Death by Robots? Automation and Working-Age Mortality in the United States

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Death by Robots?

Automation and Working-Age Mortality in the United States

Abstract: The decline of manufacturing employment is frequently invoked as a key cause of worsening U.S. population health trends, including rising mortality due to ‘deaths of despair’. Increasing automation—the use of industrial robots to perform tasks previously done by human workers—is one major structural force driving the decline of manufacturing jobs and wages. In this study we examine the impact of automation on age-sex specific mortality. Using exogenous variation in automation to support causal inference, we find that increases in automation over the period 1993–2007 led to substantive increases in all-cause mortality for both men and women aged 45–54. Disaggregating by cause, we find evidence automation is associated with increases in drug overdose deaths, suicide, homicide and cardiovascular mortality although patterns differ across age-sex groups. We go on to examine heterogeneity in effects by safety net program generosity, labor market policies, and the supply of prescription opioids.

Keywords: Mortality; Deindustrialization; Labor Demand; Automation

JEL Codes: J110; J230; O330; H700

Today a person born in the United States is expected to die on average three years sooner than persons born in other high-income countries (Ho & Hendi 2018). This was not always the case: U.S. life expectancy diverged from peer countries starting around 1980, a relative stagnation which recently culminated in a decline in expected longevity for the first time on record (Woolf & Schoomaker 2019). Demographic evidence reveals that this deterioration in U.S. population health is driven primarily by rising mortality among less-educated working-age adults. Increasing premature death in this subgroup—due to suicide, drug overdose, and other so-called ‘deaths of despair’—has received widespread attention in both academic and popular discourse (Case & Deaton 2017).

The most common explanations attribute this troubling trend to structural changes in the U.S. economy which have reduced opportunity and increased precarity for working-age adults without a four-year college degree. A growing body of empirical research supports this contention (Coile & Duggan 2019; Venkataramani et al 2020b; Naik et al 2019; Seltzer 2020). Much of this work examines the impact of the decline in economic opportunities in domestic manufacturing, a sector that historically served as a path to the middle class for those without a college degree (Cherlin 2014). For example, Venkataramani et al. (2020a) find that sharp reductions in local manufacturing jobs after automobile assembly plant closures led to an acute increase in opioid overdose mortality. Other studies have linked exposure to competition from foreign manufacturing firms—which reduces wages and employment opportunities for domestic manufacturing workers—to increases in mortality among working-age men with less education (Adda and Fawaz 2020; Autor, Dorn and Hanson 2019; Pierce and Schott 2020).

This article examines the mortality impact of another structural force behind the decline of manufacturing: automation. Since the 1980s, technological improvements, coupled with the

pressures of an increasingly competitive global marketplace, fueled the adoption of industrial robots on plant floors (Acemoglu and Restrepo 2020; Autor and Salomons 2018). Although automation in some sectors may augment opportunities and raise wages by increasing the productivity of human workers (Autor 2015; Eggleston, Lee & Iizuka 2021), this specific class of industrial robots displaced workers. According to work by Acemoglu and Restrepo (hereafter AR 2020), adoption of industrial robots led to the loss of an estimated 420,000 to 750,000 jobs over the 1990s and 2000s, the majority of which were in manufacturing; those fortunate enough to keep their jobs still experienced meaningful declines in wages (AR 2020).

The decline in economic opportunities due to automation has been borne primarily by less educated workers, the same group that has faced rising mortality rates. This suggests a causal link between automation and mortality, which we argue may operate through ‘material’ pathways by impacting current employment, wages, and access to health care, as well as through ‘despair’ pathways by reducing future economic opportunities. Although a recent consensus study report from the National Academies of Science identifies “technological advances that replace workers” as one potential driver of increasing working-age mortality (2021: p.6), this association has not been examined in the literature. With the adoption of industrial robots projected to increase by two- to four-fold in the coming decade (AR 2020)—a trend that may be further exacerbated by responses to the Covid-19 pandemic (Chernoff and Warman 2020)—understanding the potential consequences of automation on mortality outcomes is critical for policymakers. It is also instructive to examine potential heterogeneity in these relationships to identify policies that may mitigate any adverse consequences of continued automation on population health.

We use newly available measures of the adoption of industrial robots across U.S. commuting zones between 1993 and 2007 to examine the impacts of one key form of automation

on mortality. Specifically, we apply the instrumental variable strategy used by AR 2020, who create a plausibly exogenous measure of robot penetration by combining information on pre-existing employment shares in different industries in each commuting zone with the trajectory of robot adoption in each of those industries from a set of European countries. This method addresses confounding from omitted factors that may affect both automation and mortality. For example, health may have been worsening among workers even prior to automation, which may induce firms to replace sicker workers with robots. In the absence of the instrumental variable, such a process may lead us to erroneously draw a relationship between automation and population health. Combining this instrument with restricted-access U.S. death certificate data from 1993-2007, we estimate the causal effect of commuting zone-level automation on cause-specific, county-level mortality among working-age adults by age and sex in a series of first-differences models.

