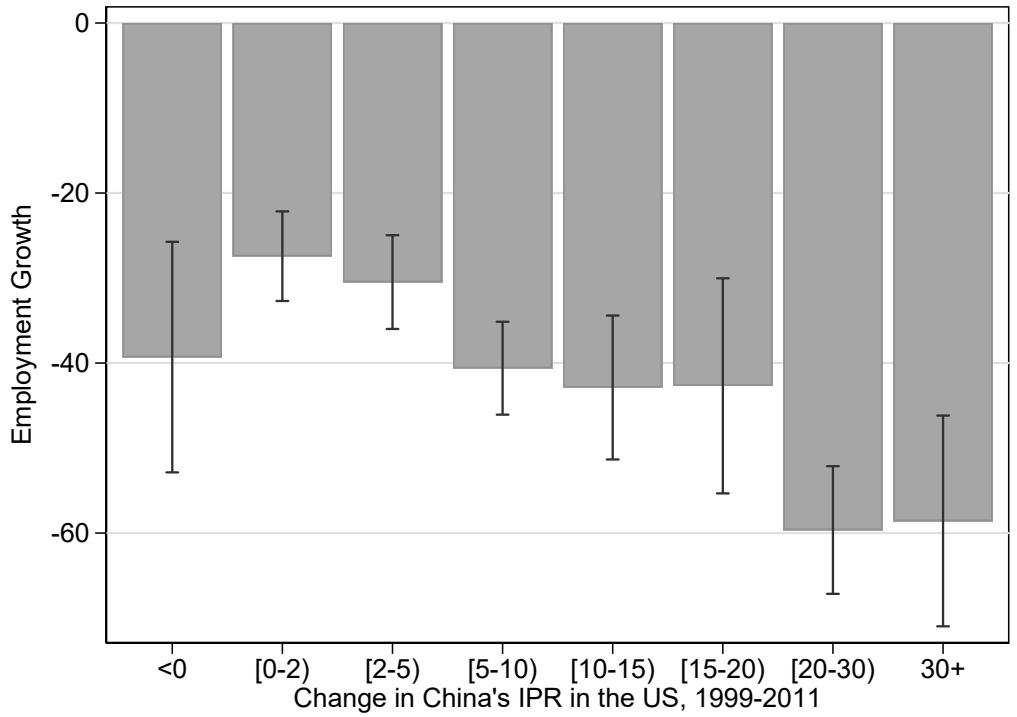

Note: Figure shows the annual index for the labor share in the manufacturing sector (solid line) and the private non-farm business sector (dashed lined). We index the labor share in both sectors to 100 in 1987. All subsequent years are percent changes relative to 2000. Data comes for the U.S. Bureau of Labor Statistics and was downloaded directly from the St. Louis Federal Reserve's economic data website. Vertical line indicates year 2000.

Figure 9: Capital Intensity for US Manufacturing and Private Non-Farm Business Sectors (Year 2000 = 100)




Note: Figure shows the annual index for the capital intensity in the manufacturing sector (solid line) and the private non-farm business sector (dashed lined). Capital intensity is defined as the ratio of capital services to hours worked in the production process. The higher the capital to hours ratio, the more capital intensive the production process is. We index the capital intensity measure to 100 in 1987. All subsequent years are percent changes relative to 2000. Data comes for the U.S. Bureau of Labor Statistics and was downloaded directly from the St. Louis Federal Reserve's economic data website. Vertical line indicates year 2000.

Figure 10: Employment Decline and Import Competition

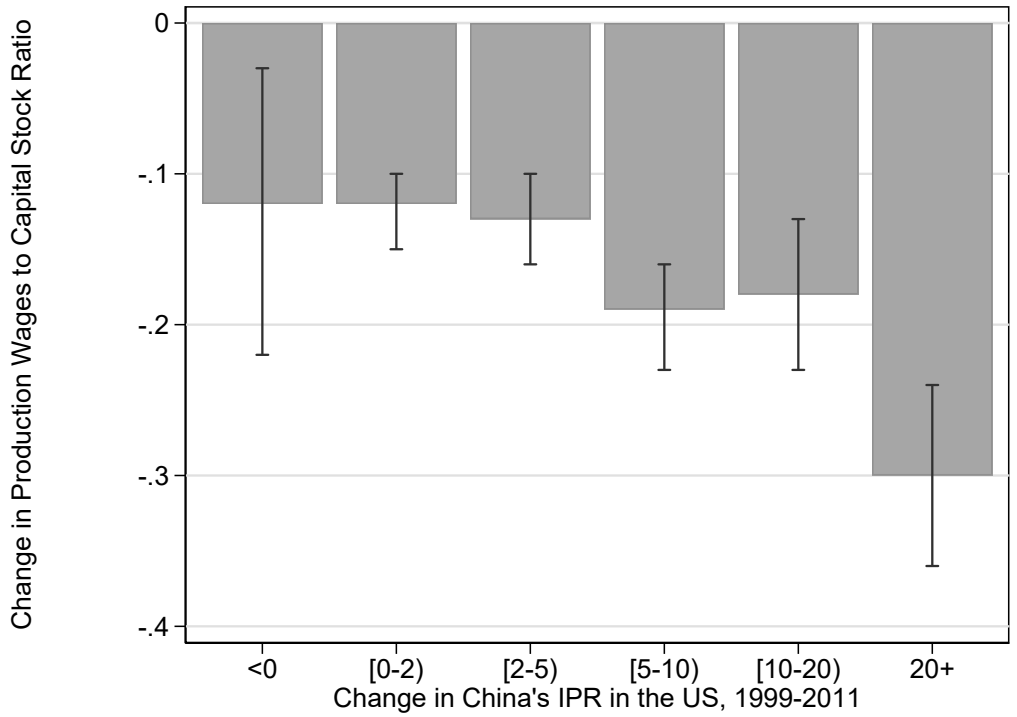



Note: Figure shows the estimated percentage change in employment by bins of the change in import penetration by China between 1999 and 2011. Each bin also shows the 95% confidence interval around the employment decline. Data on important penetration changes comes from (Acemoglu et al., 2016), and data on employment levels by manufacturing subindustry comes from NBER-CES's Manufacturing Industry Database. The import competition measure is defined as the change in imports from China over the period 1999-2011, divided by initial absorption (measured as industry shipments plus industry imports minus industry exports).

one-quarter of U.S. manufacturing decline during the 1990-2007 period.

While often analyzed in isolation, capital deepening of the manufacturing sector and import competition from China may be linked. Figure 11 shows the mean change in the ratio of real production worker wages to real capital stock for manufacturing industries between 1999 and 2011, according to the change in Chinese import competition. The large employment declines in manufacturing industries at all levels of Chinese import competition growth are matched by a marked change in the production technology, as indicated by a falling of the labor to capital ratio. The declines were largest in industries that faced the largest growth in Chinese import competition. We cannot disentangle whether the threat or reality of competition from imports induced manufacturers to automate their processes or whether imports happened to grow most in places where automation was rising for other reasons. In either case, this association between import shocks and automation suggests that policies that restrict trade with the aim of returning employment to its pre-China-shock level

Figure 11: Labor to Capital Ratio and Import Competition



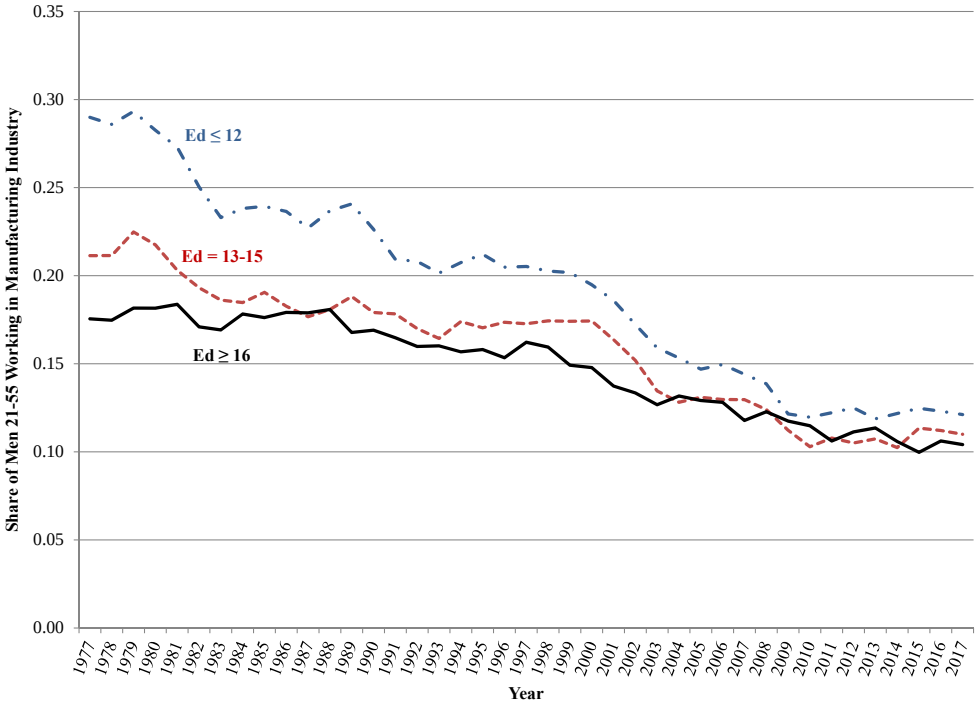

Note: Figure shows the change in the ratio of real production worker wages to real capital stock by bins of the change in import penetration by China between 1999 and 2011. Each bin also shows the 95% confidence interval around the employment decline. Data on important penetration changes comes from (Acemoglu et al., 2016), and data on the real production wages and real capital stock by manufacturing subindustry come from NBER-CES's Manufacturing Industry Database. The import competition measure is defined as the change in imports from China over the period 1999-2011, divided by initial absorption (measured as industry shipments plus industry imports minus industry exports).

confront the problem that the affected industries are now significantly more capital intensive than before. They are thus unlikely to raise labor demand to old levels even if they are protected from trade competition,

The reduction in the amount of labor used in the sector is only one of two major transformations in manufacturing. The other major change during the last two decades has been a fundamental shift in the *types* of workers whom the sector employs, as measured by their completed schooling. Using data from several years of March Supplements to the Current Population Survey (CPS), we plot the time series patterns in the share of men and women aged 21 to 55 of different education levels and regardless of employment status working in the manufacturing sector.

Figure 12 shows a large decline in the likelihood of working in manufacturing for men without any college training. Whereas three decades ago nearly one in three of such men

Figure 12: Manufacturing Share of Population for Prime Age Men 1977-2016, by Education

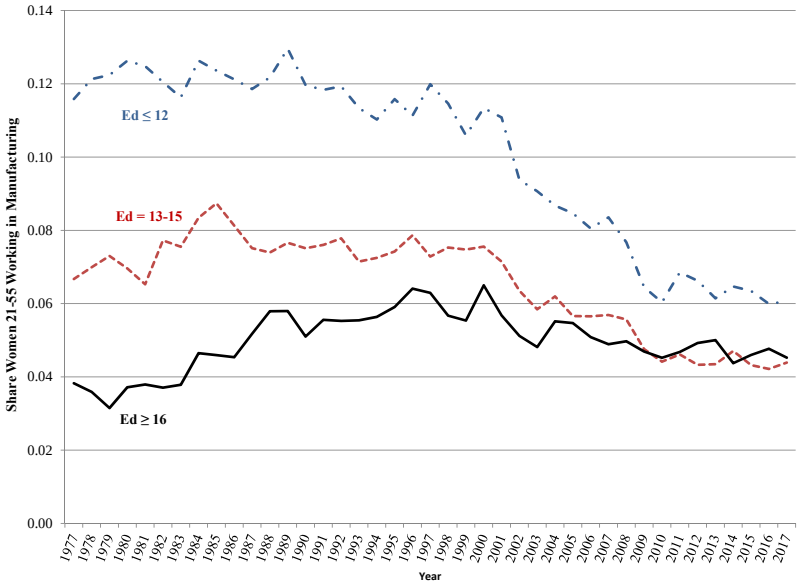



Note: Figure shows the share of men aged 21-55 who work in the manufacturing industry by educational attainment. The sample includes both men who are employed and not employed. Data comes from the CPS. See the data appendix for additional details.

worked in manufacturing, by 2017 the share had plummeted to only 12 percent. The manufacturing employment share among men with college training also fell between 1977 and 2017, but at only about 10 percentage points the decline was much smaller than that for less educated men, and occurred from a much lower initial level of around 20 rather than 30 percent. Figure 13 shows results for women. Manufacturing has and continues to play a much smaller role in women's employment compared to men's, but the figure show that the same qualitative patterns shown for men of different education levels occurred among women as well. Between 2000 and 2017, the share of prime age women with no college training who worked in manufacturing fell by about 5 percentage points, from 11 percent to 6 percent. This reduction was larger than the retreat from manufacturing work experienced by more educated women, whose propensity to work in manufacturing fell by around 2 percentage points between 2000 and 2017.

A consequence of the differential changes in manufacturing employment shares by edu-

Figure 13: Manufacturing Share of Population for Prime Age Women 1977-2016, by Education




Note: Figure shows the share of women aged 21-55 who work in the manufacturing industry by educational attainment. The sample includes both women who are employed and not employed. Data comes from the CPS. See the data appendix for additional details.

cation level in Figures 12 and 13 is that manufacturing has become a more highly-skilled sector, as measured by workers' education. As of 2017, the manufacturing sector is no longer the disproportionately important source of employment for the less-educated that it was in the late 1970s and early 1980s. At the same time, the share of manufacturing workers who are college educated and the fraction of college-educated workers employed in manufacturing have grown sharply.

Before concluding our discussion of the profound changes in the manufacturing sector, we note that another analysis might have sorted workers by occupation rather than industry. How much of what we summarize about manufacturing is really about particular occupations in the economy? Over three-quarters of the prime-aged men with less than a bachelor's degree working in manufacturing worked as production workers between 2000 and 2017, with little change in the share in that time.[12] By contrast, for prime age men with at least a bachelor's degree working in the manufacturing industry, the share working in production occupations was only 15 percent during the same time period. Most college-educated men in

[12]We define production workers as those with a 2010 occupation code over 6000.

manufacturing during the 2000s were managers, engineers, computer programmers or software developers. Consistent with the shifts in education shares during the 2000s, the share of prime age men in manufacturing working in production as opposed to other occupations fell from 61 percent in 2000 to 58 percent in 2017.[13]

## 2.3 Aggregate Relationship Between Manufacturing Decline and Declining Employment

Taken together, the changes in the manufacturing sector summarized above point to a substantial decline in labor demand in the manufacturing sector over the past two decades. In the next section, we provide causal estimates of the effects of changes in manufacturing labor demand on employment and hours. Before turning to this causal evidence, we conclude this section by presenting some associational results from aggregate time series data that is consistent with the notion that the manufacturing decline may have played an important explanatory role in the changes in employment and hours we have discussed.

