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Economic Opportunity, Drug Overdose Mortality, and Disability

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The research reported herein was performed pursuant to a grant from the U.S. Social Security Administration (SSA) funded as part of the Retirement and Disability Consortium. The opinions and conclusions expressed are solely those of the authors and do not represent the opinions or policy of SSA or any agency of the federal government. Neither the United States Government, nor any agency thereof, nor any of their employees, makes any warranty, express or implied, or assumes any legal liability or responsibility for the accuracy, completeness, or usefulness of the contents of this report. Reference herein to any specific commercial product, process, or service by trade name, trademark, manufacturer, or otherwise does not necessarily constitute or imply endorsement, recommendation, or favoring by the United States Government or any agency thereof.

Abstract

This study investigates the role of fading economic opportunity in two significant trends faced by working-age adults in the United States: worsening mortality (particularly from drug overdoses) and rising rates of application to the Social Security Disability Insurance (SSDI) and Supplemental Security Insurance (SSI) programs. Specifically, we examine the relationship between commuting-zone-level exposure to automation—which has led to reductions in labor-market opportunities in historically important sectors such as manufacturing—and county-level mortality and SSI/SSDI application rates for 18–65-year-olds. Using exogenous variation in automation (as measured by the penetration of industrial robots per 1,000 workers) to support causal inference, we find that increases in automation over the period 1993–2007 led to substantive increases in drug overdose mortality for both men and women, particularly in manufacturing counties. The largest impacts were for 30–44 and 45–54-year-old men living in manufacturing counties, for whom we also find significant increases in mortality from all causes and suicide. We also find strong effects of automation on SSDI and SSI applications, driven by applications that were ultimately denied. Collectively, the average increase in automation exposure can account for 12% of the rise in drug overdose mortality between 1993 and 2007, and 22% and 12% of the rise in SSI and SSDI applications, respectively, between 2000 and 2007. We also find meaningful heterogeneity in the relationship between automation and drug overdose mortality: counties with higher levels of social capital and higher shares of college graduates experienced fewer drug overdose deaths for similar levels of exposure to automation, as did counties in states with more generous Medicaid programs. Counties in states with lower rates of opioid prescriptions also experienced larger increases in mortality from automation.

Introduction

Mortality from drug overdoses among working-age Americans has been rising dramatically since the 1990s (Woolf and Schoomaker 2019). Applications for both Supplemental Security Disability Insurance (SSDI) and Supplemental Security Income (SSI) have also risen over the same period (Autor and Duggan 2006). Each of these trends has its own drivers, with rising opioid prescriptions postulated as the dominant force behind rising drug overdose deaths (Alpert et al. 2019; Currie and Schwandt 2020) and changes in screening practices and rising benefit values thought to explain the growth in disability insurance applications (Autor and Duggan 2006). Standard (short-run) economic measures, such as unemployment rates, appear to be only minimally correlated with drug overdose mortality (Currie, Jin, and Schnell 2018; Hollingsworth, Ruhm, and Simon 2017), although they are strongly correlated with disability application rates (Maestas, Mullen, and Strand 2015).

Gradually evolving structural changes in the economy—particularly those affecting economic opportunities among individuals who do not have a college education—may play an important, complementary role in driving the rise in both drug overdose mortality and disability application rates (Case and Deaton 2017; Cherlin 2014; Coile and Duggan 2019), as well as broader trends in health behaviors and outcomes more generally (O'Brien, Venkataramani, and Tsai 2017; O'Brien et al. 2020; Venkataramani et al. 2016; Venkataramani, Daza, and Emanuel 2020). In particular, the role of fading labor market opportunities in manufacturing, a sector that historically served as a path to the middle class, has attracted increased attention. A handful of studies have demonstrated strong links between declining employment opportunities in manufacturing, due to increased exposure to foreign trade or local plant closures, and drug overdose mortality (Adda and Fawaz 2020; Autor, Dorn, and Hanson 2019; Pierce and Schott 2020; Venkataramani et al. 2020).

Automation is a critical structural force that has reshaped the American economy. Since the 1980s, increased adoption of industrial robots has displaced workers once employed to carry out routine tasks (Acemoglu and Restrepo 2020; Autor and Salomons 2018). Acemoglu and Restrepo (2020) estimate that adoption of robots has displaced 420,000–750,000 jobs during the

1990s and 2000s, with the bulk of the losses occurring in manufacturing. They find meaningful declines in worker wages as a result of automation, as well.

The substantial decline in economic opportunities attributable to automation is borne primarily by workers without a four-year college education, the same group that has faced rising mortality and disability rates. This overlap suggests a causal link between automation, drug overdose, and disability insurance application rates. However, these links have not yet been examined in the literature. With the adoption of industrial robots projected to increase two- to fourfold in the coming decade (Acemoglu and Restrepo 2020)—a trend that may be further exacerbated by responses to the ongoing Covid-19 pandemic (Chernoff and Warman 2020)—understanding the potential consequences of automation for mortality and disability outcomes is critical for policymakers seeking to address these twin health and fiscal challenges. Identifying heterogeneity in these relationships is also critical: understanding what (if any) factors mitigate adverse consequences of continued automation on health and disability can help guide policy.

We address both of these questions in this paper. First, we use newly available measures of automation—namely, the penetration of industrial robots across U.S. commuting zones between 1993 and 2007—to examine impacts of automation on mortality and SSI/SSDI applications. Specifically, we apply the shift-share instrumental variable strategy used by Acemoglu and Restrepo (2020), who created a plausibly exogenous measure of robot penetration by combining information on existing employment shares in different industries in each commuting zone with data on the trajectory of robot adoption in each of those industries from a set of European countries. This method reduces potential bias from omitted factors that may lead to both greater robot adoption and poorer health and disability outcomes.

Combining this measure with restricted access death certificate data for 1990–2010 and SSI and SSDI applications and determinations for 2000–2007, we find that increases in automation led to substantive increases in drug overdose mortality, particularly in manufacturing counties. The largest impacts are for 30–44- and 45–54-year-old men living in counties with high concentrations of manufacturing workers ("manufacturing counties"), for whom we also find significant increases in all-cause and suicide mortality. Impacts for women were generally smaller. We also find that automation led to significant increases in SSDI and SSI applications, driven by applications that were ultimately denied. Collectively, the results suggest the average increase in robot penetration across commuting zones (about 2 robots per 1,000 workers over 1993–2007) can

account for 12% of the rise in drug overdose mortality over the 1990s and 2000s and 12% and 22% of the rise in SSDI and SSI applications, respectively, between 2000 and 2007.

Second, we investigate heterogeneity in the relationship between automation, mortality, and disability. We estimate how the impacts of automation vary by state and county-level characteristics that have been identified in the literature as fostering resilience against hard times. Focusing on working-age men as an illustrative case, we find that the impacts of automation on drug overdose mortality were greatly attenuated in counties with higher social capital and college graduation rates, and in counties in states with more generous Medicaid programs. Interestingly, we also find that the largest impacts of automation on drug overdose mortality were centered in states that had triplicate prescription programs in place, which greatly limited the marketing of prescription opioid medications from the late 1990s onwards (Alpert et al. 2019). We find little evidence of heterogeneity in automation impacts by any of these measures for SSI and SSDI applications.

This paper proceeds as follows. We first describe the data sources used in the study. We then discuss our empirical strategy. We then present findings from our analysis of the impacts of automation on mortality and SSI/SSDI applications and determinations and examine heterogeneity in these relationships. The final section discusses the policy and scientific implications of our findings.

Data

We use three core data sources for our analyses. Data for our main exposure, commuting-zone level exposure to automation, were obtained from Acemoglu and Restrepo (2020). The measure, which captures the predicted increase in industrial robots per 1,000 workers over the period 1993–2007, is constructed using 1970 commuting-zone-level data on employment shares across different industries combined with data on the growth in industrial robots in each of these industries for five European countries (Denmark, Finland, France, Italy, and Sweden).[1] The use of data from these countries, who adopted industrial robots sooner than the United States did, instead of U.S. data, allows Acemoglu and Restrepo (2020) to limit bias from endogenous commuting-

[1] Acemoglu and Restrepo (2020) use 1970 values to address potential bias from mean reversion in industrial employment shares in the 1980s.

zone labor demand factors that may have jointly influenced automation and our outcomes of interest (e.g., worsening health leading both to firms adoption of automation technologies and increased working-age mortality) (Currie, Jin, and Schnell 2018; Krueger 2017). This type of measure is known as a "shift-share instrument" in the econometrics literature (Goldsmith-Pinkham, Sorkin, and Swift, forthcoming). Figure 1 plots the spatial distribution of the automation measure by quartiles. The mean (median) commuting zone experienced an increase in industrial robots of 2.03 (1.53) per 1,000 workers. Automation was greatest in the industrial Midwest, the South, and parts of the Northeast and Southwest.