We find that increases in automation led to substantive increases in mortality, with positive and statistically significant effects on all-cause mortality for both men and women aged 45-54, the same age group that has seen mortality increase in recent years. Point estimates indicate each additional robot per 1,000 workers led to just over 8 additional deaths per 100,000 males aged 45-54 and just under 4 additional deaths per 100,000 females in the same age group. Automation therefore contributed to the slowdown in mortality improvements over this study period, portending the absolute increase observed for some subgroups in recent years (Case & Deaton 2017). Disaggregating by cause, we find automation leads to increases in drug overdose mortality for men of all age groups and for younger (20-29) women; our estimates indicate automation explains 12% of the overall increase in drug overdose mortality among all working-age adults over our study period. In addition to drug overdose mortality, we find automation led to a substantial increase in suicide mortality for males aged 45-54, contributing to the secular rise in suicide

mortality for middle-aged males observed in recent decades (Hedegaard, Curtin and Warner 2020). We also find evidence that automation is associated with increased homicide, cancer and cardiovascular mortality in specific age-sex groups. Our findings are robust to accounting for pre-existing trends in mortality and removing “outlier” commuting zones with exceptionally high penetrance of industrial robots during the study period.

This study is among the first to demonstrate a causal association between long-run secular trends of automation-induced deindustrialization and working-age mortality.⁴ Our findings are consistent with a large body of work correlating declines in manufacturing with worsening individual and population health including mortality (e.g., Seltzer 2020). It is also in line with existing research identifying the causal effect of long-run manufacturing decline on mortality in specific communities (e.g., Sullivan and Von Wachter 2009) or in response to increased exposure to foreign trade (Adda and Fawaz 2020; Autor, Dorn and Hanson 2019; Pierce and Schott 2020) or from acute shocks such as plant closures (e.g., Browning & Heinesen 2012; Venkataramani et al 2020a).

We go on to examine three contextual features of places that theory and prior work suggest could moderate the relationship between automation and mortality: social safety net policies, labor market policies, and prescription opioid supply. Several recent studies emphasize the role of state policy variation in explaining levels and trends in health disparities, including mortality (see

⁴ Closest to the present paper is a recent working paper (Gihleb et al 2020) examining the causal impact of industrial robot adoption in the U.S. and Germany on a range of outcomes finds automation is associated with an overall increase in alcohol and suicide mortality. However, their analysis pools all ages (including non-working-age adults) and genders, and includes data from a more limited time frame and more limited set of counties. Moreover, they do not consider other causes of death. Our paper also relates to work by Patel and colleagues (2018) who find that county-level measures of automation are associated with worse self-reported health, though this analysis is descriptive in nature and precludes causal interpretations. Finally, Gunadi and Ryu (2021) assess causal relationships between automation and self-reported health specifically among low-skill workers, finding improvements in health as a result of reallocation of workers to less physically-intensive tasks.

Montez 2017; Montez, Hayward and Zajacova 2019; Montez et al 2020). Consistent with this work, we find evidence that the generosity of state safety net programs—Medicaid and Unemployment Insurance—mitigates the effect of automation on mortality among middle-aged males, specifically deaths due to suicide and drug overdose. We also find evidence that state labor market policies moderate the effect of automation on mortality for middle-age males: notably the effect of automation on drug overdose mortality and suicide mortality is more pronounced in states with ‘right to work’ laws and in states with lower minimum wage rates. Taken together these findings demonstrate the central importance of public policies in moderating the effects of deindustrialization on deaths of despair.

We also examine effect heterogeneity as a function of the supply of prescription opioids in a local area, constructing estimates from national prescription drug surveillance data. We find suggestive—but imprecisely estimated—evidence that the effect of automation on drug overdose mortality may be higher in areas with higher supply of prescription opioids per capita. This evidence may inform ongoing debates over the relative roles of supply versus demand factors in driving the opioid overdose epidemic (Currie, Jin, and Schnell 2018; Hollingsworth, Ruhm, and Simon 2017; Currie & Schwandt 2020; Seltzer 2020).

In the following sections we describe the mechanisms through which automation may impact working-age mortality, drawing on a growing body of research demonstrating the impact of the economy on individual and population health. We then motivate our three potential contextual moderators before turning to our data, methods and results.

THEORETICAL PATHWAYS

Theory and existing empirical research suggest two pathways through which the rise of industrial automation may impact working-age mortality, what we term the ‘material’ pathway and the ‘despair’ pathway. These pathways are not mutually exclusive but rather complementary, inviting us to consider how the same structural economic trends may yield increases in mortality from causes as distinct as suicide and cardiovascular disease.