Figure 14 shows the association between declining manufacturing shares and employment rates for different education groups in time series data. The top panel in the figure shows that, for prime-aged men of each education level, the decline in the manufacturing share between 2000 and 2017 was nearly identical to the decline in that group's employment rate. For example, the manufacturing share for men aged 21 to 55 with a high school degree or less fell by 7 percentage points between 2000 and 2017, as was previously shown in Figure 12. This group's employment rate fell by 6 percentage points during that time period. For the other two education groups similar patterns emerge. To a first approximation, reductions in manufacturing shares for prime age men were matched by a roughly equal declines in employment rates during the 2000 to 2017 period. The patterns are most pronounced for lower educated workers.

Charles et al. (2016) and Charles et al. (Forthcoming) highlight how the construction boom during the late 1990s and early 2000s masked the adverse effects of the secular decline in manufacturing in aggregate statistics. For prime age men with less education, there is a fair degree of substitutability between the skills required in the manufacturing and construction sectors. The results in the bottom panel of Figure 14 show that any period since 1990, roughly 52 percent of men with a high school degree or less have been engaged in one of three activities at any point in time: working in manufacturing; working in construction; or not working at all. The share of all less-educated men in one of these three states at

[13] During the 2000-2017 period, roughly 60 percent of prime age women working in manufacturing with less than a bachelor's degree worked in production occupations, compared with only 10 percent of prime age women working in manufacturing with a bachelor's degree or more.

a point in time has been nearly constant over three decades despite the massive decline in manufacturing employment. This composite share, which is plotted in the figure, increased slightly during the Great Recession but by 2012 it had returned to its long-run level. During the period depicted in the figure, the share of men working in construction was quite similar in 1990, 2000 and 2017. It therefore follows that, over approximately 30 years, there has been a one-to-one mapping between declining manufacturing shares and rising non-employment rates for prime age men with a high school degree or less. At around 40 percent from 1990 to 2017, the composite share for men with some college training but no bachelor's degree was lower than than for men with only high school educations, but the flat time series trend is identical. For men with a bachelor's degree or more there is a 4 percentage point decline in this composite share over time. These patterns are consistent with the results in the top panel of the figure.

# 3 The Effect of Local Labor Market Manufacturing Shocks on Employment Since 2000

In this section, we move beyond suggestive aggregate evidence and apply instrumental variables methods to local labor market data to estimate the causal effect of declining local manufacturing labor demand in the 2000s on changes in local annual hours and employment rates for prime-aged men and women.

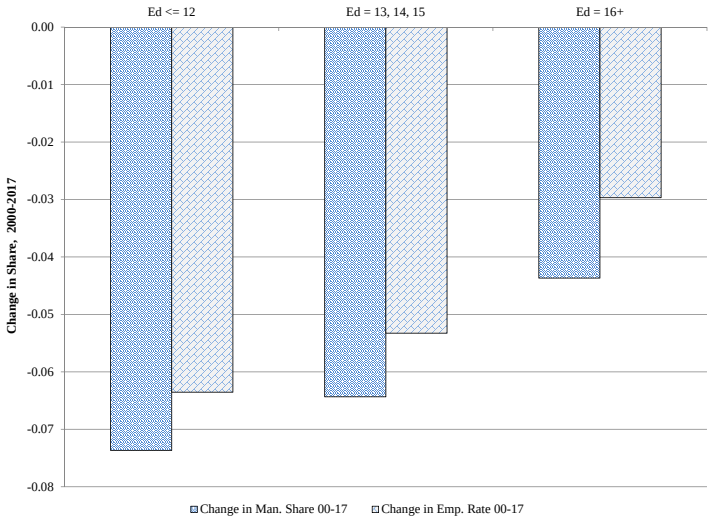
We use data from the 2000 U.S. Census and the pooled 2014-2016 American Community Surveys (ACS). For ease of exposition, we will refer to the latter as 2016 data. Unlike the CPS, the large sample sizes in the Census and the ACS allow us to explore labor market variables at detailed sub-regions of the U.S.[14] As with the CPS analysis shown previously, we restrict the sample to non-military individuals between 21 and 55 who live outside of group quarters. The local labor market we analyze is the commuting zone, which we classify using the commuting zone definitions in Autor et al. (2013). There are 741 of these areas in our sample. These are relatively self-contained areas where the vast majority of residents also work. Unlike metropolitan areas, commuting zones span the entire U.S. In the analysis, we weight commuting zones by the size of their population of prime age workers in 2000 to mitigate the larger measurement error in sparsely populated commuting zones.

Figure 15 shows the commuting zones in the U.S. identified by the size of their manufacturing share of the population among 21 to 55 year olds in 2000. Darker shading in a commuting indicates a higher manufacturing share. This regional variation will be a com-

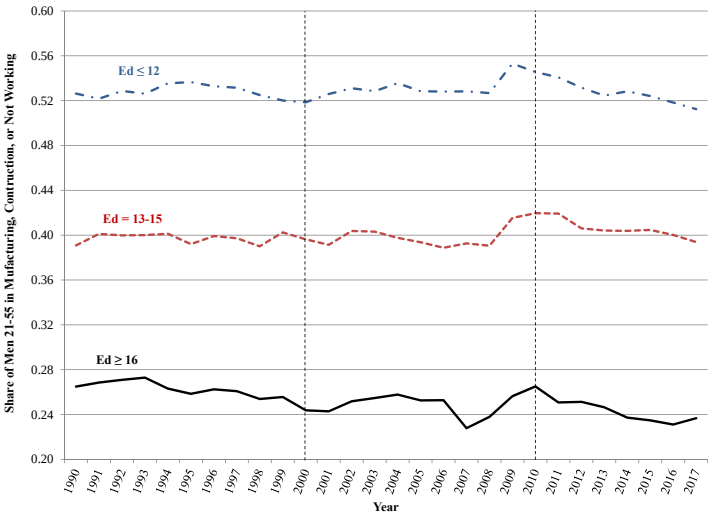
[14]The time series patterns in the Census/ACS and the CPS are nearly identical during this period.

Figure 14: Time Series Relationship Between Manufacturing Shares and Employment Rates, Prime Age Men

(a) Change in Manufacturing Share and Employment Rate 2000-2017

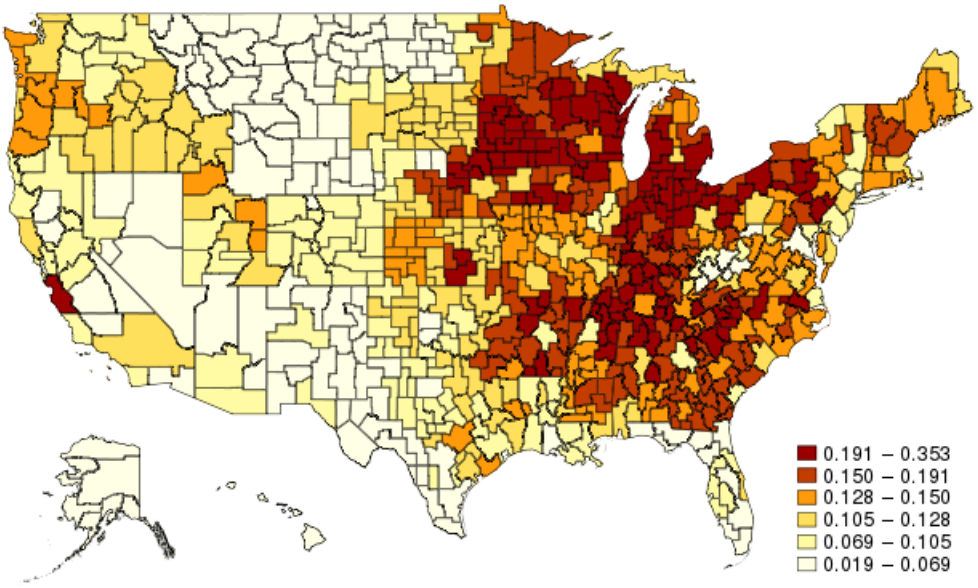



(b) Share Working in Manufacturing, Construction or Not Working At All, 1990-2017




Note: The top panel of the figure shows the decline in the manufacturing share (left bar) and the decline in the employment rate (right bar) between 2000 and 2017 for men aged 21-55 in the CPS of differing years of accumulated schooling. The bottom panel shows the share of men 21-55 over differing education levels that either work in the manufacturing industry, construction or who do not work at all.

Figure 15: Manufacturing Share of Prime Age Population by Commuting Zone, 2000




Note: Figure shows the manufacturing share of the the 21-55 year population by commuting zone from the 2000 Census. The shaded areas represent six quantiles of commuting zones based on their 2000 manufacturing share. Commuting zones that are grey indicate no data. The darker the commuting zone, the higher the manufacturing share in 2000.

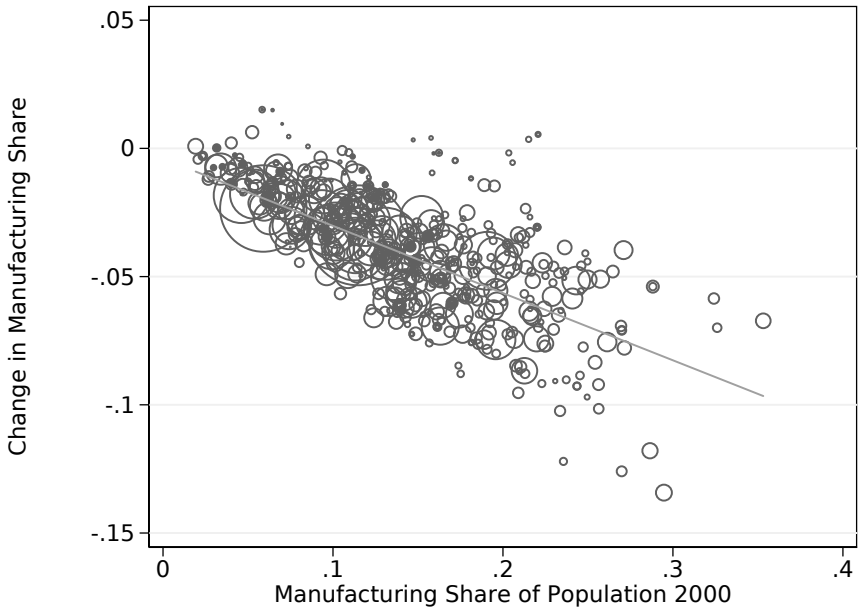
ponent of our identification strategy.

The figure shows that community zones varied widely in terms of the importance of their manufacturing industries in 2000. For example, in most commuting zones in Nevada less than 7 percent of the prime age population worked in manufacturing in 2000. Conversely, in Indiana most commuting zones had manufacturing shares of at least 15 percent. Another pattern the figure shows is that much of the manufacturing industry in the U.S. was concentrated in the Mid-west and South East in 2000. For example, states like Georgia, Indiana, western Kentucky, Michigan, Minnesota, North Carolina, Ohio, Pennsylvania, South Carolina, Tennessee, West Virginia and Wisconsin had commuting zones with very large fractions of the population working in the manufacturing sector as of 2000.

Figure 16 shows that commuting zones with the largest manufacturing share in 2000 experienced the largest decline in the manufacturing share between 2000 and 2016. This is not surprising. As aggregate employment in the manufacturing industry declined, regions that specialized in manufacturing were most adversely effected. The weighted regression line through the scatter plot in Figure 16 suggests that a 10 percentage point higher manufacturing share in 2000 was associated with a 2.6 percentage point decline in the manufacturing share between 2000 and 2016.

Figure 17 provides some preliminary evidence linking declines in the manufacturing sector

Figure 16: Change in Manufacturing Share 2000-2016 vs. 2000 Manufacturing Share




Note: Figure shows the change in the manufacturing share for prime age workers between 2000 and 2016 versus the initial manufacturing share in 2000. Each observation is a commuting zone. The size of the circle reflects the size of the 2000 prime age population in each commuting zone. The figure includes the weighted regression line of the scatter plot. The slope of the regression line is -0.26 with a robust standard error of 0.02.

in a local area to changes in employment rates of prime age men and women during the 2000s. The figure presents a scatter plot of the initial manufacturing share in the commuting zone in 2000 against the change in the employment rate of men (top panel) and women (bottom panel) in the commuting zone between 2000 and 2017. The manufacturing share, as above, is defined for all individuals aged 21 to 55 regardless of sex and education. The figure shows the strong negative relationship between a commuting zone's manufacturing share in 2000 and the subsequent change in employment rates there between 2000 and 2016. For men, a 10 percentage point increase in the manufacturing share in 2000 is associated with a 3 percentage point decline in their employment rate (standard error = 0.4). The R-squared of the simple scatter plot for men was 0.24. For women, the results are similar, with a 10 percentage point increase in the commuting zone's manufacturing share reducing their employment rate by 2.5 percentage points (standard error = 0.6). There is thus a strong cross-sectional relationship between initial manufacturing intensity and the subsequent long run change in employment rates for both prime age men and women.