Age-adjusted drug overdose mortality rates per 100,000 working-age individuals (18–65-year-olds) were constructed from restricted-access death certificate data obtained from the U.S. National Center for Health Statistics (National Center for Health Statistics, 2018) and annual age-sex-specific population estimates from the U.S. Census Bureau. To match the automation data, we compute changes in mortality rates per 100,000 working-age individuals between 1993 and 2007.

Importantly, although our exposure is at the commuting-zone level, the spatial level that best reflects changes in local labor markets, we compute *county*-specific mortality rates. We do so to best capture the population at risk of being affected by the exposure (Venkataramani et al. 2020). For most states, death certificate data do not include information on occupation, and information on educational attainment is incomplete. These challenges make it difficult to track impacts of structural labor market changes on mortality, as the at-risk population is not known. However, the use of county-level data provide a way around this issue. Specifically, through linkages to county-level census data, it allows assessment based on where individuals whose employment opportunities are most likely to be affected by automation—namely, manufacturing workers—tend to live.

We use sex-specific mortality rates throughout our analyses. We also compute sex-specific mortality rates for the 18–29, 30–44, 45–54, and 55–65-year-old age groups, to assess heterogeneity by age. While our primary focus is on drug overdose mortality, we also examine a broader set of causes of death, including all-cause mortality, suicide mortality, homicide mortality, mortality from unintentional injuries (e.g., automobile or firearm accidents), and mortality from organ system diseases (e.g., cardiovascular and respiratory diseases),[2] that have tended to receive

[2] We do not examine alcohol-attributable mortality, due to difficulties in reconciling ICD-9 and ICD-10 cause of death codes for 1993 and 2007 with the broad definition of alcohol mortality currently being used in the literature.

less attention in "deaths of despair" literature, but for which midlife mortality rates have also risen (Woolf and Schoomaker 2019). Appendix Table 1 provides the ICD-9 and ICD-10 codes used to compute mortality rates.

Figure 2 plots the spatial distribution of changes in working-age drug overdose mortality rates by quartile between 1993 and 2007 (rates at baseline, i.e., in 1993, are provided in Appendix Table 2). This pattern is more diffuse than that for automation, although there is some overlap in key areas, such as the industrial Midwest and the South.

Finally, data on SSI and SSDI applications and determinations were obtained from the U.S. Social Security Administration (SSA). At this writing, we have access to SSA Form 831 data from 2000 onwards. To match the automation data from Acemoglu and Restrepo (2020), we restrict our focus to changes in applications (and determinations) per 1,000 working-age population for the period 2000–2007. Doing so helps eliminate bias from right censoring in the analysis of determinations, as decisions may come years after initial application. While we again use county-level data, we note that the construction of these data from underlying zip code–level aggregates may make it more difficult to identify the at-risk population, given overlap in zip and county boundaries. However, this may be less of an issue with SSI and SSDI applications, given that these outcomes are less rare than mortality, providing greater statistical power in our analyses.

Figure 3 plots the spatial distribution of changes in disability application rates (SSI and SSDI combined) by quartile (application rates at baseline, i.e, in 2000, are provided in Appendix Table 3). These spatial patterns follow closely with those observed for changes in drug overdose mortality rates.

Research Strategy

Main Analyses

To estimate the impact of automation on working-age mortality rates and SSI and SSDI applications and determinations, we estimate versions of the following first differences model:[3]

[3] For mortality, the specification we use corresponds to the long-difference model used by Acemoglu and Restrepo (2020). While the relevant analyses are not shown here, our substantive findings are also robust to using Acemoglu and Restrepo's "stacked first-differences" model (which incorporates changes over two times periods, 1993–2000 and 2000–2007, with a period-fixed effect to capture secular trends across these periods). For disability, we use data for 2000–2007, based on the SSI/SSDI application and determination data we have at present.

$$\Delta Y_{i,j,r,t1-t0} = \alpha_1 \times \Delta Automation_{j,r,t1-t0} + \boldsymbol{\beta} \times \boldsymbol{BaselineChar}_{j,r,t0} + \theta_r + e_{i,j,r,t}$$

where *i* indexes the county, *j* indexes the commuting zone, and *t1* and *t0* index the end line (2010 for mortality, 2007 for disability applications) and baseline (1990 for mortality, and 2000 for disability applications), respectively. $\Delta Y_{i,j,r,t1-t0}$ represents the change in the outcome of interest (endline – baseline) at the county level and $\Delta Automation_{j,r,t1-t0}$ represents the change in the number of industrial robots per 1,000 workers at the commuting-zone level.

α_1, which captures the association between exposure to automation and mortality and disability outcomes, is our parameter of interest. This parameter captures both direct and indirect effects: direct effects of automation-led job and benefit loss and indirect effects of structural changes in the economy, which might affect workers seeking employment opportunities in sectors affected by automation (Venkataramani et al. 2020) and still-employed workers who might be affected by falling wages and opportunities for occupational mobility (Elser et al. 2019), as well as shifting social factors (e.g., changes to marriage markets, destruction of social capital) that might affect health and disability outcomes in still more distant ways (Cherlin 2014; Wilson 1996). Our research design and data limitations make it difficult to distinguish between these different pathways, and we flag this distinction as an important area for future research.

Because shift-share instrumental variables strategies are susceptible to bias if the baseline characteristics (here, commuting-zone industrial shares in 1970) used to create the instrument are correlated with other baseline characteristics whose subsequent trends may also affect the outcomes of interest (e.g., educational attainment) (Goldsmith-Pinkham, Sorkin, and Swift, forthcoming), we follow Acemoglu and Restrepo (2020)'s preferred specification and adjust the rich set of baseline characteristics (denoted by the vector $\boldsymbol{BaselineChar}_{j,r,t0}$), including commuting-zone demographics (age distribution, race/ethnicity population shares) and socioeconomic characteristics (shares completing high school and college education, share employed in manufacturing, share employed in routine occupations, and exposure to foreign trade). We also include fixed effects for the nine census divisions (denoted by θ_r), to account for regional patterns in the evolution of automation and our main outcomes (Figures 1-3).

We estimate the model separately by sex, by cause of death, and by disability program and determination status. We then estimate models for mortality outcomes separately by sex, cause,

and age groups. Because manufacturing areas were most affected by automation, we also estimate all of these models separately for the counties in the highest quartile of the share of workers employed in manufacturing ("manufacturing counties," plotted in the map in Appendix Figure 1). Doing so allows us to best capture the at-risk population in analyses of relatively rare outcomes like mortality. In all analyses, we cluster standard errors at the state level, to account for potential geographic correlation in exposure and outcomes, and weight by appropriate (sex-age group) population size.

Robustness Checks

Even with the use of a theoretically motivated instrumental variable strategy and the inclusion of a rich set of covariates, we test the sensitivity of our substantive findings in several robustness checks. First, we reestimate our models for 18–65-year-olds after removing outlier commuting zones—those whose adoption of industrial robots distinctly outpaced the rest of the United States. Second, we assess preexisting trends. Focusing specifically on drug overdose mortality, we examine whether automation between 1993 and 2007 predicts differences in mortality rates between 1980 and 1990. Third, we examine whether selective migration may explain a substantive portion of our findings, by estimating whether exposure to automation led to changes in the county-level share of individuals with a college education. Acemoglu and Restrepo (2020) find that the bulk of the effects of automation on labor market outcomes are unlikely to be explained by migration; migration in general appears to play a minor role in other studies examining the link between economic opportunity and health (Autor, Dorn, and Hanson 2019; Schwandt and von Wachter 2020; Venkataramani et al. 2020).

Analysis of Heterogeneity

To examine heterogeneity in the effects of automation on mortality rates and disability insurance application rates, we estimate the versions of the above first-differences model, including interactions in which we interact all of the right-hand variables with county- and state-level factors that have been posited to foster resilience to short- and long-run economic shocks. The theoretical motivation for examining both local and state-level factors follows from the existing literature on the importance of social conditions and policymaking at these levels on health outcomes (Karas Montez 2017; Karas Montez, Hayward, and Zajacova 2019; Monnat et al. 2019).

Specifically, we examine whether automation impacts vary by county-level measures of social capital (Rupasingha and Goetz 2008; Rupasingha, Goetz, and Freshwater 2006), educational attainment (the share of adults completing a bachelor's degree or higher, from the Social Explorer), and state-level measures of welfare program generosity (new indices measuring generosity of Medicaid and TANF benefits, obtained from Fox et al. (2020)).

We run separate models for each of these variables. Wherever possible, we restrict our measures of program heterogeneity to the baseline period or earlier (1990 for the mortality rate variables and 2000 for the disability application variables), but data limitations do not always allow us to find true baseline values.[4] For this reason, and given that interactions estimated using these types of models may be confounded by other unobserved interactions, we consider this part of our analysis a descriptive, hypothesis-generating exercise.

Finally, given the important role of prescription opioid supply in driving drug overdose deaths, we also examined whether automation impacts varied by drug supply, using historical state triplicate programs (which prevented widespread marketing of these drugs in the 1990s and 2000s) as our measure of the supply environment (Alpert et al. 2019). Because only five states—California, Idaho, Illinois, New York, and Texas—had triplicate programs in place, we consider this analysis, too, to be descriptive and hypothesis generating.

Results

Graphical Evidence

Figures 4 and 5 plot the relationship between the automation measure and changes in county-level drug overdose mortality rates by sex (per 100,000 18–65-year-olds) over the period 1990–2010 and combined SSI and SSDI applications (per 1,000 18–65-year-olds) over the period 2000–2007, respectively. The unadjusted relationships in these figures are consistent with the econometric evidence we provide in the next subsection.

Across all counties, we see a positive relationship between automation and change in drug overdose deaths, with the association being larger for men and for manufacturing counties. We similarly see a positive relationship between automation and SSI/SSDI applications, with the

[4] Data on social capital and the share of college graduates are available for 1990. Data on per capita county government expenditures are available for 2000, as are the indices of social program generosity.

similar slopes for the overall sample and manufacturing counties likely reflecting the difficulty of assigning applications to manufacturing vs. non-manufacturing counties in the aggregation from zip codes to counties (see the discussion in the "Data" section).

Econometric Evidence

Table 1 provides estimates for models examining changes in mortality outcomes between 1990 and 2010 among men and women ages 18–65. Across all counties, we find a statistically significant impact of automation on changes in drug overdose mortality. The coefficient estimate implies that the (weighted) average increase in robots per 1,000 workers over the study period (2.03 for the full sample, which is also roughly equivalent to the interdecile range for this variable) led to an increase in drug overdose mortality rates of 1.76 deaths per 100,000. This increase is equivalent to 12.5% of the average increase in drug overdose mortality rates across counties over the study period (14.1 deaths per 100,000).

Coefficient estimates for men in the full county sample for other all-cause mortality and other diseases are small and not statistically significant. However, when focusing solely on manufacturing counties, we find both larger impacts on drug overdose mortality and evidence of statistically significant impacts on suicide and homicide mortality among men, as well. Estimates for drug deaths in this sample from the same average increase in industrial workers implies that automation may account for 20% of the increase in drug overdose mortality among working-age men living in manufacturing counties (an increase of 3.9 deaths per 100,000 divided by the weighted sample mean of 19.0 deaths per 100,000). The estimates for suicide mortality imply a much larger relative contribution from automation of nearly 67%.

Among working-age women in the full sample of counties, we find small and generally insignificant effects of automation on mortality. We do, however, find impacts within manufacturing counties, with a 2 robot per 1,000 worker increase in the automation measure resulting in an increase of 1.2 drug overdose deaths per 100,000. This implied effect represents 10% of the mean increase in drug overdose mortality rates among women in manufacturing counties.

Stratification by age groups (Figures 6 and 7) reveals additional heterogeneity in the impacts of automation, again with the bulk of effects driven by manufacturing counties. For example, among manufacturing counties, men in all age groups experienced increases in drug

overdose mortality, with these effects detectable even in the full sample of counties. Middle-aged men (30–44-year-olds and 45–54-year-olds) in manufacturing counties also saw large increases in all-cause mortality, driven predominantly by drug and suicide mortality. Among women in manufacturing counties, increases in drug overdose mortality were noted among 18–29 and 30–44-year-olds, with the latter group experiencing increases in all-cause mortality and mortality from cancer. Consistent with prior work showing a countercyclical relationship between mortality from unintentional injuries and economic downturns, 18–29-year-old men and women in manufacturing counties experienced declines in mortality from injuries with increasing automation.

Results examining impacts on changes in SSI and SSDI applications and determinations per 1,000 working age population over 2000–2007 are presented in Table 2. For both SSI and SSDI, we find statistically significant impacts of commuting-zone-level automation on county-level application rates. Applying the average increase in automation (about 1.3 robots per 1,000 workers over the period 2000–2007) suggests an increase of 0.37 SSI applications and 0.32 SSDI applications per 1,000 working-age population. These estimates are equivalent to 22% and 12% of the rise in applications for each program, respectively. Estimates for the sample of manufacturing counties are similar in magnitude, again likely owing to the difficulty of assigning applications and determinations to manufacturing vs. non-manufacturing counties in the context of aggregation from zip codes to counties.

Consistent with research on business-cycle fluctuations and disability applications, we find that all of the effect of automation on disability applications is driven by applications that were ultimately denied. The null findings for successful disability applications implies that automation did not lead to increases in disability rolls. In Appendix Table 4, we provide additional evidence for this contention, showing that the stock of working age individuals on disability (per 1,000 working-age population) did not increase more in areas exposed to greater rates of automation.

Robustness Checks

The substantive findings for mortality estimates were robust to excluding commuting zones with outlying rates of industrial robot adoption (Appendix Table 5, first panel). Automation between 1993 and 2007 was either not associated with, or negatively associated with, lagged changes in mortality rates (over 1981–1992), which suggests that, if anything, our results may be biased downward by preexisting trends or mean reversion (Appendix Table 5, second panel).

Finally, we do not find any evidence of selective migration, at least on the margin of education: we found no association between automation and county-level changes in the share of college graduates between 1990 and 2000 (analysis available upon request).

Heterogeneity in the Impacts of Automation

Estimates of the heterogeneity in the impacts of automation on drug overdose mortality among working-age men are provided in Table 3. Each set of rows represents marginal effect estimates of the impacts of the automation measure on changes in drug overdose mortality among men ages 18–65 at the 25th and 75th percentile of the heterogeneity variable listed in the first column.

We find that areas with the lowest quartile levels of social capital, shares of college graduates, and state Medicaid generosity experienced large increases in drug overdose mortality, while areas in the highest quartiles of these variables saw more muted increases (if any). In additional analyses (not shown here), we see a similar (if not starker) pattern in manufacturing counties.

The impacts of automation were greatest in counties in states with triplicate programs, which limited the marketing and prescription of opioid pharmaceuticals. Figure 8 (an unadjusted plot) illustrates this result most clearly, with the slope between automation and changes in drug overdose mortality rates steeper in counties in these states, while counties in nontriplicate states (where opioid prescription was more widespread) had higher average increases in drug overdose mortality throughout. The corresponding adjusted regression coefficient suggests a nonsignificant marginal increase in drug deaths of 0.41 deaths per 100,000 18–65-year-old men in nontriplicate states (for a one-unit change in the automation measure, i.e., one robot per 1,000 workers), as compared to a change of 3.08 deaths per 100,000 in the same population with the same marginal increase in automation among the triplicate states (p-value on the interaction, 0.042).[5]

In contrast to the results for mortality, we do not find any meaningful heterogeneity in the impacts of automation on SSI and SSDI application rates. That is, regardless of the level of the

[5] Of note, the results in Table 3 hold even when we restrict the sample to nontriplicate states. That is, the positive and significant impacts of automation in areas with lower social capital, lower socioeconomic outcomes, and less generous social welfare programs—and the null impacts in better-performing areas on these margins—held in this restricted sample, as well.

county or state social or policy attribute, the point estimates are generally similar to those presented in Table 2.

Discussion

Technological change has led to increases in the automation of routine tasks, a trend that is expected to continue in coming decades. Since the 1990s, increasing adoption of labor-displacing automation technologies in U.S. labor markets has coincided with rising rates of mortality (mainly from drug overdoses) and disability insurance program applications, particularly among individuals with lower levels of education. Our study suggests a causal link between these trends, with (average) increases in automation accounting for 12% of the rise in drug overdose mortality between 1990 and 2010, and 22% and 12% of the rise in SSI and SSDI applications (respectively) between 2000 and 2007. We also find important impacts of automation on suicide rates for men and show that the rise in disability insurance applications attributable to automation has been driven fully by rejected applications.