We assume that the relationship between a commuting zone's decline in the manufacturing share and labor market outcomes is given by

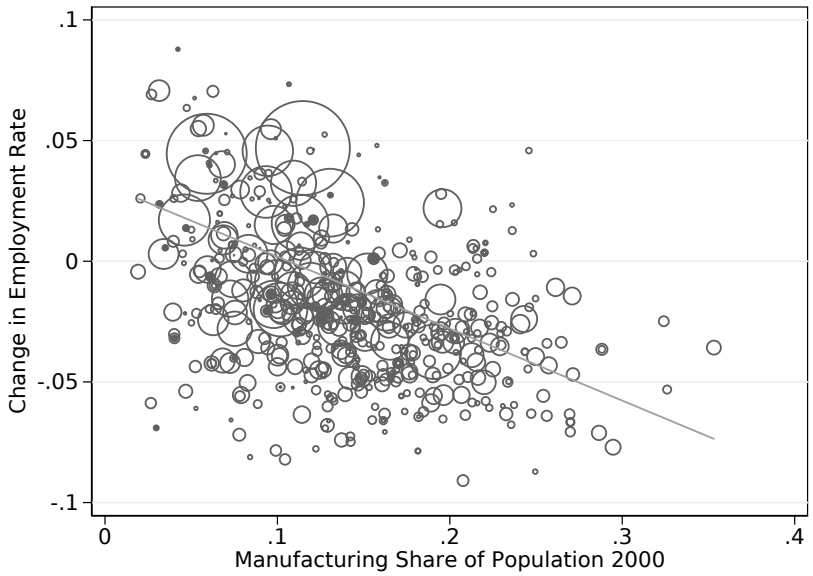
$$\Delta L_{t+1}^{g,k} = \alpha^g + \beta^g \Delta Man_{t+1}^k + \Gamma^g X_t^k + \epsilon_{t+1}^{g,k} \tag{1}$$

In the above specification, $\Delta Man_{t+1}^k$ denotes the change in the manufacturing share in commuting zone $k$ between period $t$ (2000) and $t+1$ (2016) for all persons 21-55 years old. The variable $\Delta L_{t+1}^{g,k}$ measures the change in labor market outcomes between 2000 and 2016 in commuting zone $k$ for demographic group $g$ based on sex and education. The outcomes studied for each group $g$ in $k$ are the change in log average annual hours worked, the change in the employment rate, and the change in log hourly wages (described in the data appendix). All regressions include a vector of year 2000 controls for $k$, denoted $X_t^k$, which include the share of the prime age population with a bachelor's degree, the prime age female labor force participation rate, and the share of the population that is foreign born. These controls capture other potential determinants of labor market outcomes that might be correlated with initial manufacturing share. Our coefficient of interest is $\beta^g$, the responsiveness of local labor market conditions to changes in the local manufacturing share.

There are at least two potential threats to identification from estimating equation (1) via OLS. First, local labor supply shifts can simultaneously reduce local employment rates and draw individuals out of the manufacturing sector. For example, if individuals in a given area were to acquire a distaste for work, then observed employment might fall. As individuals stop

Figure 17: Change in Employment Rate 2000-2016 vs. 2000 Manufacturing Share

(a) Men 21-55




(b) Women 21-55

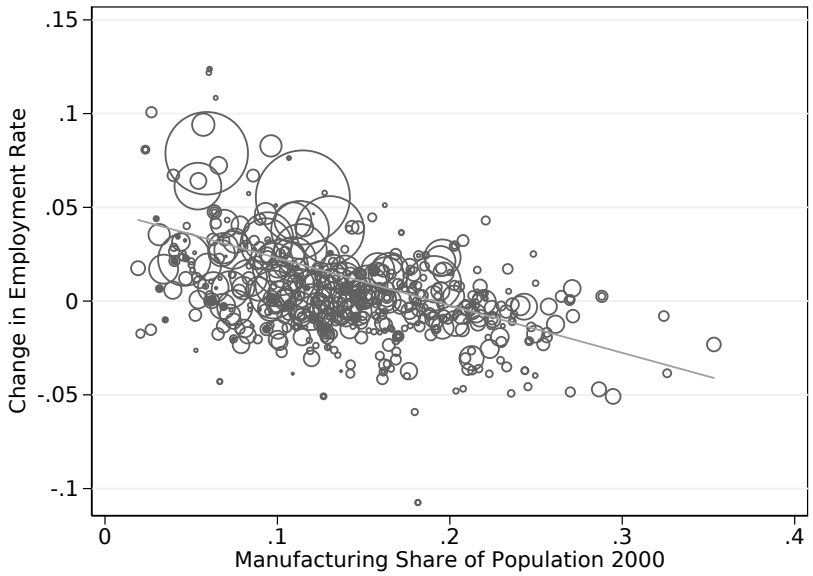



Figure shows the change in the employment rate for prime age individuals between 2000 and 2016 versus the initial manufacturing share in 2000. Panel (a) of figure shows the change for men while panel (b) shows the changes for women. Each observation is a commuting zone. The size of the circle reflects the size of the 2000 prime age population in each commuting zone. Each panel of the figure includes the weighted regression line of the scatter plot. For panel (a), the slope of the regression line is -0.30 with a standard error of 0.04. For panel (b), the slope of the regression line is -0.25 with a standard error of 0.06.

working, some may be drawn out of the manufacturing sector. Thus, a positive correlation between changes in local employment rates and changes in local manufacturing shares need not imply that the decline in manufacturing labor demand caused a fall in local employment rates. Likewise, an increase in labor demand for a non-manufacturing sector, such as the energy sector, could pull individuals out of the manufacturing sector and simultaneously increase local employment rates. This would cause a negative correlation between changes in local manufacturing shares and changes in local employment rates that is not due to the causal channel we wish to capture.

To overcome potential endogeneity concerns, we use a Two Stage Least Squares (TSLS) approach, in which we use an instrumental variable (IV) for changes in the local manufacturing employment shares. Following Charles et al. (Forthcoming), our IV, $S^k_{t+1}$, is given by:

$$S^k_{t+1} = \sum_{n=1}^{J} \psi^k_{j,2000}(Man^{-k}_{j,2016} - Man^{-k}_{j,2000}) \tag{2}$$

where $\psi^k_{j,2000}$ is the share of prime age individuals in commuting zone $k$ working in detailed manufacturing sub-industry $j$ in year 2000.[15] The shares are defined over all prime age individuals regardless of sex and education. The term in the brackets of (2) represents the change in aggregate employment shares in manufacturing industry $j$ during the 2000s. When calculating the instrumental variable for region $k$, we calculate the aggregate change in employment in industry $j$ excluding any changes in that industry within $k$. We define the change in aggregate employment shares within $j$ for all 21 to 55 year olds in the Census/ACS data.

The IV is an example of the well-known "shift-share" (or "Bartik") instrument, which has become a commonly-used tool for identifying local labor demand shocks.[16] The instrument isolates two sources of variation that help with causal identification. First, as seen in Figure 15, some commuting zones are more manufacturing intensive than others, so part of the identifying variation comes from a comparison across areas with high versus low initial manufacturing intensity. Second, because of differences in their specific industrial mix within the manufacturing sector, some commuting zones that were initially manufacturing intensive specialized in industries that declined more during the 2000s.

[15] We use the 2000 census industry codes to define these 74 detailed manufacturing sub-industries.

[16] See Murphy and Topel (1987), Bartik (1991), Blanchard and Katz (1992), Bound and Holzer (2000), Charles et al. (2016), Charles et al. (Forthcoming), Autor et al. (2013), Acemoglu and Restrepo (2017) and Goldsmith-Pinkham et al. (2017) for examples of other papers that employ variants of this shift share instrument.

The validity of the shift-share instrument hinges on two assumptions. First, national changes in employment shares in manufacturing industry $j$ need to be uncorrelated with local labor market conditions aside from their effect on local manufacturing labor demand. Second, initial local industry shares should be uncorrelated with changes in local labor market conditions aside from their effect on changes in local manufacturing labor demand. It is, as always, impossible to prove that the exclusion restriction holds. However, the literature has stressed that important components of national changes in manufacturing are the result of factors like import competition and trade policy at the national level (see Autor et al. 2013) and the exogenous secular changes at national and international level in the development and adoption of automation and technology (Acemoglu and Restrepo 2017). These factors are arguably orthogonal to the factors other than manufacturing labor demand that determine local labor demand and labor supply.

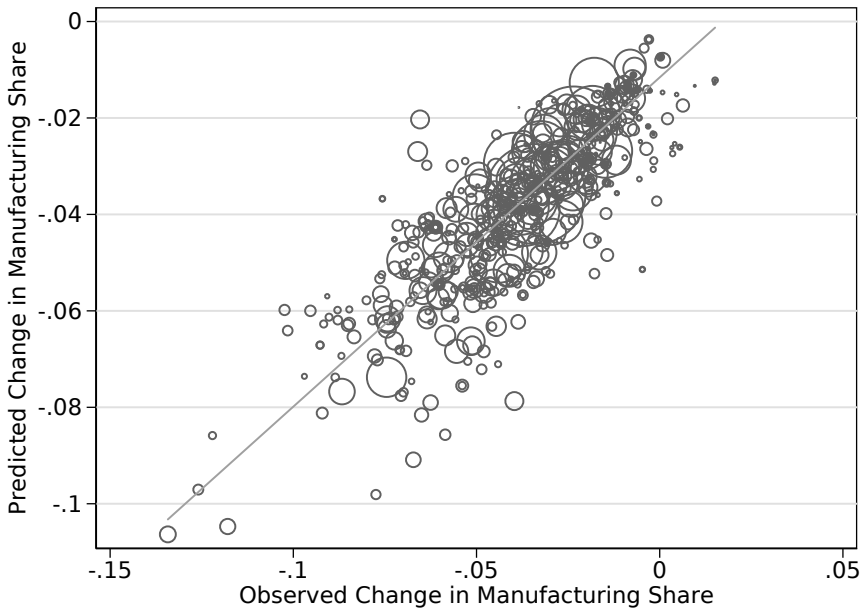
Figure 18 relates the observed change in manufacturing in a commuting zone, $\Delta lnMan^k_{t+1}$, to the change predicted by the shift share instrumental variable, $\Delta \widehat{lnMan^k_{t+1}}$. The figure shows that the IV strongly predicts actual changes in local manufacturing shares. Areas that had larger predicted declines in their manufacturing share had systematically larger actual declines in their manufacturing share. The slope coefficient from the simple weighted regression line of the scatter plot is 0.68 (standard error = 0.03) with a R-squared of 0.68 and an F-statistic of 498.

Table 2 shows estimates of $\beta^g$ from estimating equation (1) by TSLS and instrumenting for $\Delta lnMan^k_{t+1}$ with $S^k_{t+1}$. We present separate estimates for different sex and education groups. Across the different regressions, the labor market dependent variables are specific to sex×education groups, but both the change in manufacturing share and our instrument are defined at the commuting zone level. Having the same independent variable of interest facilitates comparisons of the coefficients across the various specifications.

We find that the decline in manufacturing shares between 2000 and 2016 led to large reductions in employment rates and annual hours worked for prime age men and women. The 90-10 difference in the decline in manufacturing shares across commuting zones was roughly 5.7 percentage points.[17] Thus, commuting zones at the 10th percentile of the manufacturing change distribution experienced a decline in the employment rate for prime age men between 2000 and 2016 (pooling across all education groups) that was 2.11 percentage points larger than commuting zones at the 90th percentile of the manufacturing change distribution (0.057 * 0.37 * 100). The difference in the declines in annual hours worked for prime age men

[17]The 10th percentile of the actual decline in manufacturing shares across the 741 commuting zones was -0.065 while the 90th percentile was -0.008. Essentially all commuting zones experienced a decline in the manufacturing share of prime age individuals during the 2000 to 2016 period, with the mean decline being -0.034 and a standard deviation of 0.023.

Figure 18: Predicted Change in Manufacturing Share 2000-2016 vs. Change in Manufacturing Share 2000-2016




Note: Figure shows the relationship between the predicted change in the manufacturing share between 2000 and 2016 and the observed change. The change is predicted using our shift share instrument and local area baseline controls. Each observation is a commuting zone. The size of the circle reflects the size of the 2000 prime age population in each commuting zone. The figure includes the weighted regression line of the scatter plot. The slope of the regression line is 0.68 with a robust standard error of 0.03.

Table 2: IV Regression of Changing Manufacturing Employment on Changing Labor Market Conditions 2000-2016, by Sex and Education Groups

| | Education | | | |
|---|---|---|---|---|
| | All | $\leq 12$ | 13-15 | $\geq 16$ |
| Change in Employment Rate | | | | |
| Men | 0.37 | 0.46 | 0.35 | 0.13 |
| | (0.08) | (0.13) | (0.08) | (0.06) |
| Women | 0.27 | 0.56 | 0.14 | 0.09 |
| | (0.08) | (0.08) | (0.08) | (0.08) |
| Change in Log Average Annual Hours Worked | | | | |
| Men | 0.54 | 0.79 | 0.67 | 0.04 |
| | (0.15) | (0.24) | (0.18) | (0.11) |
| Women | 0.55 | 1.15 | 0.43 | 0.08 |
| | (0.15) | (0.21) | (0.16) | (0.11) |
| Change in Log Average Wage | | | | |
| Men | 1.23 | 1.83 | 1.41 | 0.68 |
| | (0.36) | (0.34) | (0.33) | (0.35) |
| Women | 1.00 | 1.34 | 1.28 | 0.60 |
| | (0.30) | (0.25) | (0.36) | (0.31) |

Note: Table shows the two-stage least squares estimates of the effect of the change in the manufacturing share on changes in local labor market conditions. The change in the manufacturing share is instrumented using our shift share instrument. In all specifications, we include the baseline share of the prime age population with a bachelor's degree, the baseline prime age female labor force participation rate, and the baseline share of the population that is foreign born as controls. Real wages are adjusted to account for the changing demographic composition between 2000 and 2016. Robust standard errors are shown in parentheses.

between the 10th and 90th percentiles was 3.08 percent (0.057 * 0.54 * 100). The magnitudes were very similar for prime age women.

Employment rates and annual hours worked of less educated men and women were affected particularly strongly by a declining local manufacturing sector. For example, comparing the 10th and 90th percentile commuting zones with respected to manufacturing decline, the decline in employment rates was 2.6 percentage points larger and the decline in annual hours worked was 4.5 percent larger for prime age men with a high school degree or less.

The comparable numbers for prime age men with a bachelor's degree or more were much smaller, at 0.74 percentage points and 0.2 percent, respectively. Manufacturing decline had smaller effects on employment rates and hours worked the more educated the worker.

Table 2 also shows how changes in local manufacturing share affected average demographically adjusted real wages. As employment and hours fell, so did wages in the commuting zone. We take this as strong evidence that the reductions in employment and hours that we estimate do not primarily reflect reduced labor supply, but instead are primarily the product of decreased labor demand in commuting zones. Comparing the coefficients from the wage and hours regression provides a rough estimate of local labor supply elasticities.