Our findings have a number of implications for policymakers and researchers. First, they support findings from an emerging body of research showing that fading economic opportunity, whether through automation or increased exposure to international trade, may have significant negative consequences for population health outcomes and administration of and participation in disability insurance programs. Second, the mortality consequences of fading opportunity driven by automation, while most dominantly seen in drug overdose deaths among men, have been heterogeneous by gender, age, and cause of death. For example, while the largest impacts were for 30–44 and 45–54-year-old men living in manufacturing counties (for whom we also find significant increases in mortality from all causes and suicide), we also find important impacts on drug overdose, cancer, and all cause mortality for younger women. Collectively, these findings suggest that the "Deaths of Despair" narrative may actually be more nuanced than previously suspected. Third, the finding that the impacts on SSI and SSDI applications were driven purely by denied applications is consistent both with findings regarding the effects of short-term economic downturns on disability applications (Maestas, Mullen, and Strand 2015) and more recent work suggesting that an increasing rate of marginal disability applications may itself serve as a sign of rising despair in the face of structural economic change (Coile and Duggan 2019; O'Brien 2019).

Public policy may be able to counteract these negative trends. For drug overdose mortality rates, we find that areas with higher levels of social and socioeconomic capital and more generous public welfare policies experienced little (if any) increase in drug overdose deaths when faced with the same levels of automation as other places. We do not find a similar heterogeneity for the relationship between automation and disability insurance applications, although this result may be due to the limited set of policy levers we examined in this work. Finally, our findings that automation-led increases in drug overdose areas were largest in areas where the growth in prescription opioid availability was restricted for *ex ante* policy reasons suggests that the dynamic between opioid supply and demand in explaining drug overdose deaths is perhaps more complex than previously assumed.

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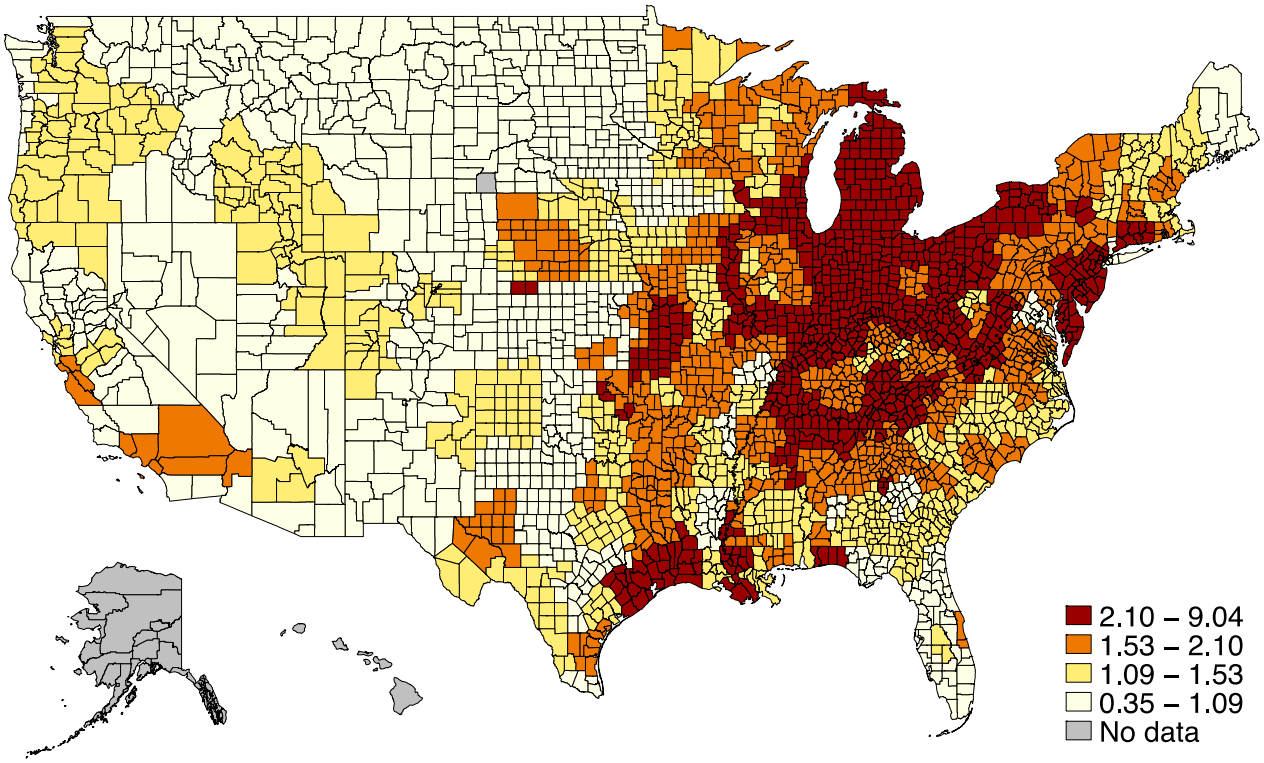
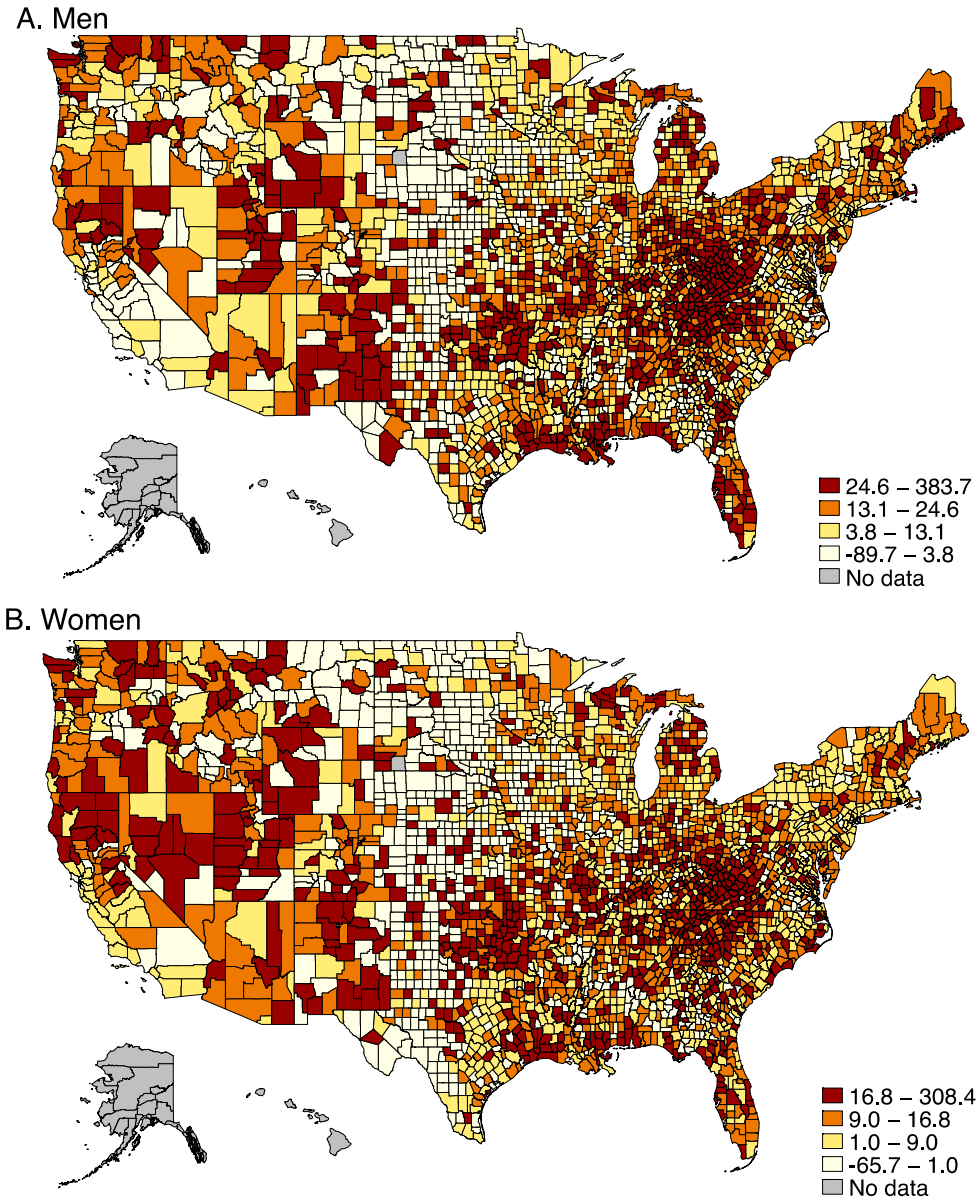
Figures and Tables