As noted above, the TSLS results in Table 2 based on the shift-share instrumental variable ultimately come from two types of comparisons. One of these is the contrast between commuting zones with large rather than small *pre-existing* manufacturing shares - the importance of manufacturing in the area at the start of our study period. The other comparison is the contrast across areas based on whether the *composition* of their manufacturing industry in 2000 led there being bigger or smaller reductions when manufacturing declined nationally during the 2000s. One potential concern with the results in Table 2 is that places with large manufacturing shares in 2000 might have been systematically different from places where manufacturing shares were smaller. To explore whether this concern is valid, we re-estimated all the results in Table 2, including the initial manufacturing share in 2000 as an additional regressor. Doing this generally increased both the coefficients and standard errors reported in Table 2. However, the results are not statistically different from what we show in the table. For example, for all prime age men, the coefficients on the change in the employment rate and the change in log annual hours worked become 0.64 (standard error = 0.21) and 0.81 (standard error = 0.45) when the 2000 manufacturing share is included as an additional control.

The estimates from the commuting-zone analysis shed light on how much the decline in manufacturing explains the aggregate decline in employment rates and hours worked for prime age men and women. It should be stressed that cross-area estimates only provide an accurate assessment of the effects of aggregate manufacturing decline on aggregate changes in employment rates and labor market conditions under a stringent set of conditions. This point has been made in recent work by Beraja et al. (2016), Nakamura and Steinsson (2014), and Adao et al. (2017). The cross-region estimates ignore the mobility of labor, capital and goods across space, changes in national monetary, fiscal and regulatory policy that affect all regions, and the financial flows across regions through government transfer policies. All of these factors imply that the local employment elasticity to a local shock (like the decline in manufacturing labor demand) differs from the aggregate employment elasticity to the same

aggregate shock.

Given these concerns, we do not use estimates from our local labor market analysis to provide an exact counterfactual of how aggregate manufacturing declines affect aggregate employment rates. Instead, these estimates enable us to give a sense of the potential magnitudes of the role of declining aggregate manufacturing employment in explaining aggregate declines in employment and hours for prime age workers, while holding these other general equilibrium forces and margins of adjustment constant.

Table 3 has two panels and shows four columns of results. Columns 1 and 3 show, respectively, the actual change in the employment rates (in percentage points) and the actual change in log annual hours (in percent) for different demographic groups for the entire U.S. between 2000 and 2016. Columns 2 and 4 show the predicted change in these variables for the different demographic groups during the same period. To calculate the predicted change, we multiply the demographic group specific coefficients in Table 2 by the actual change in the manufacturing share for prime age workers during the 2000 to 2016 period.[18] Between 2000 and 2016, the decline in the prime age manufacturing share using CPS data was 6.3 percentage points. The top panel of Table 3 shows the results for men while the bottom panel shows the results for women. Within each panel, we show results for the pooled education groups as well as for individuals with a high school degree or less, some college but no bachelor's degree, and a bachelor's degree or more.

One of the headline results from Table 3 is that our regressions suggest that declining manufacturing employment was an important explanation of the aggregate decline in hours worked and employment rates for both men and women during the 2000s, holding potential general equilibrium forces constant. For example, our estimates suggest that 50 percent of the employment rate decline (-0.023/-0.046) and 35 percent of the annual hours decline (-0.034/-0.097) can be attributed to the decline in the manufacturing share of employment. For women, -1.7 percentage points of the -2.8 percentage points decline in employment rates can be attributed to declining manufacturing. Collectively, these results suggest that the decline in the manufacturing sector was likely an important explanation for why employment rates and annual hours worked declined so sharply during the 2000s. As the literature evolves, understanding the general equilibrium forces associated with the decline in manufacturing will be an important contribution to the literature.[19]

[18] As noted above, for each demographic group, we defined the change in the manufacturing share in equation 1 for all prime age workers.

[19] Some authors use detailed tables on input-output linkages to assess the spillover effects of declining local demand on other regions. Incorporating this general equilibrium force tends to amplify the aggregate effects relative to the naive calculation. See, for example, Acemoglu et al. (2016) for a discussion of these issues with respect to increased import competition from China.

Table 3: Predicted Employment Rate and Annual Hours Change Due to Declining Manufacturing, by Sex and Education Groups

| | Δ Emp. Rate (in percentage points) | | Δ Ln Annual Hours (in percent) | |
|---|---|---|---|---|
| | Actual Change | Predicted Change | Actual Change | Predicted Change |
| Men | | | | |
| Ed = All | -4.6 | -2.3 | -9.7 | -3.4 |
| Ed ≤ 12 | -6.4 | -2.9 | -11.6 | -5.0 |
| Ed = 13, 14 and 15 | -5.3 | -2.2 | -12.4 | -4.2 |
| Ed ≥ 16 | -3.0 | -0.8 | -7.4 | -0.3 |
| Women | | | | |
| Ed = All | -2.8 | -1.7 | -4.2 | -3.5 |
| Ed ≤ 12 | -7.5 | -3.5 | -14.1 | -7.2 |
| Ed = 13, 14 and 15 | -4.9 | -0.9 | -9.1 | -2.7 |
| Ed ≥ 16 | -1.6 | -0.6 | -0.7 | -0.5 |

Note: Table shows the predicted and actual changes in the employment rate (in percentage points) and log annual hours (in percent) for different demographic groups for the entire U.S. during the 2000 to 2016 period. The predicted change is calculated by multiplying the demographic group specific coefficients in Table 2 by the actual change in the manufacturing share for prime age workers during the 2000 to 2016 period. Between 2000 and 2016, the decline in the prime age manufacturing share using CPS data was 6.3 percentage points.

Table 3 also reinforces the results in the aggregate time series patterns. Our cross region regressions imply that manufacturing declines have a greater impact on less-educated workers. As the time series patterns showed, these workers experienced the largest declines in employment rates and annual hours worked. Our estimates imply that manufacturing decline is responsible for a decline in annual hours worked of about 5 percent for prime age men with a high school degree or less. By contrast, we find that manufacturing decline explains essentially none of the decline in annual hours for college-graduates. While hours and employment fell for these more highly educated persons at the aggregate level, our estimates imply that essentially none of that decline can be explained by a declining manufacturing sector, holding other general equilibrium forces constant.

The shift-share IV strategy discussed above captures the combined exogenous effect on local manufacturing of *all* national factors that change labor demand in the manufacturing sector: capital deepening and technology, Chinese import competition, new management techniques, etc. Yet, knowing something about these separate effects of the different factors

might be important to policy-makers contemplating alternative policies that affect specific mechanisms driving local manufacturing demand changes. Data limitations prevent us from providing evidence on the separate effects of the many different types of national shocks to manufacturing. However, because we have a direct measure of trade shocks in a commuting zone, we can say something about how the local effect of trade-related shocks compare to the local effect of all other shocks that are statistically orthogonal to trade.[20]

Our approach is straightforward. To isolate the part of the shift share instrument that is purged of the effect of increased Chinese import competition, we estimate the following regression:[21]

$$S^k_{t+1} = \omega_0 + \omega_1 Import^k_{t+1} + \omega_2 X^k_t + \nu^k_{t+1} \tag{3}$$

where $S$ and $X$ are defined as above and $Import^k_{t+1}$ is the instrument for Chinese import competition measure as defined in Acemoglu et al. (2016). The residuals from this regression, which we denote $\tilde{S}^k_{t+1}$, are the portion of the shift-share measure that is orthogonal to the Chinese import competition measure ($S^k_{t+1} - \hat{\omega}_0 - \hat{\omega_1} Import^k_{t+1} - \hat{\omega}_2 X^k_t$). We leave the instrument for Chinese import competition as is, so that any common component of the two instruments is loaded onto the import competition measure. We then predict the change in the local manufacturing share between 2000 and 2016 using the residualized shift-share measure and the Chinese import competition instrument:

$$\Delta Man^k_{t+1} = \gamma_0 + \gamma_1 \tilde{S}^k_{t+1} + \gamma_2 Import^k_{t+1} + \Gamma X^k_t + \nu^k_{t+1} \tag{4}$$

Given the estimates from equation 4 we define the following two variables for each commuting zone:

$$\Delta \widehat{Man_{t+1}}^{\tilde{S},k} = \hat{\gamma}_1 \tilde{S}^k_{t+1} \tag{5}$$

$$\Delta \widehat{Man_{t+1}}^{Import,k} = \hat{\gamma}_2 Import^k_{t+1} \tag{6}$$

$\Delta \widehat{Man_{t+1}}^{Import,k}$ and $\Delta \widehat{Man_{t+1}}^{\tilde{S},k}$ are the percentage point change in a commuting zone's

[20] Recall, for example, our previous discussion showing that there was a correlation between technology adoption and capital deepening. Our approach would isolate the effect of trade and any the portion of technology correlated with trade.

[21] We downloaded the import competition instrument directly from David Dorn's website.

manufacturing share predicted by the Chinese import competition instrument and all other factor, respectively. We then estimate the regression below on the sample of prime age men:

$$\Delta L_{t+1}^{k} = \alpha + \beta^{S} \Delta \widehat{Man_{t+1}}^{\tilde{S},k} + \beta^{I} \Delta \widehat{Man_{t+1}}^{I,k} + \Gamma X_{t}^{k} + \epsilon_{t+1}^{k} \tag{7}$$

The results of the above regression are shown in Table 4. The dependent variable in the regression is the change in the commuting zone's employment rate between 2000 and 2016. Columns (1) includes the same $X$ vector of controls as in Table 2 while column (2) follows the work of Autor et al. (2013) and Acemoglu et al. (2016) and includes the initial manufacturing share out of total population in year 2000 as an additional control. In column (2) the identification comes from variation in trends in manufacturing employment among commuting zones with similar manufacturing shares in 2000.

The key takeaway from Table 4 is that the local labor market effects of local manufacturing employment due to Chinese import competition are very similar to the local labor market effects of manufacturing declines due to other forces. For example, a 10 percentage point reduction in the manufacturing share caused by the increased Chinese import competition leads to a decline in local male employment rates of 4.2 percentage points, whereas the male employment rate decline from a 10 percentage point decline in the manufacturing share from forces orthogonal to increased Chinese import competition is 2.5 percentage points. These estimates are not statistically different from each other. If we control for initial manufacturing share the small difference between these two estimated effects effectively disappears. These finding suggest that, in terms of local employment effects, it is the *fact* of a local manufacturing shock that matters, and not its precise *source*.

At first blush, the findings above seem inconsistent with Autor et al. (2015), whose results suggest that the labor market response to trade shocks were much larger than the labor market response to technology shocks. This is not the case. When Autor et al. measure the effect of a local area's exposure to routine occupations across *all* sectors, including services, they find automation has little effect on overall employment. This is due to the offsetting effect of increased demand for abstract work, which typically dominates in areas with large service sectors. When Autor et al. measure an area's exposure to routine occupations using only the manufacturing sector, however, they find that automation does produce employment losses. This finding, which, like our work, exploits variation from *within* the manufacturing sector, is consistent with our findings that manufacturing areas subject to Chinese import competition experienced labor market outcomes that are similar to manufacturing areas that experienced declining employment for other reasons (including increased automation).

Table 4: Response of Changing Employment Rate 2000-2016 to Different Variation in Manufacturing Decline, Prime Age Men

| | Δ Employment Rate | |
|---|---|---|
| | (1) | (2) |
| $\Delta ln\widehat{Man}_{t+1}^{\tilde{S},k}$ | 0.25 | 0.66 |
| | (0.16) | (0.24) |
| $\Delta ln\widehat{Man}_{t+1}^{I,k}$ | 0.42 | 0.63 |
| | (0.08) | (0.20) |
| p-value of Difference | 0.37 | 0.92 |
| Total R-Squared | 0.69 | 0.69 |
| Controls | | |
| Base Controls From Table 2 | Yes | Yes |
| 2000 Manufacturing Share | No | Yes |

Note: Table shows the coefficients from a regression of changes commuting zone employment rate between 2000 and 2016 on $\Delta ln\widehat{Man}_{t+1}^{S,k}$ and $\Delta ln\widehat{Man}_{t+1}^{I,k}$. Each observation is a commuting zone. The results in column (1) include our base controls from Table 2 as regressors. In column (2), we also control for the manufacturing share in the commuting zone in year 2000 as an additional regressor. Bootstrapped standard errors are in parenthesis.

# 4 Effect of Manufacturing Decline on Wellbeing: Evidence from Opioid-Use

The findings in the previous section show that the declines in the manufacturing sector lowered employment and wages of prime-aged workers. These findings, which are consistent with reductions in the the demand for labor rather than voluntary labor supply shifts, suggest that manufacturing decline may have substantial adverse effects on agents' wellbeing in local markets. In this section, we provide some novel evidence about changes in wellbeing by examining the relationship between local manufacturing shocks and opioid drug use and addiction.[22]

[22]Our examination of the link between opioid use and deteriorating local labor market conditions arising from broad manufacturing decline extends an emerging literature that studies the relationship economic conditions and different measures of wellbeing. This includes the analysis of Case and Deaton (2017) documenting rising mortality rates for non-Hispanic whites; recent work by Ruhm (2018) and Currie et al. (2018) on labor market conditions and drug use; and work by Pierce and Schott (2017) and Autor et al. (2018) studying how local exposure to trade liberalization affects drug deaths and suicides.

According to the U.S. Center for Disease Control (CDC), drug overdoses accounted for the deaths of nearly 64,000 people in the U.S. in 2016, and are now the leading cause of death for Americans under age 50. Opioid overuse accounts for much of the growth in drug-related deaths over the past two decades and for a growing addiction problem that has attracted the concerned attention of policymakers and analysts. Furthermore, according to the American Society of Addiction Medicine, 2.6 million Americans in 2016 were addicted to prescription pain relievers or heroin.[23] The opioid crisis facing the country was recently described by the New York Times as the "deadliest drug crisis in American history".[24]

While there is agreement among doctors and policymakers that the opioid epidemic started with a rapid increase in opioid prescriptions as pain relievers in the late 1990s and early 2000s, there is still some debate about the link between opioid use and labor market outcomes.[25] While there is a correlation between high opioid use and low employment rates (Krueger, 2017), there is little work interpreting causation. As labor market conditions worsen, and workers see their wages and employment prospects decline, the associated reduction in their wellbeing might induce an increased demand for opioids. On the other hand, local shocks to opioid demand, which presumably reduce worker productivity and reliability, might make firms unwilling to hire in an area.

Did local adverse shocks to manufacturing increase opioid use in the area? To address this question, we use data from the US Center for Disease Control (CDC) that tracks the amount of per capita opioids prescribed by doctors at both county and state levels. The data is provided at the level of morphine milligram equivalents (MME) which allows for a comparison of different opioid prescriptions in similar units of potency.[26] Figure 19 graphically represents the amount of opioids prescribed (in MME equivalents) per 1,000 individuals, separately by commuting zones. The darker red areas show a higher per-capita prescription rate.[27] The figure shows that opioid prescriptions were much higher in the West, Midwest and the Southeast - the latter two being places that experienced particularly large reductions in manufacturing employment.

The simple scatter plot in Figure 20 shows that there is a large, statistically significant relationship between the log of MME's prescribed per 1,000 individuals in the commuting

[23] See https://www.asam.org/docs/default-source/advocacy/opioid-addiction-disease-facts-figures.pdf

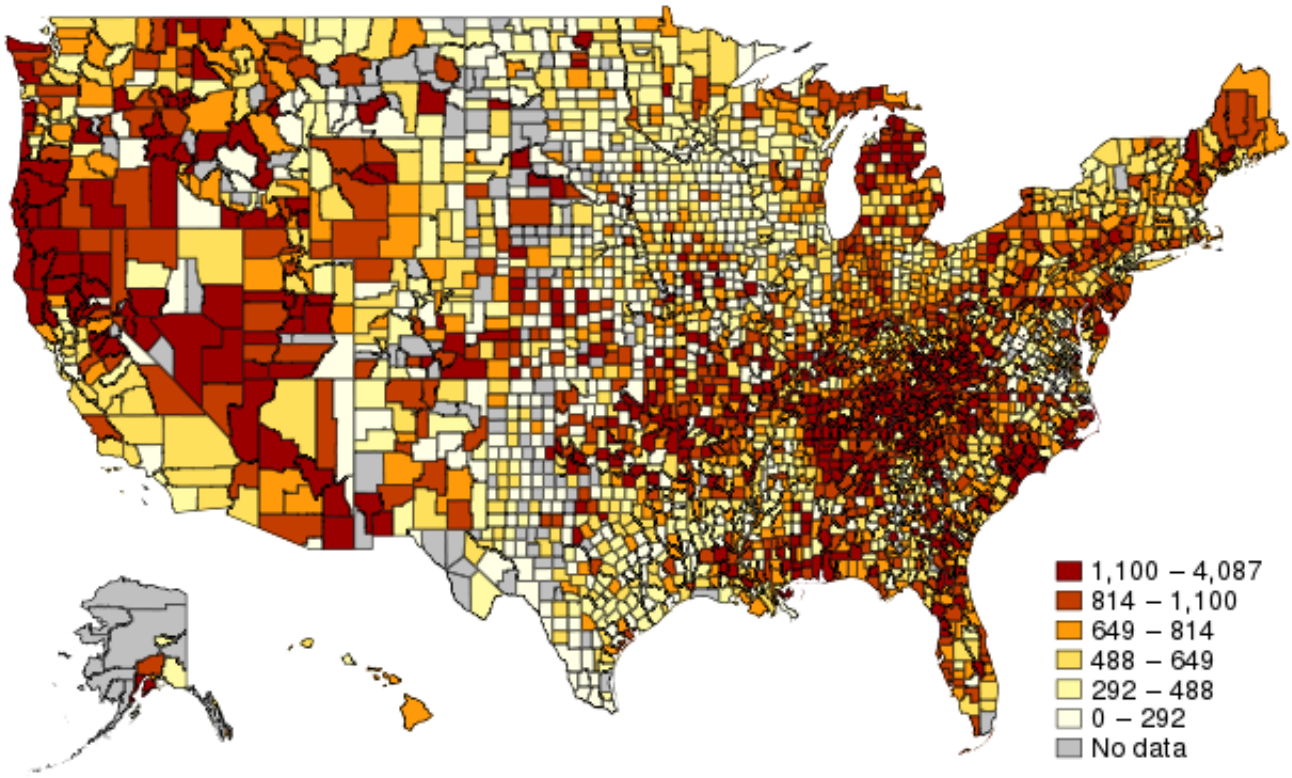
[24] "The Opioid Epidemic: A Crises Years in the Making", New York Times (October 26, 2017).

[25] Laird and Nielsen (2016) exploit variation across doctors in Denmark to show that doctors with a higher propensity to prescribe opioids have patients with lower subsequent employment rates.

[26] This data was also used in Krueger's Brookings Paper "Where Have All the Workers Gone? An Inquiry into the Decline of the U.S. Labor Force Participation Rate " (2017). We accessed the data from https://www.brookings.edu/bpea-articles/where-have-all-the-workers-gone-an-inquiry-into-the-decline-of-the-u-s-labor-force-participation-rate.

[27] Note that the CDC does not provide prescription data for all commuting zones. As a result, some parts of the map are blank.

Figure 19: Morphine Milligram Equivalents Prescribed per Capita, 2015



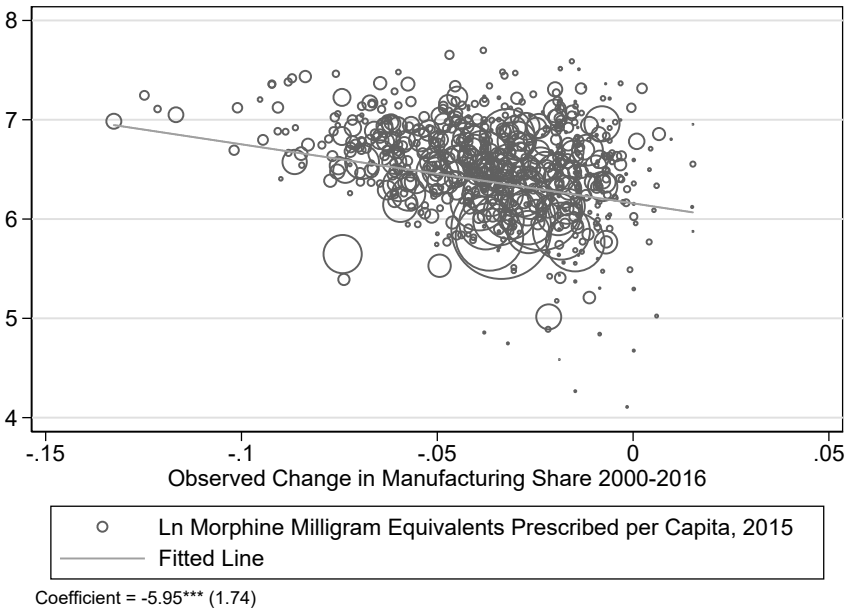

Note:

zone in 2015 and the change in the commuting zone's manufacturing share between 2000 and 2016. A 5.7 percentage point decline in a commuting zone's manufacturing share (the 90-10 difference) is associated with a 34 log point increase in MME prescribed per 1,000 individuals - an economically very large effect. Systematically, the commuting zones with the largest declines in the share of workers in the manufacturing sector are the commuting zones with the largest amounts of opioid prescriptions.

Column 1 of Table 5 shows the response of log MME prescribed in commuting zone $k$ in 2015 as a function of the change in the commuting zone's manufacturing share of prime age workers between 2000 and 2016 ($\Delta Man^k_{t+1}$), as well as controls for the commuting zone's age distribution.[28] We control for the age distribution in the commuting zone to account for the fact that older residents are more likely to be issued prescription medication. The top panel of the table presents OLS results. In the bottom panel, we present 2SLS results which instrument for $\Delta Man^k_{t+1}$ using the shift-share instrument discussed above. The 2SLS results

[28]Specifically, we include the three variables measuring the fraction of commuting zone residents between the ages of 21 and 40 in 2000, between 41 and 60 in 2000, and over 60 in 2000. We use the 2000 ACS to create these measures.

Figure 20: Decline in Manufacturing Share 2000-2016 vs Morphine Milligram Equivalents Prescribed per Capita 2015




Note: Figure shows the observed change in the manufacturing share of population between 2000-2016 and log per capita milligram morphine equivalents prescriptions in 2015. Each circle represents a commuting zone, and the size of the circle represents the commuting zone population in 2000. The weighted regression line is shown. The estimated coefficient is -5.95 with a robust standard error of 1.74.

suggest that opioid prescription use in 2015 (as measured by MME) is about 20 log points higher in the commuting zone at 10th percentile of the manufacturing decline distribution relative to the commuting zone at the 90th percentile (0.057 * -3.54).

Column 2 shows the cross-state relationship between opioid prescriptions and the decline in the manufacturing share.[29] Comparing the commuting zone results in column 1 with the state-level results in column 2 shows that aggregating to the state level yields a stronger estimated relationship between 2015 opioid prescriptions and the change in local manufacturing shares. According to the state regressions, a 5.7 percentage point decline in the state level manufacturing share (the 90-10 difference) would increase local opioid prescriptions per 1,000 individuals by about 49 log points. These findings are consistent with deteriorating labor market conditions leading to higher opioid use. It appears that in places with declining demand for manufacturing workers, doctors prescribe more opioids - presumably to meet patient demand. Collectively, these results suggests that some of the opioid increase stems from weak labor market conditions resulting from the decline in labor demand.

A limitation of the results above is that the data on which they are based only allow us to estimate how the *level* of prescription opioid use varies with the *change* in manufacturing employment. There may therefore be a concern that the level of latent opioid demand was already higher in places where manufacturing declined the most. To further explore the relationship between deteriorating manufacturing employment and increased drug use, we use two additional measures from the CDC which track *changes* in per capita drug overdose deaths. The first measure tracks all drug overdose deaths while the second measures only deaths from opioid drug overdoses.[30]

Because the CDC suppresses drug overdose counts in counties with few overdose deaths, there are many counties with missing information. Given this, we explore the relationship between increased drug overdose deaths and manufacturing decline using state level variation. To do so, we use age-adjusted drug and opioid overdose deaths per 1,000 individuals provided at the state level by the CDC.[31] Our dependent variable is the change in age-adjusted death rates for each state per 1000 individuals between 1999-2003 (averaged across years at state level) and 2012-2016 (averaged across years at the state level). Figure 21 shows a simple scatter plot of the relationship between the percentage point change in age adjusted per capita drug overdoses during the 2000s and our measure of the decline in

[29]For this analysis, we recreate our measures of $\Delta Man^k_{t+1}$ and $S^k_{t+1}$ at the state level using the Census/ACS data. As before, we exploit changes in the manufacturing share at the state level between 2000 and 2016.

[30]The primary difference between the two measures are deaths associated from overdoses of cocaine and methamphetamines.

[31]The CDC provides age adjusted death rates given that different types of deaths (like drug overdoses) occur with a higher frequency for some ages than others. Our results are nearly identical if we used the unadjusted drug overdose measures.

Table 5: OLS and IV Regressions of Opioid Use on Manufacturing Decline

| | Dependent Variable | | | | |
|---|---|---|---|---|---|
| | Opioid Prescriptions Per Capita 2015 | Opioid Prescriptions Per Capita 2015 | $\Delta$ Drug Deaths per 1,000 | $\Delta$ Opioid Deaths per 1,000 | Positive Drug Test Rate 2012-16 |
| OLS | | | | | |
| Coefficient on $\Delta Man^k_{t+1}$ | -4.06 | -8.59 | -3.42 | -2.34 | -26.7 |
| | (1.29) | (3.03) | (1.46) | (1.01) | (5.78) |
| R-Squared | 0.33 | 0.41 | 0.16 | 0.14 | 0.30 |
| IV | | | | | |
| Coefficient on $\Delta Man^k_{t+1}$ | -3.54 | -8.65 | -4.13 | -2.24 | -27.5 |
| | (1.66) | (3.23) | (1.64) | (1.18) | (8.6) |
| R-Squared | 0.33 | 0.41 | 0.15 | 0.14 | 0.30 |
| Unit of Observation | Commuting Zone | State | State | State | State |
| Sample Size | 724 | 51 | 47 | 45 | 51 |

Note: Table shows the response of various measures of opioid use to changes in the manufacturing share. Column (1) examines cross commuting zone variation in opioid prescriptions in 2015. Specifically, we use a measure of morphine milligram equivalents prescribed per capita as compiled by the U.S. Center for Disease Control. In column (2), we aggregate the data prescription data to the state level and perform a cross-state analysis. In columns (3) and (4) we measure cross state variation in the age-adjusted change in drug deaths and opioid deaths per 1,000 individuals between pooled 1999-2003 years and pooled 2012-2016 years. In column (5), we measure the fraction of drug tests that are failed at the state level pooled over the 2012 to 2016 years. In columns (1), (2) and (5), we include controls for the location's age distribution in 2000. In all specifications, we instrument the change in manufacturing share between 2000 and 2016 with our shift share instrument. See the text for additional details. Robust standard errors shown in parentheses.

state level manufacturing share between 2000 and 2016. As seen from the figure, there is a strong statistically significant relationship between declining manufacturing employment and increasing death rates from drug overdose.

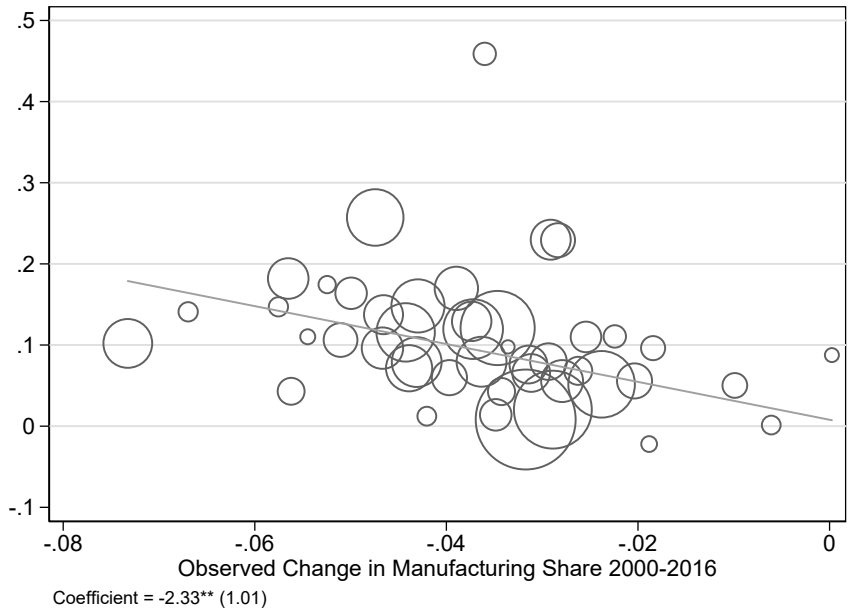
Columns 3 and 4 of Table 5 show the OLS and IV estimates of the effect of declining manufacturing employment on both increased drug overdose deaths and increased opioid drug overdose deaths. For every one percentage point decline in the manufacturing employment share of prime age workers between 2000 and 2016, drug and opioid death rates per 1,000 individuals increased by 0.04 and 0.02, respectively, during the same time period. The mean drug overdose rate and opioid overdose rate per 1000 in the pooled 1999-2003 years was 0.10 and 0.06, respectively, for the U.S. as a whole. For the pooled 2011-2015 years, the national mean drug overdose rate and opioid overdose rate was 0.25 and 0.16. Our cross region estimates are large relative to the time series trends in aggregate death rates. While without more structure it is hard to extrapolate the cross region estimates to the aggregate, the results in Table 5 suggest that declining manufacturing demand - potentially through weakening employment conditions - had a role in increased opioid deaths at the aggregate level.