Figure 1. Exposure to automation, 1993–2007



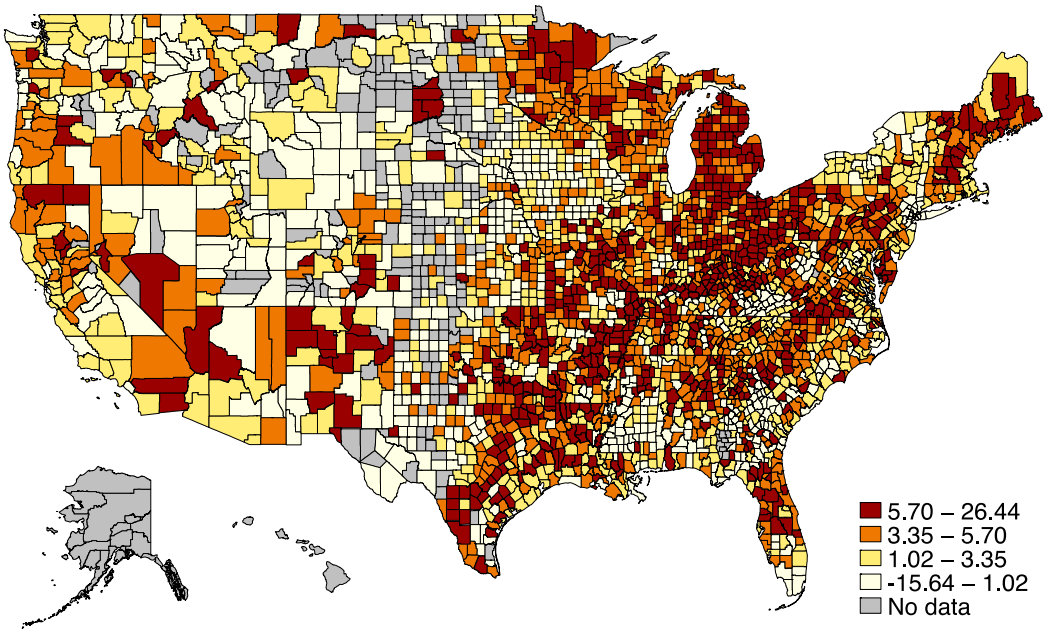
Notes: Figure maps quartiles of commuting-zone-level exposure to automation, as measured by change in the number of industrial robots per 1,000 workers, 1993–2007. Map shows county borders. Data were obtained from Acemoglu and Restrepo (2020).

Figure 2. Changes in drug overdose mortality among working age adults, 1990–2010



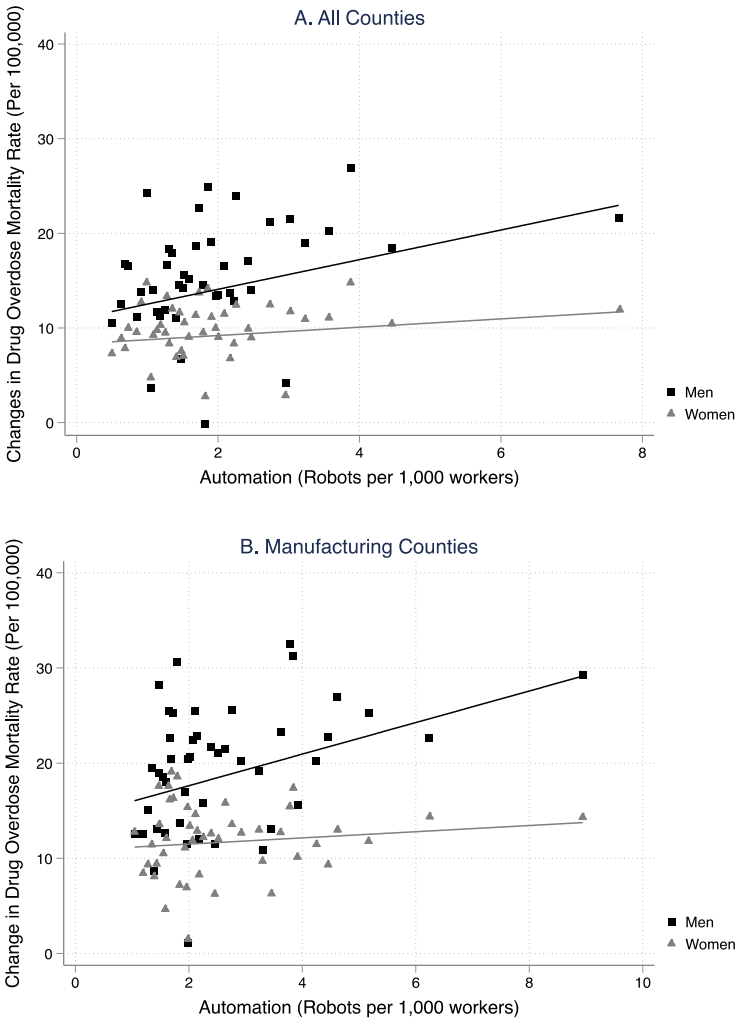
Notes: Figure maps quartiles of county-level changes in drug overdose mortality rates per 100,000 18–65-year-olds by sex between 1990 and 2010. Mortality data were obtained from restricted-access death certificate data from the National Center for Health Statistics (2018).

Figure 3. Changes in SSI/SSDI applications per 1,000 working age adults, 2000–2007



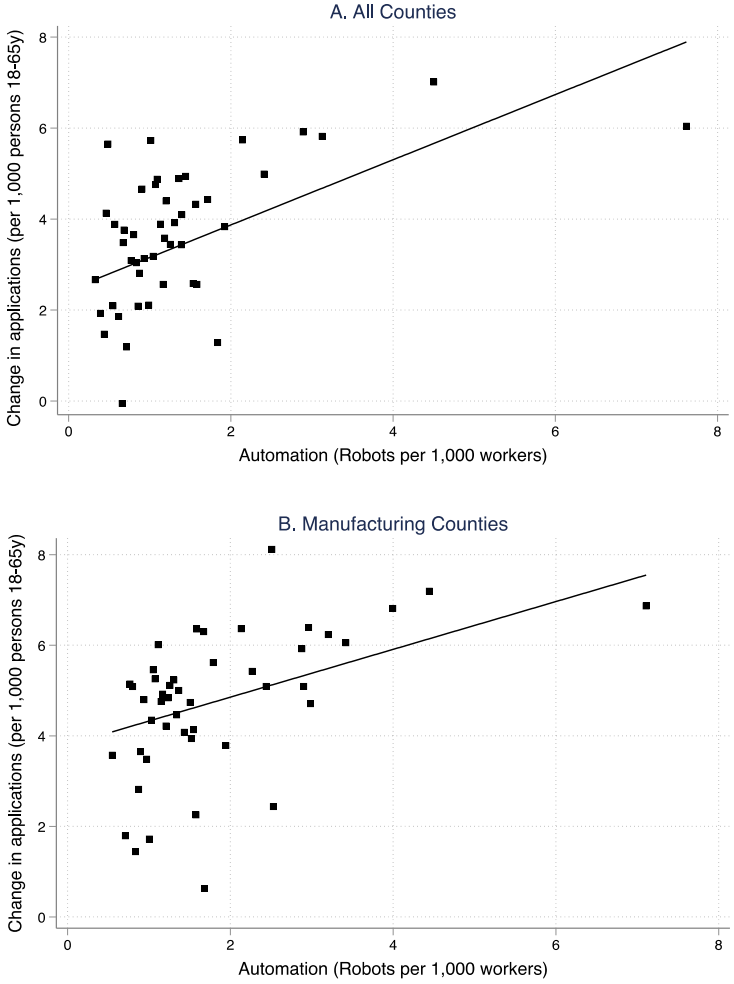
Notes: Figure maps quartiles of county-level changes in SSI and SSDI applications per 1,000 18–65-year-olds between 2000 and 2007. Disability insurance program application data were obtained from restricted-access death certificate data from the U.S. Social Security Administration, Form 831 files.