Our results complement recent analysis by Krueger (2017). Krueger documents that opioid prescriptions are higher in counties where employment rates have fallen the most. He interprets access to opioids as being an important causal factor explaining why employment rates in the U.S. have fallen during the 2000s. His analysis controls for initial manufacturing share when documenting the cross county relationship between opioid prescriptions and declining employment rates. Our results suggest that declining manufacturing demand might partly explain why opioid use has increased during the 2000s. The shift share instrument isolates arguably exogenous reductions to manufacturing demand in a local areas. We find that opioid use rose the most in precisely places that experienced the biggest exogenous adverse shocks to manufacturing. Weak labor demand could be a factor contributing to the rising opioid epidemic in the U.S. during the 2000s.[32]

The results thus far leave open the question of which specific persons in the community increase their drug use when jobs disappear. It might be persons who lose work or family members whose income falls when breadwinners are displaced. Similarly, the results shown thus far do not distinguish between increased use for persons who will be seeking jobs and those who will not. To the extent that current or future job-seekers are led to use drugs because of an adverse shock to wellbeing when their labor market opportunities worsen, even

[32]This direction of causality is consistent with recent work by Autor et al. (2018), who show that commuting zones that experienced greater manufacturing trade shocks had more deaths due to drugs and alcohol among 20-39 year old men by 2015.

Figure 21: Change in Manufacturing Share vs Change in Per Capita Opioid Overdose Death Rate 1999-2016, State Level Variation




Note: Figure shows the observed change in the manufacturing share of population between 2000-2016 and the change in per capita opioid overdose death rates between the early 2000s (1999-2003 pooled) and the late 2000s (2011 - 2015 pooled). Each circle represents a U.S. state, and the size of the circle represents the state population in 2000. The weighted regression line is shown. The estimated coefficient is -2.33 with a robust standard error of 1.01.

temporary wellbeing shocks might lead to *future* reductions in employment if job-seekers who become addicted to drugs find it difficult to find a new job or to acquire the skills necessary to fill open jobs. In other words, opioid use, manufacturing loss and employment might be connected through employment hysteresis.

How does manufacturing decline affect drug use among people currently working or looking for work? To answer this question, we examine the incidence of positive results on drug tests given by employers to current and potential workers. We use novel data from Quest Diagnostics. Quest Diagnostics is a private company that performs and analyzes a number of health and wellness programs for employers. Among the services provided to employers is drug testing of existing and potential employees. Using their data, Quest Diagnostics puts out a Drug Testing Index that measures the fraction of their urine-based drug tests resulting in a positive result.[33] Underlying their Drug Testing Index are millions of individual drug tests. In 2016 alone, Quest Diagnostics performed about 9 million urine-based drug tests on existing and potential employees. While the sample is large, there are two potential selection issues with their data. First, the data is limited to only current and prospective employees of the firms that contract with Quest Diagnostics. To the extent that there is selection in these firms, this could make their Drug Testing Index not nationally representative. For example, Quest has a large sample of firms that are federally mandated to drug test their employees (e.g., pilots, truck drivers, workers in nuclear power plants, etc.). Second, within a given firm, not all drug tests are random. While many firms test all potential employees prior to starting an employment relationship or randomly drug test existing employees, firms also drug test employees for cause. According to the Quest data, employees drug tested for cause have a probability of a positive drug test that is five times higher than a typical new employee. When compiling their Drug Testing Index, Quest pools together the results of potential new employees, randomly tested existing employees, and existing employees tested for cause.

Despite these caveats, we think it is interesting to use the data to explore both time series and cross-region trends in their Drug Testing Index. In terms of units, the index measures the fraction of potential or existing employees with a positive drug test.[34] According to the Quest data, the propensity to fail a drug test has increased steadily since after the Great Recession. In 2010, 3.5 percent of their sample had a positive drug test. By 2016, the positive drug test rate increased to 4.2 percent. The increase was most pronounced in positive tests for marijuana, amphetamines, and opioids.

[33] For more information see https://www.questdiagnostics.com/home/physicians/health-trends/drug-testing.

[34] All data was manually collected from the information provided on the Quest Diagnostics website (http://www.dtidrugmap.com/).

Since 2007, Quest has published state level measures of the Drug Testing Index on their web page. Given that the data is only available from 2007 onwards, we cannot do a long difference to explore changes in the propensity for a positive drug test. Instead, we only explore the relationship between current propensity to have a positive drug test and the decline in the manufacturing share between 2000 and 2016. To average out potential noise in the index, we pool together the state level Drug Testing Index over the five year period between 2012 and 2016. Figure 22 shows the relationship between the state level Drug Testing Index (averaged between 2012 and 2016) and the change in the state level manufacturing share for prime age workers between 2000 and 2016 ($\Delta lnMan^{k}_{t+1}$). The figure shows that states that experienced large declines in their manufacturing shares between 2000 and 2016 were much more likely to be home to a failed drug test in the 2012-2016 period. According to the simple scatter plot, a 5.7 percentage point decline in the manufacturing share (the 90-10 difference) is associated with a 1.5 percentage point increase in the probability of failing an employer provided drug test (p-value $< 0.01$). Given the base probability of testing positive for drugs is about 4 percent, the findings suggest an economically large relationship between manufacturing decline and the probability of testing positive for drugs.

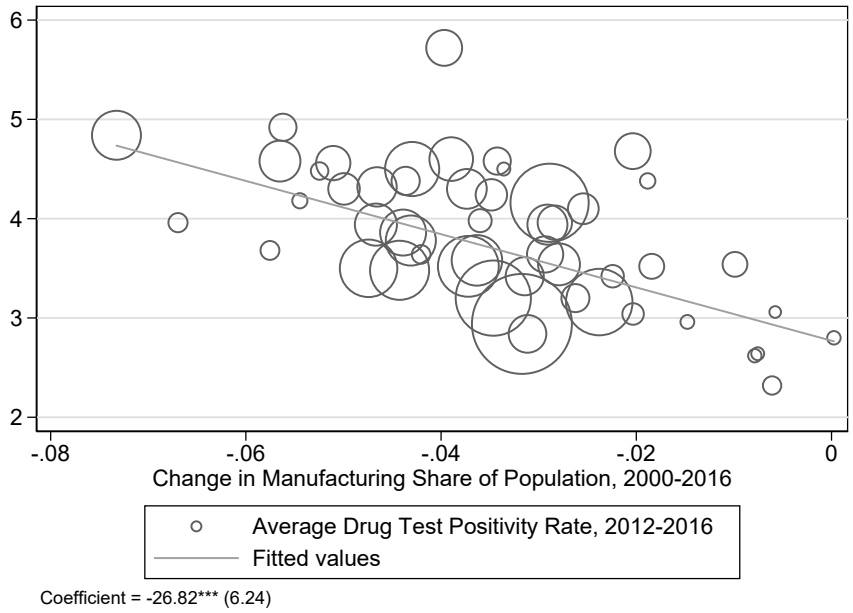
Column 5 of Table 5 shows more causal estimates. The results in column 5 are analogous to column 2 of the table except that the dependent variable is the state level Drug Testing Index (pooled over the 2012 - 2016 years). Like the results in column 2, we also control for the state's age distribution in 2000. Focusing on the 2SLS results, a 5.7 percentage point decline in the manufacturing share results in a 1.5 percentage point increase in the propensity to have a positive drug test.

On the whole, our results strongly suggest that local wellbeing losses associated with job and wage reductions from local manufacturing decline led to greater opioid use and increased drug and opioid deaths at the local level. While some of this increased use might have been among others in the community, it seems that workers and job-seekers accounted for some of the increased use, based on the results of drug test firms conduct on their workers. This latter finding raises the possibility that workers hurt by manufacturing decline, who salve the negative shock to their wellbeing by using drugs, may confront worse employment prospects in the future than would have otherwise been true.

# 5 Why A Persistent Employment Effect?

The fact that the adverse employment effects from the decline in manufacturing have lasted as long as they have is both striking and puzzling. Different sectors, including manufacturing at other times, have always routinely grown and declined in the economy, yet various me-

Figure 22: Average Positive Drug Test Rate (2012-2016) vs. Change in Manufacturing Share 2000-2016




Note: Figure shows the average drug test positivity rate by state between 2012-2016 and the observed change in the manufacturing share of the population between 2000 and 2016. Circle size indicates state population in 2000. The slope on the linear fit is -26.8 (robust standard error = 6.2).

diating mechanisms ensure that affected workers generally do not have lowered employment prospects years after the initial dislocation. It is clear that some of the mediating mechanism have not worked, or else were not large enough, for post-2000 manufacturing change. For example, from our local labor market results we know that many workers of a given level of skill living in a particular market who lost their jobs in manufacturing did not get jobs requiring the same skill in another industry in their same locality. Had this traditional mechanism of adjustment worked strongly, then we would not have estimate negative within-location, within-skill employment effects from manufacturing decline. In this section, we provide some evidence about the operation and importance of three other mediating mechanisms: public and private insurance, skill-mismatch, and mobility.

## 5.1 Disability and Private Transfers

One mediating mechanism that might be expected to affect the speed at which workers transition from job losses associated with sectoral decline is the availability of alternative sources of income to replace lost earnings because of non-work. To the extent that worker are insured against earnings losses, from public or private sources, their transitions out of non-work might be slowed. How important have public and private insurance been for affected workers since 2000?

Recent scholarship has argued that reduced labor demand for lower educated workers has led to increased disability take-up.[35] Autor et al. (2013) use regional variation in the exposure to their Chinese import competition shock to show that declining manufacturing shares in a local area results in higher government transfers to that local area during the early 2000s. Using this previous work as motivation, we examine changes in government transfer take-up over the 2000s in response to our broader manufacturing changes. We measure the extent to which increased receipt of government transfers is associated with the dramatic decline in employment in response to declining manufacturing during the 2000s. We conclude that if the receipt of government transfers contributed to the low employment rates of prime age workers during this period, its effect was most likely small.

We use our Census/ACS sample to conduct this analysis. From these data, we know whether individuals receive Supplemental Security Income (SSI) inclusive of Social Security Disability Insurance (SSDI) income. For persons in age range we study, essentially all of this income is SSDI associated with disability or blindness. Table 6 examines the fraction of individuals receiving SSI/SSDI income for various sex and age demographic groups. We

[35]See, for example, Autor and Duggan (2003) and Sloane (2017) for evidence. The issue has also received attention in the popular press. See, for example, "Trends with Benefits" (NPR's *American Life*, March 22, 2013.)

Table 6: Share Receiving SSI/SSDI Income Received 2000 and 2016, By Demographic Group

| | Share Receiving SSI/SSDI: All | | Share Receiving SSI/SSDI: Non-Working | |
|---|---|---|---|---|
| | 2000 | 2016 | 2000 | 2016 |
| Men | | | | |
| Age 21-40 | 0.01 | 0.02 | 0.06 | 0.10 |
| Age 41-55 | 0.02 | 0.03 | 0.10 | 0.16 |
| Women | | | | |
| Age 21-40 | 0.01 | 0.02 | 0.04 | 0.06 |
| Age 41-55 | 0.03 | 0.04 | 0.08 | 0.11 |

Note: Table shows the share of individuals by age and sex that received Supplemental Security Income (SSI) inclusive of Social Security Disability Insurance (SSDI) income in 2000 and 2016. Columns (1) and (2) does not restrict the sample based on employment status, while columns (3) and (4) restrict the sample to non-working individuals.

split our sample into a younger group (aged 21-40) and an older group (aged 41-55). The age split allows us to compare labor market patters between groups that are more likely to receive disability income (the older group) and are less likely to receive disability income (the younger group).

The first two columns of Table 6 show the fraction of each group receiving SSI/SSID income in 2000 and 2016. The third and fourth columns show similar statistics for non-working members of each group. There are four key facts from Table 6. First, only between 1 percent and 4 percent of all prime age persons receive SSI/SSDI benefits in either 2000 or 2016. Second, the propensity to receive SSI/SSDI benefits is much lower for younger individuals relative to older individuals. Third, all four sex-age groups increased their propensity to receive SSI/SSDI benefits between 2000 and 2016. Fourth, and most importantly, most young and old non-working individuals did not receive SSI/SSDI benefits in either 2000 or 2016. For example, only 10 percent of younger non-working men and 16 percent of older non-working men received SSI benefits in 2016. Collectively, the table shows that the receipt of SSI/SSDI benefits is relatively rare among non-working prime age individuals.

Although rare, it is possible that SSI/SSDI benefits could explain a portion of the decline in employment rates in the 2000s. As seen from Table 6, SSI/SSDI receipt has increased by 1 percentage point nationally for all prime age-sex groups between 2000 and 2016. Employment

rates have fallen by about 4 percentage points for both younger and older men during this period. At most, increased access to disability could explain one-quarter of declining employment rates for prime age men during this period. That is an upper limit given that these aggregate relationships do not imply that access to disability caused declining employment.