Figure 4. Unadjusted relationships, exposure to automation and drug overdose mortality



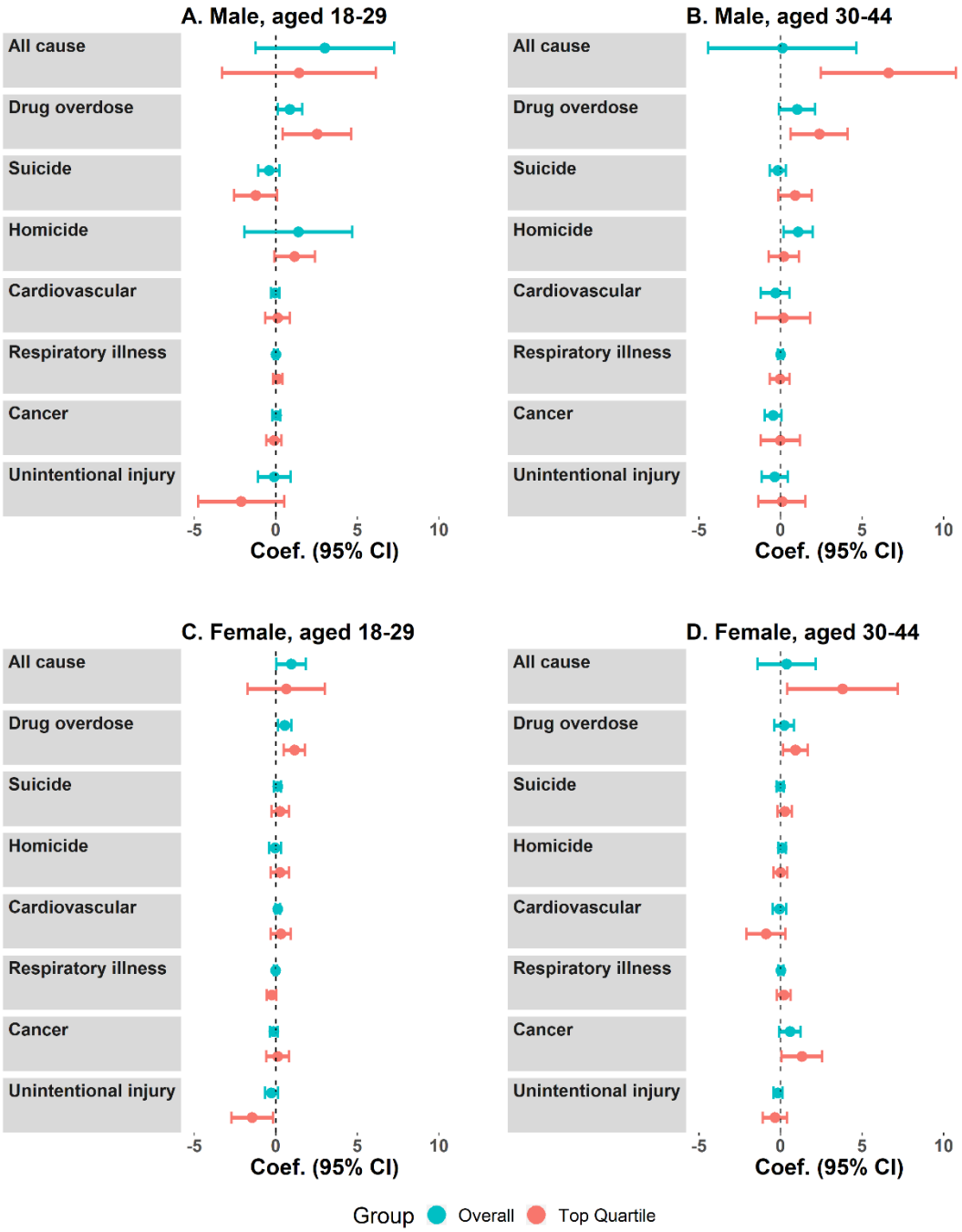
Notes: Binscatter plots of the unadjusted relationship between automation (the change in the number of robots per 1,000 workers between 1993 and 2007) and changes in drug overdose mortality rates per 100,000 18–65-year-old men and women 1990–2010 for the all U.S. counties (panel A) and counties in the highest quartile of the 1990 share of workers employed in manufacturing (manufacturing counties, panel B).

Figure 5. Unadjusted relationships, exposure to automation and SSI and SSDI applications



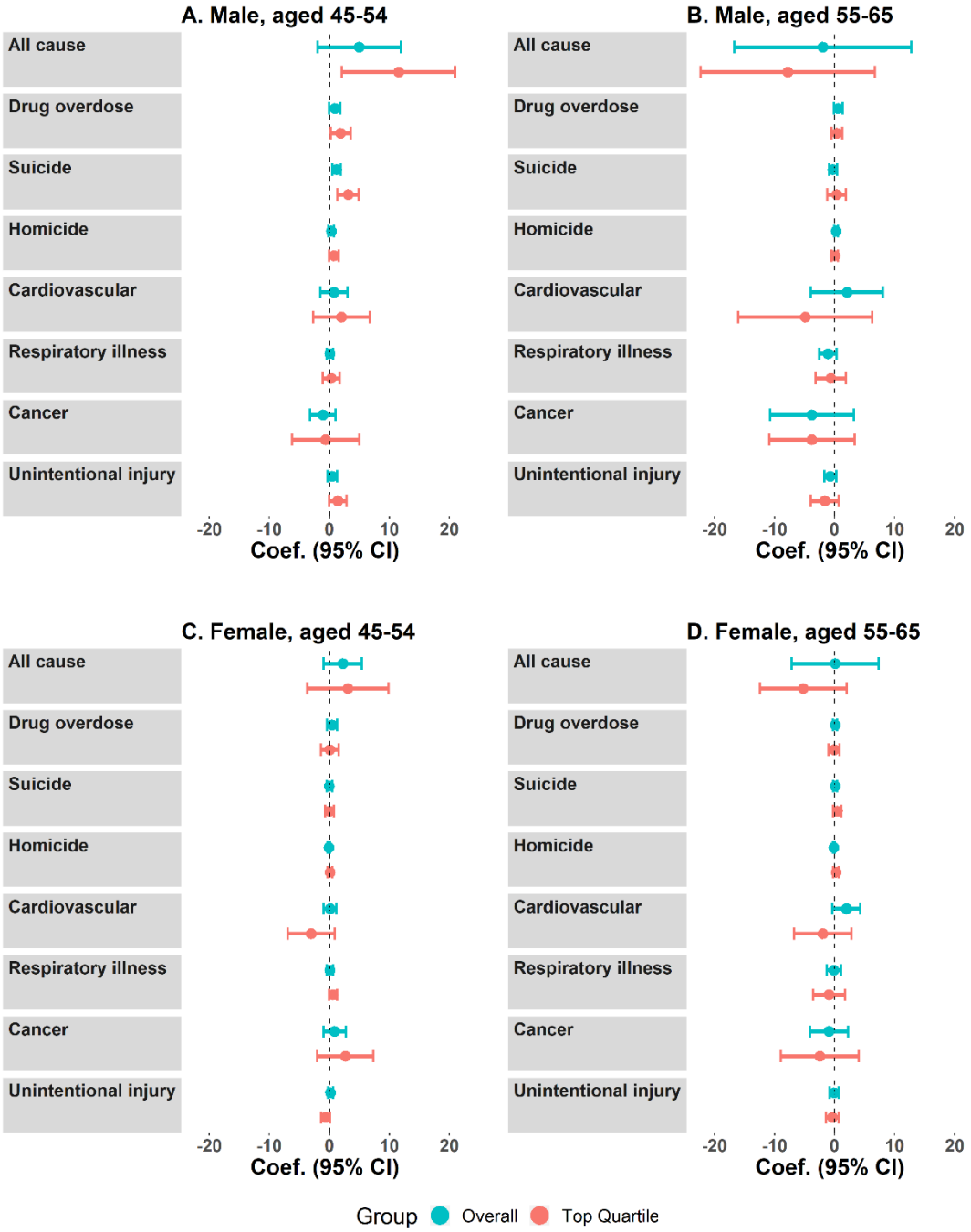
Notes: Binscatter plots of the unadjusted relationship between automation (the change in the number of robots per 1,000 workers between 2000 and 2007) and changes in SSI and SSDI applications (combined) per 1,000 18–65-year-old men and women 2000–2007 for all U.S. counties (panel A) and counties in the highest quartile of the 1990 share of workers employed in manufacturing (manufacturing counties, panel B).

Figure 6. Impacts of automation on mortality among 18–29 and 30–44-year-olds



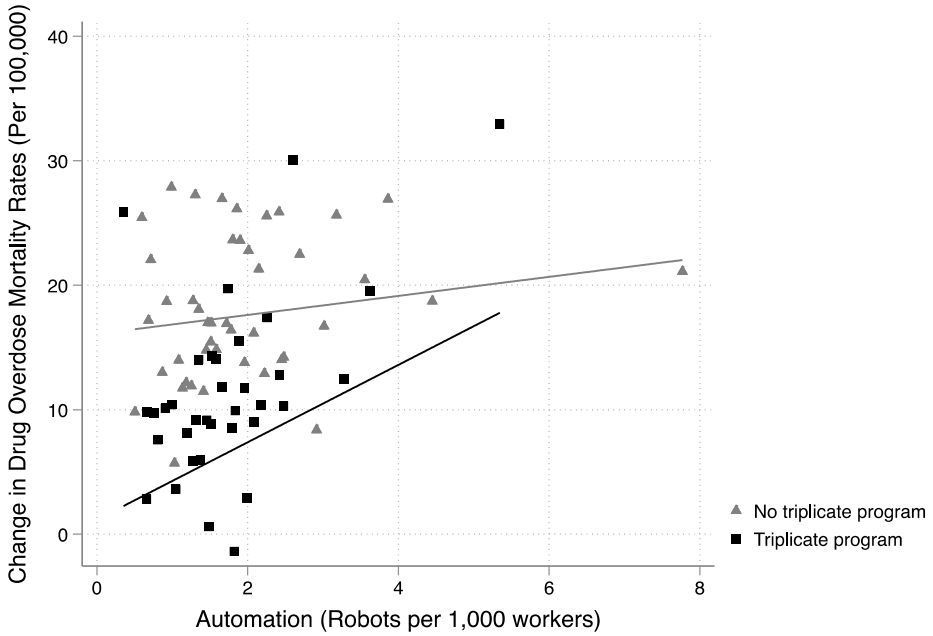
Notes: Estimates from a first differences model regressing changes in mortality rates (per 100,000) for each listed age-gender group, 1990–2010, on automation, expressed as the change in the number of industrial robots per 1,000 workers between 1993 and 2007. Each point (and 95% CI) represents estimates from a separate regression, with blue denoting estimates for all counties (n=3,107) and red denoting estimates for manufacturing counties (n=777). All models adjust for a rich set of 1990 commuting-zone demographic (age distribution, race/ethnicity population shares) and socioeconomic characteristics (shares completing high school and college education, share employed in manufacturing, share employed in routine occupations, and exposure to foreign trade), as well as census-division fixed effects.

Figure 7. Impacts of automation on mortality among 45–54 and 55–64-year-olds



Notes: Estimates from a first differences model regressing changes in mortality rates per 100,000 for each listed age-gender group, 1990–2010, on automation, expressed as the change in the number of industrial robots per 1,000 workers between 1993 and 2007. Each point (and 95% CI) represents estimates from a separate regression, with blue denoting estimates for all counties (n=3,107) and red denoting estimates for manufacturing counties (n=777). All models adjust for a rich set of 1990 commuting-zone demographic (age distribution, race/ethnicity population shares) and socioeconomic characteristics (shares completing high school and college education, share employed in manufacturing, share employed in routine occupations, and exposure to foreign trade), as well as census-division fixed effects.

Figure 8. Relationship between automation and mortality in states with and without triplicate pharmaceutical programs



Notes: Binscatter plots of the unadjusted relationship between automation (the change in the number of robots per 1,000 workers between 1993 and 2007) and changes in drug overdose mortality rates per 100,000 18–65-year-old men for counties in states with and without triplicate pharmaceutical programs. The five states with triplicate programs are California, Idaho, Illinois, New York, and Texas.

Table 1. Model estimates, impacts of automation on working-age mortality, by gender and cause of death

	Men		Women	
	All counties	**Manufacturing counties**	**All counties**	**Manufacturing counties**
All causes	0.79 (2.19)	3.19 (2.14)	0.72 (1.02)	1.13 (1.06)
Drug overdose	0.88** (0.38)	1.93** (0.74)	0.36 (0.22)	0.60* (0.30)
Suicide	0.08 (0.16)	0.83*** (0.24)	0.04 (0.09)	0.24 (0.16)
Homicide	0.92 (0.64)	0.55** (0.25)	–0.01 (0.09)	0.13 (0.11)
Cardiovascular	–0.17 (0.68)	–1.05 (1.24)	0.25 (0.32)	–1.43** (0.71)
Respiratory illnesses	–0.16 (0.16)	–0.04 (0.29)	0.001 (0.13)	0.002 (0.24)
Cancer	–1.16* (0.64)	–1.11 (0.99)	0.11 (0.38)	0.58 (0.80)
Unintentional injury (w/o drug overdose)	–0.13 (0.32)	–0.36 (0.63)	–0.09 (0.11)	–0.68** (0.25)
N, counties (clusters)	3,107 (48)	777 (34)	3,107 (48)	777 (34)

Notes: Estimates from a first differences model regressing changes in mortality rates for 18–65-year-old men and women (per 100,000) 1990–2010 on automation, expressed as the change in the number of industrial robots per 1,000 workers between 1993 and 2007. Each cell reports a coefficient estimate (standard error) from a separate regression model (with the last row of the table reporting the number of observations and number of state clusters in parentheses). All models adjust for a rich set of 1990 commuting-zone demographic (age distribution, race/ethnicity population shares) and socioeconomic characteristics (shares completing high school and college education, share employed in manufacturing, share employed in routine occupations, and exposure to foreign trade), as well as census-division fixed effects. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 2. Model estimates, impacts of automation on SSI and SSDI applications and determinations

	All counties	Manufacturing counties
SSI		
Applications	0.29**	0.25***
	(0.13)	(0.09)
	2,893	768
Succeeded	0.02	0.004
	(0.04)	(0.05)
	2,551	751
Denied	0.27***	0.26***
	(0.08)	(0.07)
	2,733	763
SSDI		
Applications	0.16***	0.17***
	(0.06)	(0.06)
	2,932	769
Succeeded	–0.04	–0.06
	(0.04)	(0.05)
	2,664	756
Denied	0.21***	0.25***
	(0.04)	(0.07)
	2,761	765

Notes: Estimates from a first differences model regressing changes in disability program application and determination rates per 1,000 18–65-year-old persons, 2000–2007, on automation, expressed as the change in the number of industrial robots per 1,000 workers over the same period. Each cell reports a coefficient estimate (standard error) from a separate regression model, with the sample size provided below. These sample sizes are smaller than for our mortality models because data for some counties with small application counts were suppressed for privacy purposes. All models adjust for a rich set of commuting-zone demographic (age distribution, race/ethnicity population shares) and socioeconomic characteristics (shares completing high school and college education, share employed in manufacturing, share employed in routine occupations, and exposure to foreign trade) for the year 2000, as well as census-division fixed effects. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

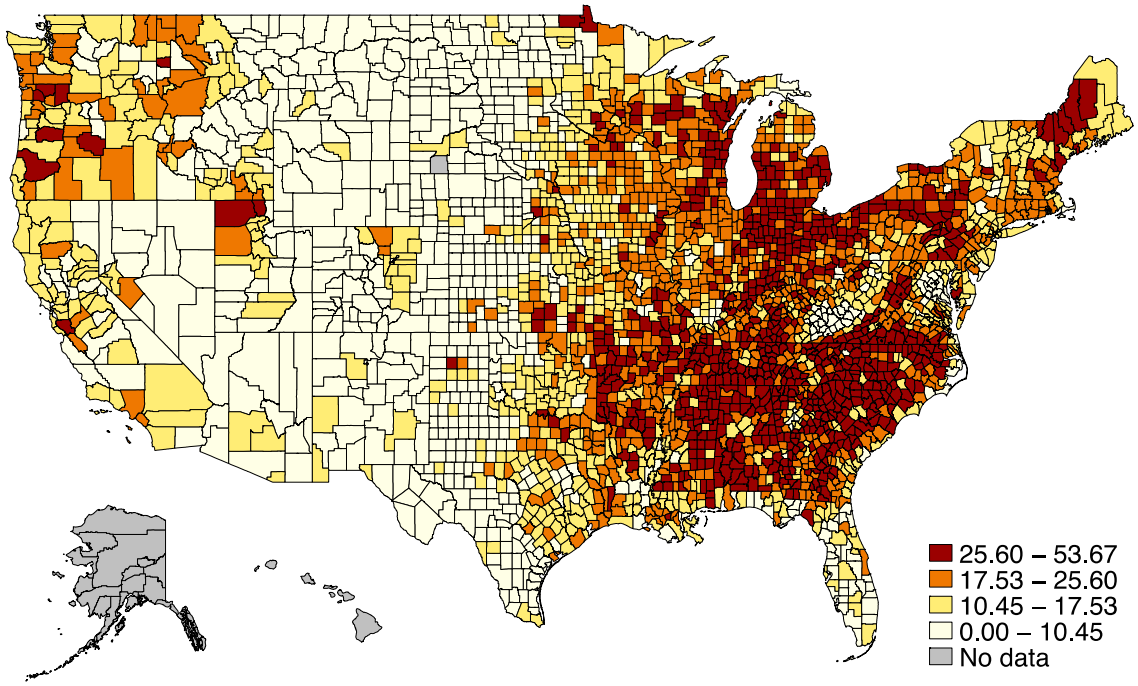
Table 3. Heterogeneity in the impacts of automation on drug overdose mortality rates among working age men

	p25	p75
Social Capital	1.93***	–1.0*
	(0.54)	(0.61)
College Graduate Share	2.87***	1.54***
	(0.56)	(0.45)
Medicaid Generosity Index	1.75**	0.34
	(0.86)	(0.41)
TANF Generosity Index	0.72	1.06
	(0.56)	(0.88)
N, counties (clusters)	3,107 (48)	