Table 7 uses the cross-region variation exploited previously in the paper to more carefully assess how the change in the fraction of a group receiving SSI/SSDI/SSDI payments during the 2000s responds to changes in the manufacturing share. Specifically, we re-estimate equation (1) with the dependent variable being the change in share of each demographic group withing a commuting zone receiving SSI/SSDI benefits between 2000 and 2016 (column 1) and reestimate the change in the share of the demographic group employed within a commuting zone between 2000 and 2016 (column 2). Each entry in the table is the coefficient on the change in the manufacturing share in the commuting zone between 2000 and 2016 from different regression. The various regressions differ by dependent variable and demographic group. We only show the 2SLS estimates where we instrument for $\Delta Man^k_{t+1}$ with $S^k_{t+1}$.

Column 1 of the table shows that manufacturing decline does raise SSI/SSDI receipt. For every 10 percentage point decline in the manufacturing share, SSI/SSDI receipt by younger men, older men and younger women increases by between 0.5 and 0.8 percentage points. There is no statistically significant effect on SSI/SSDI receipt for older women. These results are consistent with the findings in Autor et al. (2013) showing that manufacturing decline driven by increased import competition from China resulted in an increased take up of public transfers during the early 2000s. However, Table 7 also highlights why it is very unlikely that increased SSI/SSDI participation is a dominant driver of persistently low employment rates. Column 2 shows the change in the employment rate during the 2000s in response to the declining manufacturing share for the different demographic groups. The response of the change in the employment rate is roughly 5 to 7 times larger than the response of the change in SSI/SSDI take up rate. This suggests SSI/SSDI participation could explain at most 15 to 20 percent of the persistent decline in employment during the 2000s. We conclude that access to SSI/SSDI is at best only a small part of the story of why employment rates have remained low as manufacturing employment has declined during the 2000s.

Apart from any public source, workers displaced from manufacturing might also receive insurance against earnings losses from private sources, especially in form of different types of assistance from friends and loved ones. Moving in with relatives might be one such form of assistance. Aguiar et al. (2017) document that there has been a dramatic shift in the propensity for young individuals (those aged 21-30) to live with their parents or another close relative during the 2000s. For example, they find that roughly 30 percent of young men live

Table 7: IV Regression of Changing SSI/SSDI Receipt and Changing Employment Rates to Changes in Manufacturing Share 2000-2017, by Sex-Age Groups

| | Dependent Variable | |
|---|---|---|
| | Δ Share Receiving SSI/SSDI 2000-2016 | Δ Employment Rate 2000-2016 |
| Men | | |
| Age 21-40 | -0.08 | 0.40 |
| | (0.02) | (0.10) |
| Age 40-55 | -0.05 | 0.35 |
| | (0.03) | (0.07) |
| Women | | |
| Age 21-40 | -0.06 | 0.27 |
| | (0.02) | (0.11) |
| Age 40-55 | 0.00 | 0.30 |
| | (0.03) | (0.08) |
| Sample size | 741 | 741 |

Note: Table shows the coefficients from a regression of changes in the share of individuals receiving SSI/SSDI transfers (column 1) or changes in employment rate between $t$ and $t+1$ by age and sex on $\Delta lnMan^k_{t+1}$ (column 2) instrumented with $S^k_{t+1}$. Each observation is a commuting zone. All regressions include our base set of additional controls. Robust standard errors are in parenthesis.

with a parent or close relative in 2000. By 2015, 45 percent of young men report living with a parent or close relative. Given these time series trends, we explored whether the propensity for young individuals to cohabitate with their parents or other close relatives increased more in places that experienced a larger declining in the manufacturing share during the 2000s. The results suggest that cohabitation patterns of 21-30 year olds are not systematically related to declining manufacturing employment. The results of a regression of the change in the propensity to live with a parent between 2000 and 2015 by younger households on the decline in the manufacturing share in our base TSLS specification suggest that cohabitation patterns are not systematically related to declining manufacturing employment.[36] Based on this important measure of family support, we think that private insurance via cohabitation is not a first order explanation for why declining manufacturing employment is leading to persistent declines in employment rates for young workers.

## 5.2 Changes in Skill Composition of Manufacturing Sector

A mechanism by which workers can adjust to sectoral transformation would be switch to new jobs, either in their former sector or a new one. A factor that might act as a brake on the smooth operation of this adjustment mechanism, and lead to persistently lower employment, is if workers affected by sectoral transformation of the sort that occurred in manufacturing in the 2000s lack the requisite skills for work in either their transformed former sector or in another new sector. How important a role has this played in explaining the persistent employment losses we document?

The possible importance of "skill mismatch" has appeared frequently in the popular press in recent years.[37] Proponents of the view that rising skill mismatch is a primary driver of increasing labor market effects of manufacturing decline see evidence in support of their hypothesis in the sharp increase in the job opening rate for the manufacturing sector during the 2000s. The job opening rate is measured as the number of job openings in a given industry divided by the sum of employment in that industry and the number of job openings in that industry. We use data from the BLS's Job Opening and Labor Turnover Survey (JOLTS) to create Table 8. This table documents the trend in the job opening rate for the total US economy and for various industries between 2001 and 2017.[38] As the table shows,

[36]The full set of results provided by the authors upon request.

[37]See, for example "Manufacturing's Big Challenge: Finding Skilled and Interested Workers" (Chicago Tribune, December 17, 2016), "As Skill Requirements Increase, More Manufacturing Jobs Go Unfilled" (Wall Street Journal, September 1, 2016) and "The Future of U.S. Manufacturing Jobs Will Require More Brain than Brawn" (NPR's American Made series, November 7, 2014).

[38]The JOLT's data comes monthly. For our yearly measures we take the simple average of the monthly measures during the year.

Table 8: Job Opening Rate By Industry, 2001 - 2017

| | 2001 Rate | 2017 Rate | Change in Rate | Log Difference |
|---|---|---|---|---|
| All Industries | 3.32 | 4.16 | 0.85 | 0.23 |
| Manufacturing | 1.84 | 3.08 | 1.24 | 0.52 |
| Retail Trade | 2.66 | 3.80 | 1.14 | 0.36 |
| Professional Services | 3.98 | 4.97 | 0.99 | 0.22 |
| FIRE | 3.53 | 4.25 | 0.72 | 0.19 |
| Leisure/Hospitality | 4.49 | 4.82 | 0.33 | 0.07 |
| Construction | 2.53 | 2.69 | 0.17 | 0.06 |
| Education/Health | 4.63 | 4.74 | 0.10 | 0.02 |

Note: Data downloaded directly from the BLS's Job Opening and Labor Turnover Survey. See https://www.bls.gov/data/. To make yearly measures, we take the simple average of monthly observations over the year. For column (3), the change in rate is defined as the simple difference between the 2017 and 2001 job opening rate. For column (4), the log difference is defined as the difference in the log job opening rate in 2017 relative to the log job opening rate in 2000.

the job opening rate has increased for the economy as a whole as well as for each broad industry. However, between the early 2000s and 2017, the largest increase in the job opening rate (in both absolute changes and percentage changes) was in the manufacturing sector. The job opening rate in manufacturing nearly doubled during the 2000s from an initial rate of 1.8 percent to the current rate of 3.1 percent.

The most obvious potential explanation for the increased job opening rate in the U.S. economy is that it has become cheaper to post job openings. However, skill mismatch is an alternative explanation. In addition to firms posting more vacancies because it is now cheaper to do so, skill mismatch would cause vacancies firms post to stay unfilled longer because of the difficulty of finding qualified workers. The available information on job openings data does not allows to distinguish between these two explanations. However, it is interesting to note that the job opening rate has grown the most (in both levels and percentage change) within the manufacturing industry. Since there is no particular reason to suppose that is somehow harder to post a job in manufacturing than in other sectors, this fact is consistent with job mismatch being more important for manufacturing that for other sectors in the economy. Construction is another sector that employs less educated men. Notice that the job finding rate in construction has not increased that much at all during the 2000s.

To further explore the potential for skill mismatch in the manufacturing industry during the 2000s, Table 9 looks at the educational composition of the manufacturing sector over

Table 9: Percent Bachelor's Degree or More By Industry Over Time, Men Aged 25-30

| | 1998-2001 Share | 2014-2017 Share | Change in Share |
|---|---|---|---|
| All Men 25-29 | 26.5 | 31.9 | 5.4 |
| Men 25-29 Working in Manufacturing | 21.1 | 26.6 | 5.5 |
| Men 25-29 Working Retail Trade | 16.6 | 20.2 | 3.6 |
| Men 25-29 Working in Construction | 8.6 | 12.1 | 3.5 |

Note: Data from our CPS sample. We use the 1990 industry classification to define the Manufacturing, Retail Trade and Construction industries. Table shows the share of men aged 25-29 with at least a bachelor's degree in the total population (row 1), working in the manufacturing industry (row 2), working in the retail trade industry (row 3) and working in the construction industry (row 4) in different years.

this time period. Our measure of educational composition is the share of workers who have at least a bachelor's degree within the industry. To illustrate the educational composition of the manufacturing sector over time, we use our CPS sample. To facilitate exposition, we focus on men between the ages of 25 and 29. The age restriction is imposed to look at workers post bachelor's degree but still young enough to be responsive to changing industry level skill demands. Given the narrow age range, we pool our CPS data over 4 year intervals between 1998-2001 (starting period) and 2013-2017 (ending period). We show results for all 25-29 year old men (row 1) as well as men working in the manufacturing, retail trade and construction industries. These three industries employ 45 percent of all working 25-29 year olds and 57 percent of all working 25-29 years with a high school degree or less in the 1998-2001 period. We pool data over the 1889-2001 samples (column 1) and the 2014-2017 samples (column 2).

We would like to highlight three results from Table 9. First, young men working in manufacturing, retail trade, and construction tend to be relatively less skilled compared young men in the economy overall. In all periods, the share of men aged 25-29 with Bachelors degrees overall is higher than the proportion of 25-29 year olds in these three industries who have college degrees. Second, young men in these sectors, as in the economy overall, became more skilled during 2000s, as least as measured by the bachelors' degree holding. Finally, the manufacturing sector has experienced the largest increase in the share of young men with a bachelor's degree or more over this time period compared to retail trade and construction. In the early 2000s, one in five younger workers in manufacturing had a bachelor's degree. By 2017, one in four workers in manufacturing had a bachelor's degree. The 5.5 percentage

point increase in the bachelor's degree share was larger than the increase in either retail trade or construction. Additionally, it was on par with the increase in the bachelor's degree share for the population as a whole. Again, these results provide some additional evidence that the manufacturing sector is becoming more skilled relative to other historically industries populated by lower educated workers such as construction and retail trade during the 2000s.

Collectively, the above results suggest a potential role for skill mismatch in explaining the sluggish response of employment to local manufacturing labor demand during the 2000s. While many formerly lower skilled sectors attracted more educated workers during the 2000s and whereas job opening rates have increased in all sectors during the 2000s, the increases have been largest in the manufacturing sector. This is consistent with the substantial capital deepening that took place in the manufacturing sector during this time period. Overall, we conclude that skill mismatch can potentially explain some of the sluggish response of employment rates to declining employment needs in the manufacturing sector. Displaced manufacturing workers may not have the skills to fill the jobs currently available in their former sector. However, future work needs to be done to assess how quantitatively important this mechanism is relative to other mechanisms.[39] If the skill mismatch hypothesis is quantitatively important, it suggests that policies to promote the manufacturing sector may not substantively increase employment rates among less educated men.

## 5.3 Regional Mobility

A final mediating mechanism for adjustment to regional shocks of the sort that occurred in manufacturing during the 2000s is cross-region migration. If a region experiences a decline in labor demand relative to other areas, its residents may be more likely to out-migrate and people from other areas may be less likely to migrate in. Both the increased out-migration and the reduced in-migration will lower the number of potential workers in the affected region to shrink. Because of cross-region migration, declining local labor demand shocks can lead to declining local labor supply. As local labor supply responds to declining local labor demand, equilibrium wage and employment responses are muted. This is the mechanism at the heart of the seminal work of Blanchard and Katz (1992).

It is well documented that cross-region migration rates have fallen sharply in the U.S. between over time . For example, Molloy et al. (2011) use data from the CPS, Census/ACS and IRS to show that cross-region migration rates have consistently declined over the last

[39] Our results are broadly consistent with the recent findings of Weaver and Osterman (2017). Weaver and Osterman survey plant managers about their ability to hire qualified workers for their manufacturing facilities. Their survey evidence finds that while many manufacturers do not have trouble finding qualified workers, about one-quarter of the manufacturers they surveyed may show signs of not being able to hire qualified workers.

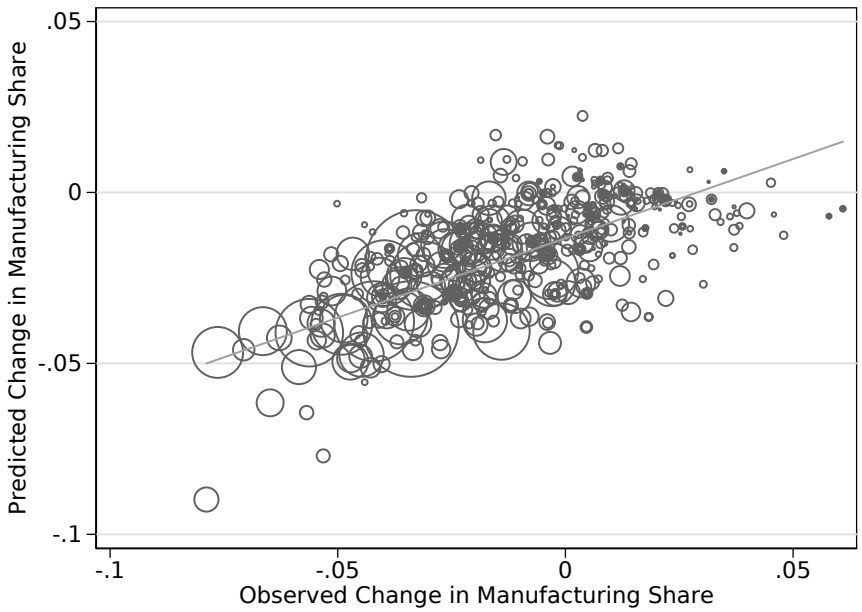
35 years. While the magnitudes of the declines differed across the surveys, all three surveys showed declining inter-state mobility in the U.S. since 1980. Kaplan and Schulhofer-Wohl (2017) further explore the decline in cross-region mobility in the U.S. Using data from the CPS, they find that for individuals between the ages of their early 20s and 55, annual interstate mobility rates have fallen from about 4 percent in 1990 to under 2 percent in 2011. Dao et al. (2017) find that interstate mobility in response to local labor demand shocks has been declining since the early 1990s, and Autor et al. (2014) find that workers in trade-exposed areas in 1994 do not increase employment or earnings in other commuting zones, suggesting that they do not shift labor supply across geographic areas. Not only are individuals moving across regions less over time, but they are also less likely to move across regions in response to relative changes in labor market conditions. Declining cross-area mobility and a reduced mobility response to local labor demand shocks might explain, in part, why local sectoral shocks in the 2000s are more likely to result in declining employment rates.