Notes: Estimates from a first differences model regressing changes in mortality rates for 18–65-year-old men and women (per 100,000) 1990–2010 on automation, expressed as the change in the number of industrial robots per 1,000 workers between 1993 and 2007. Unlike the models in Table 1, these models include the full set of interactions with each of the county- and state-specific socioeconomic and policy factors listed in the left-hand column. Each set of rows reports the marginal effects (standard error) obtained from a separate regression model, with margins evaluated at the 25th and 75th percentile of the national distribution of the heterogeneity variable of interest. As before, all models adjust for a rich set of commuting-zone demographic (age distribution, race/ethnicity population shares) and socioeconomic characteristics (shares completing high school and college education, share employed in manufacturing, share employed in routine occupations, and exposure to foreign trade) for the year 2000, as well as census-division fixed effects, along with the interactions between all of these covariates and the heterogeneity variables of interest. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Appendix

Appendix Figure 1. Identifying manufacturing counties



Notes: Map plots quartiles of county shares of workers ages 16 and above employed in the manufacturing industry as of 1990. Data were obtained from Social Explorer.

Appendix Table 1. ICD-9 and ICD-10 codes for causes of death

Cause of death	ICD-9	ICD-10
Suicide	950–959	X60–X84, Y87.0
Homicide	960–978	X85–X99, Y0–Y9, Y35, Y87.1, Y89.0
Drug overdose	850–858, 950.0–950.5, 962.0, 980.0–980.5	X40–X44, X60–X64, X85, Y10–Y14
Cardiovascular	390–459	I0–199
Cancer	140–208	C0–C97
Respiratory illness	34.0, 460–465, 470–478, 490–519	J0–J7, J30–J47, J60–J98
Unintentional injury (without drug overdose)	800–849, 860–869, 880–929	V0–V99, W0–W99, X0–X39, X45–X59, Y85–Y86

Notes: ICD-9 and ICD-10 codes used to identify specific causes of death in our analysis. ICD-9 codes are used in all registered U.S. death certificates between 1979 and 1998 and ICD-10 codes have been used for all registered death certificates since 1999.

Appendix Table 2. Baseline mortality rates per 100,000 18–65-year-olds, 1990

	Men		Women	
	All counties	**Manufacturing counties**	**All counties**	**Manufacturing counties**
All causes	483.32	512.34	259.41	278.24
Drug overdose	5.72	3.33	3.22	2.61
Suicide	23.25	24.98	5.90	5.67
Homicide	19.88	12.99	4.61	3.90
Cardiovascular	147.08	176.36	65.65	77.34
Respiratory illnesses	14.62	17.09	10.76	12.01
Cancer	120.37	135.69	103.96	108.10
Unintentional injury (w/o drug overdose)	46.51	59.41	14.31	18.67
N (counties)	3,108	778	3,108	778

Notes: Table presents baseline mortality rates per 100,000 18–65-year-old men and women for 1990 (specifically, the average for 1989–1991). Mortality data were obtained from restricted-access death certificate data from the National Center for Health Statistics (2018).

Appendix Table 3. Baseline disability program application rates per 1,000 working-age population, 2000

	All counties	Manufacturing counties
SSI applications	7.67 (2,915)	8.51 (768)
SSI successes	2.98 (2,616)	3.05 (754)
SSI denials	4.64 (2,778)	5.33 (764)
SSDI applications	6.41 (2,954)	8.32 (770)
SSDI successes	2.77 (2,715)	3.43 (759)
SSDI denials	3.65 (2,812)	4.90 (766)

Notes: Table presents baseline SSI and SSDI application and determination rates per 100,000 18–65-year-old men and women for the year. Data were obtained from SSA Form 831 files. Sample sizes are smaller than for our mortality data, because data for some counties with small application counts were suppressed for privacy purposes.

Appendix Table 4. Sensitivity analyses, SSI and SSDI applications

	All counties	Manufacturing counties
Change in disabled workers per 1,000 working-age persons	0.004 (0.18) 2,791	0.27 (0.28) 705

Notes: Models are identical to estimates in Table 2, except here the dependent variable is 2000–2007 change in the number of disabled workers per 1,000 working-age (18–64) persons. Data for this new dependent variable were obtained from the U.S. Social Security Administration (annual county-level data on the number of OASDI beneficiaries, each year). The mean change in the number of disabled persons per capita was 14.8 (s.d. 7.7). These data do not include counties in the states of Alaska, Hawaii, Maryland, Missouri, Nevada, and Virginia, and another 26 counties were excluded due to missing data for the year 2007. See Table 2 for further details on the estimation model. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Appendix Table 5. Sensitivity analyses, mortality

		Remove most heavily automated areas		Preexisting trends in mortality	
	Cause of death	**Men**	**Women**	**Men**	**Women**
All counties	All causes	3.13 (3.50)	0.93 (1.72)	–4.64** (1.79)	–0.56 (1.16)
	Drug overdose	1.31** (0.63)	0.70* (0.42)	–0.37 (0.29)	–0.07 (0.10)
	Suicide	0.25 (0.34)	0.16 (0.15)	–0.67*** (0.20)	–0.36*** (0.11)
	Homicide	2.24** (0.93)	0.20 (0.12)	–0.21 (0.47)	–0.08 (0.07)
	Cardiovascular	–0.46 (1.20)	–0.35 (0.57)	–2.34*** (0.85)	0.04 (0.38)
	Respiratory illnesses	0.15 (0.29)	0.46** (0.23)	–0.10 (0.16)	–0.06 (0.10)
	Cancer	–1.86 (1.25)	–0.52 (0.81)	–0.28 (0.54)	–0.39 (0.42)
	Unintentional injury (w/o drug overdose)	0.39 (0.47)	–0.21 (0.29)	–0.42 (0.43)	–0.42*** (0.14)
	N, counties (clusters)	3,082 (48)		3,102 (48)	
Manufacturing counties	All causes	4.47 (3.61)	1.23 (2.40)	–2.61 (2.22)	–0.60 (1.33)
	Drug overdose	2.17** (0.87)	0.45 (0.53)	0.12 (0.15)	–0.19*** (0.07)
	Suicide	0.91** (0.70)	0.07 (0.21)	–0.89* (0.45)	–0.32* (0.17)
	Homicide	1.26*** (0.42)	0.03 (0.27)	0.16 (0.28)	–0.15 (0.13)
	Cardiovascular	0.34 (2.41)	–2.62 (1.65)	–3.69* (1.95)	–0.27 (0.69)
	Respiratory illnesses	0.33 (0.59)	0.62 (0.76)	0.14 (0.30)	–0.10 (0.15)
	Cancer	0.13 (1.90)	–0.16 (1.62)	–0.07 (0.78)	0.10 (0.73)

	Unintentional injury (w/o drug overdose)	–1.05 (1.19)	0.01 (0.52)	1.32** (0.63)	–0.13 (0.20)
	N, counties (clusters)	765 (34)		777 (34)	

Notes: Models in the first panel are identical to estimates in Table 1, except here we exclude outlier commuting zones (areas where the increase in the number of robots per 1,000 workers is greater than 4; first two columns). In the second panel, we estimate the same models, except the dependent variables reflect the change in mortality rates between 1981 and 1991. *** p<0.01, ** p<0.05, * p<0.10.

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