On the surface, the persistent employment effects we find for the manufacturing changes in the 2000s are strongly consistent with the strongly reduced role of the mediating mechanism of mobility. To explore this declining mobility hypothesis further, we examine how manufacturing declines in 1980s affected employment rates during that time period and then compare cross-regional mobility in the earlier period to the 2000s. We proceed in two parts. First, we re-do our cross-region analysis on the link between manufacturing decline and labor market outcomes for the 1980 to 1990 period. As seen from Figures 12 and 13, employment shares in manufacturing declined steadily during the 1980s. Figure 23 shows the shift share instrument defined for the 1980s also has strong predictive power during the 1980-1990 period.[40] Specifically, predicted manufacturing decline based on initial manufacturing shares and national trends between 1980 and 1990 are strongly predictive of actual manufacturing shares at the commuting zone level between 1980 and 1990. The scatter plot shows that the shift-share instrument predicts changes in the commuting zone's manufacturing share in the 1980s as well as the 2000s version does for the recent period (R-squared = 0.46, F-stat = 189.13).

Row 1 of Table 10 shows our IV estimates of manufacturing decline on employment rates of prime age men and women during the 2000-2016 period (column 1) and during the 1980-2000 period (column 2). The column 1 results in row 1 are analogous to those in Table 2 except in this table we pool together men and women for ease of exposition. As before, during the 2000s, a ten percentage point decline in the manufacturing share reduced prime age employment rates by 3.4 percentage points. The patterns during the 1980s are

[40] We define our $S^k_{t+1}$ variable for the 1980s analogously to the way we computed it for the 2000s.

Figure 23: Predicted Change in Manufacturing Share 1980-1990 vs. Change in Manufacturing Share 1980-1990




Note: Figure shows the relationship between the predicted change in the manufacturing share between 1980 and 1990 and the observed change. The change is predicted using our shift share instrument and local area baseline controls. Each observation is a commuting zone. The size of the circle reflects the size of the 1980 prime age population in each commuting zone. The figure includes the weighted regression line of the scatter plot. The slope of the regression line is 0.46 with a robust standard error of 0.03.

Table 10: IV Response of Change in Log Population to Change Manufacturing Share Over Time, Individuals Aged 21-55

| Dependent Variable | Time Period | |
|---|---|---|
| | 2000-2016 | 1980-1990 |
| $\Delta$ Employment Rate | 0.34 | -0.15 |
| | (0.07) | (0.10) |
| $\Delta \ln \text{Pop}^k_{t+1}$ | 0.86 | 3.84 |
| | (0.45) | (1.04) |
| Standard Controls | Yes | Yes |
| Sample size | 741 | 741 |

Note: The first row of the table shows the coefficient on predicted manufacturing decline from a regression of changes in the employment rate between $t$ and $t+1$ to $\Delta lnMan^k_{t+1}$ instrumented with $S^k_t$ and additional controls. The second row of the table shows the coefficient on predicted manufacturing decline from a regression of changes in log population between $t$ and $t+1$ to $\Delta lnMan^k_{t+1}$ instrumented with $S^k_t$ and additional controls. Each observation is a commuting zone. The results in column (1) use $t = 2000$ and $t+1 = 2016$ while the results in column (2) use $t = 1980$ and $t+1 = 1990$. All regressions include our base set of additional controls, while the population change regressions additionally include census division fixed effects. Robust standard errors are in parentheses.

quite different. In column 2 we show that a decline in the local manufacturing share had no statistically significant effect on local employment rates. During the 1980s, there was essentially no persistent effect of manufacturing decline on local employment rates.[41]

To examine whether differential mobility patterns may have contributed to the differential findings between the 1980s and today, we estimate the following regressions on both our 1980-2000 and 2000-2016 samples:

$$\Delta \ln Pop^k_{t+1} = \alpha + \beta \Delta Man^k_{t+1} + \Gamma X^k_t + \epsilon^k_{t+1} \tag{8}$$

where $\ln Pop^k_t$ is the log of all individuals between the ages of 21 and 55 living in $k$ in period $t$ and $\Delta \ln Pop^k_{t+1}$ is the change in $lnPop^k$ between periods $t$ and $t+1$. As above, we instrument

[41] These findings hold if we look at men and women separately or if we look at different sex-skill groups. Additionally, our results are in line with the finding of Bound and Holzer (2000) which found demand shifts away from manufacturing had a small but significant effect on employment rates of men during during the 1970s and 1980s.

$\Delta Man^k_{t+1}$ using our time period specific shift share instrument. This regression is analogous to the regressions in Tables 2 except that the dependent variable is the change in prime age population rather than the change in labor market outcomes. When estimating regression 8, we follow the lead of Autor et al. (2013) and control for census division fixed effects, in additional to the same $X^k$ vector of controls in the models presented in Table 2. Given the secular shifts in population from the northeast and the midwest to the south and western states during the last half century, one needs to include such controls when assessing the the causal relationship between manufacturing decline and changes in population.

The second row of Table 10 presents the estimation results for regression (8). The table shows that a 1 percentage point change in the manufacturing share caused population to respond by only 2.3 percent over the 2000 to 2016 period and by roughly 4.0 percent over the 1980 to 1990 period. These results are consistent with the finding of Doa et al. (2017) showing that the population response to local labor market shocks is smaller in recent periods than it was in the 1980s. We also wish to note that the number of years over which the population is changing is not the same across the two regressions. Our 2000s regressions are over a 16 year period while the 1980s regressions are over a 10 year period. If there is some sluggishness in the population response, a longer time period may allow for more population adjustments. However, if we annualized the coefficients, the differences between the 2000s and the 1980s become even more dramatic.[42] When we omit the census division controls, the same qualitative patterns emerge in that manufacturing decline has a larger effect on population changes in the 1980s than it does in the 2000s.

These results suggest that declining cross-region mobility might, in fact, be an important reason for the large and persistent effects of manufacturing decline on employment rates during the 2000s compared to the 1980s. A question that arises immediately, however, is why mobility rates (and mobility in response to shocks) have fallen as much as they have. Although much more work needs to be one on this question, results from work by Molloy et al. (2014) indicates that reduced gains from job switching might be an especially key driver of these changes in mobility over time, compared to demographic factors like population aging or homeownership. Might these reduced gains workers receive from switching jobs, if true in manufacturing, be related to standardization of production processes through robotics or consolidation in firm ownership in the sector? If so, declining mobility would itself be a *result* of a change in the manufacturing sector rather than an explanation for why manufacturing

[42]Our results contrast somewhat with the results of Autor et al. (2013) suggesting that the Chinese import shock did not have an effect on local population. In addition to using a broader source of variation, our sample period is over a much longer horizon. They examined patterns through 2007. We are looking at patterns through 2016. If migration is sluggish, the longer time period allows us to better uncover the sluggish population response to manufacturing decline.

reductions currently have larger employment effects than they one did. Questions of this sort remain to be answered before definitive conclusions can be drawn about the role of falling population mobility for the larger effect that manufacturing changes have on labor market outcomes today compared to the 1980s.

# 6 Discussion and Conclusion

Employment rates and annual hours worked have fallen substantially throughout the 2000 to 2017 period. The declines have been most pronounced among those with lower levels of accumulated schooling. For example, prime age men without a bachelor's degree are working over 200 hours per year less than their counterparts in 2000. Much of this decline is due to individuals who have persistently left the labor market.

In this paper, we highlight the importance of the structural change in the manufacturing sector in explaining these patterns. Exploiting cross-region variation, we document that the persistent long run decline in employment and hours for prime age workers did not occur evenly across the United States. Furthermore, we document a strong cross-region correlation between declining manufacturing employment and declining employment rates of prime age workers. Using a shift share instrument, we find that a 10 percentage point decline in the local manufacturing share reduced local employment rates of by 3.7 percentage points for prime age men and 2.7 percentage points for prime age women. To put the magnitude in perspective, naively extrapolating the local estimates suggests that between one-third and one-half of the decline in employment rates and annual hours for prime age workers can be attributed to the decline in the manufacturing sector. This naive estimate ignores many important general equilibrium effects that will certainly alter the exact quantitative magnitude. However, the naive results suggest that the decline of the manufacturing sector is a first order factor in the depressed labor market outcomes for prime age workers in the United States.

We present novel evidence showing how local manufacturing decline has adversely affected local wellbeing. Using data from a variety of sources, we document that declining manufacturing employment is associated with increased prescription opioid use and increased death rates from drug overdoses. There is a growing literature suggesting that physician behavior is in part responsible for the opioid epidemic within the U.S. Our results highlight how local economic conditions are interacting with these other potential causes of opioid behavior. These results suggest that a combination of both opioid supply and opioid demand are contributing to the rise in opioid use and opioid deaths during the 2000s.

One natural question is why the decline in the manufacturing sector is leading to per-

sistent declines in employment rates. The U.S. economy has experienced sector declines throughout its history, and the manufacturing sector itself has, at other periods, shed large numbers of jobs. Yet, rarely are the negative employment rate effects of these changes been as large or persistent - presumably because of various mediating mechanisms that, in general, might be expected to ease employment transitions. We present evidence relevant to the operation of three of these mediating mechanism during the 2000s: transfer receipt from public and private sources; skill-mismatch and job finding; and regional migration. Our results suggest that whereas the other factors play some role in explaining long-term adverse employment outcomes from manufacturing loss, the reduced propensity of workers to move across regions is a striking feature of the data during recent periods relative to prior periods.

Our finding that opioid drug use has risen in areas hard-hit by manufacturing decline may have implications for *future* employment prospects in these areas. To the extent that these workers become addicted to drugs, which they might have taken in the first place because of the shock of a job loss, their likelihood of getting and retaining a job in the future will be lower. We know that employers are testing more for drug use and that the incidence of positive result on these tests is rising. Even if those individuals who are taking drugs want to find a job, employers may screen them out at the application phase.[43] Increased drug use in a local area arising from manufacturing job loss might itself lead to further reductions in employment. In other words, opioid use, manufacturing loss and employment might be connected through employment hysteresis.

Finally, our results contribute to ongoing debates about policies concerning the manufacturing sector. There has been much recent discussion from policymakers about industrial, environmental, and trade policy - all with the aim of promoting employment in the manufacturing sector. Behind these discussion appears to be the view that if policies like freer trade contributed to the decline in U.S. manufacturing employment, restricting trade should cause lost manufacturing jobs to come back. As we have discussed, results from Pierce and Schott (2016), Autor et al. (2013), Acemoglu et al. (2016) do indeed suggest that import competition has played an important role in the decline of U.S. manufacturing employment during the 2000s.

However, our results also suggest that imposing trade barriers against the rest of the world is unlikely to substantially increase the employment prospects of workers with lower levels of accumulated schooling. For one thing, we have shown that the manufacturing sector is becoming increasingly highly skilled in terms of the education of the workers it hires. We

[43] In recent years, the popular press has reported that firms are struggling to hire workers who can pass a drug test. See, for example, "Hiring Hurdle: Finding Workers Who Can Pass a Drug Test" (New York Times, May 17, 2016).

have also shown that manufacturing has become much more capital intensive since 2000. Those manufacturing sectors that were most exposed to the trade shock from China actually experienced the largest declines in the labor share, suggesting that if they were to rebound they would do so with a much higher capital share relative to the early 2000s. Finally the specific factories whose closings accounted for much of trade-related job loss during the 2000s were likely using "20th century", more labor-intensive technology. Should trade barriers be erected, the new manufacturing plants that would created in the U.S. would almost surely use more capital-intensive, "21st century" technologies than the plants that were wiped out by trade shocks. While certain policies to support the manufacturing sector (like imposing tariffs on imports) may increase U.S. manufacturing output, they will likely not have large effects on the employment rates of workers with lower levels of education.

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# 7 Data Appendix

**Capital intensity** The value of capital services relative to the value of hours worked in the production process.

**Chinese Import Competition** The change in imports from China over the period 1999-2011, divided by initial absorption (measured as industry shipments plus industry imports minus industry exports). Source: Acemoglu et al. (2016).

**Manufacturing Share** Also referred to as the "Manufacturing Share of the Population", and "Manufacturing to Population Ratio", and measured in the CPS, ACS, and Census, the manufacturing share is the ratio of the number of persons aged 21-55 in the relevant group working in manufacturing to the number of all such persons between 21 and 55, regardless of employment status. The data are weighted using survey weights provided in the relevant survey.

**Demographically Adjusted Real Wages at the Commuting-Zone Level** We make wage measures by diving annual labor earnings by annual hours worked for all individuals with positive labor earnings. We then compute average wages within each commuting zone. To adjust wages for demographic traits, we re-weighted the 2016 sample to match the age, education, and gender distribution within each commuting zone in 2000, using five-year age bins and three education groups. Finally, we compute the change in log demographically adjusted wages within each commuting zone.

**Annual Hours in the CPS** To create the annual hours measure, we multiply an individual's report of the number of weeks they worked during the prior calendar year by their report of usual hours worked per week. We then average the individual reports for annual hours worked over all prime age males by year. Individuals who report not having worked at all during the prior year are assigned zero hours. Given the CPS sample design, individuals from survey year $t$ report their annual hours worked in survey year $t-1$. Throughout the paper, we will refer to years in which hours were worked, not when they were reported. Thus, for CPS sample, hours worked in 1976 was reported by respondents in 1977.

**Annual Hours in the ACS** To create the annual hours measure in the ACS, we follow the same procedure as in the CPS, using intervalled weeks worked from 2000-2016, since these are the only measure of weeks worked in the later years. Given the ACS sample design, individuals from survey year $t$ report their annual hours worked in the

previous 12 months. For this reason, we assign hours worked to the survey year, not the prior year as in the CPS.