A. Material Pathway

The first pathway through which automation may impact working-age mortality is by shaping material outcomes known to impact individual and population health, including employment and wages. Acemoglu and Restrepo (2020) find that the rise of industrial robots had substantial negative effects on employment both directly through displacement of manufacturing workers and indirectly by depressing local economic demand, thereby reducing jobs in other industries such as the service sector. In addition to lower employment rates, A&R find a substantial negative effect on average wages in the commuting zone, experienced by even those who remain employed. These direct and indirect effects of automation on employment and wages are likely in turn to impact health outcomes. Previous research has established a link between manufacturing decline and working-age mortality, examining both long-term secular trends (e.g., Seltzer 2020) and acute declines in employment opportunities due to plant closures (e.g., Venkataramani et al 2020). Moreover, a large body of work across the social sciences finds income and employment to be key determinants of health; individuals with higher incomes live longer (Chetty et al 2016) and areas with higher average income have higher average life expectancy (Dwyer-Lindgren et al 2017).

Employment and wages are not the only mechanisms through which automation may impact material outcomes with consequences for health. For example, most working-age persons

in the United States rely on employer provided health insurance benefits; manufacturing is one sector where less-educated workers were historically provided such non-wage benefits. To the extent automation decreases the total number of jobs that provide health insurance coverage it may decrease health care access and utilization, particularly for preventative and diagnostic visits (see Freeman et al 2008 for a review). This in turn could drive increased mortality for conditions such as cancer and heart disease. At the community level, increasing automation and worker displacement may lead to lower tax revenues, reducing public sector spending on everything from health to education.⁵ To the extent automation reduces public sector investment in health care services, we would expect that increase mortality on the margins.

It is possible that automation may also improve health for some subsets of the population, particularly if tasks done by industrial robots allow existing workers to focus on less dangerous or taxing tasks. For example, recent work suggests that adoption of industrial robots may improve self-reported health among some types of workers, likely due to reductions in physical tasks (Gihleb et al 2020; Gunadi and Ryu 2021). However, given the substantial overall negative effect of automation on the material economic outcomes of affected workers and their communities, we expect to find an association between the changing intensity of robot penetration and working-age mortality across U.S. counties.

B. Despair Pathway

The second pathway through which automation may impact working-age mortality is by shaping real and perceived economic opportunity of residents in affected areas. Analyzing the social and economic correlates of recent trends in mortality for different subpopulations, Siddiqi

⁵ Feler and Senses (2017) found exactly that in analyzing the impact of foreign trade exposure on the local provision of public goods.

and colleagues (2019) found that the ‘material’ pathways described above cannot entirely account for worsening mortality among middle-aged whites given the same adverse trends also impacted Black Americans who, in contrast, did not experience the same increases in mortality until more recently. The authors attribute increasing mortality among middle-aged whites to perceived status loss due to declining relative group position, specifically vis a vis racial and ethnic minorities. In addition, recent work demonstrates that occupational *expectations* are stronger predictors of death from drug overdose and suicide than actual occupational attainment (Muller et al. 2020). These findings are consistent with emerging work showing that area-level prospects for social mobility are strongly associated with a range of individual- and area-level measures of health behaviors and physical and mental health outcomes, even after adjusting for socioeconomic status (Venkataramani et al 2016, 2017), as well as evidence that white middle-aged mortality increased more in areas characterized by low economic mobility (O’Brien et al 2017). How people understand and conceive of their position in the social hierarchy, and the opportunities and possibilities available to them, can impact health outcomes regardless of the material reality.

We argue the decline of manufacturing employment is likely to have a negative impact on perceived economic opportunity and future expectations, particularly for residents of the industrial heartland. Historically, regions of the U.S. with high levels of manufacturing employment have been characterized by high rates of intergenerational economic mobility, the likelihood that children will achieve the American dream of doing better than their parents in adulthood (Berger & Engzell 2020); indeed, recent work finds the decline in manufacturing is a key driver of declining rates of economic mobility in many parts of the industrial Midwest and Northeast (Connor & Storper 2020). To the extent automation reduces local area economic opportunity—

or the perception thereof—we might expect increased mortality from drug overdose, suicide, and other so-called “deaths of despair” (Case & Deaton 2017). Compounding these forces is the fact that areas facing deindustrialization also experience shifts in key social factors—e.g., changes in marriage markets and destruction of social capital—that may further worsen health outcomes (Cherlin 2014; Wilson 1996).

The ‘material’ and ‘despair’ pathways through which automation may impact mortality detailed above are complementary and mutually reinforcing; they also reveal how the determinants of health and mortality cannot be neatly categorized as processes occurring at either the ‘individual’ or ‘ecological’ levels. Automation is a technological shock that has implications for both individuals and their communities. Whether and to what extent the material hit to an individual—say in the form of job loss or lower wages—translates into heightened mortality risk is likely to vary as a function of the overall economic health of the local area. At the same time, residing in an area hit hard by automation-driven deindustrialization may heighten mortality risk even among those whose own immediate material reality is unchanged by dimming prospects for the future economic mobility and weakening the public sector. In the analysis below, we estimate change in mortality at the county level, capturing the net effect of these distinct but related pathways.

POTENTIAL CONTEXTUAL MODERATORS

The United States is a large and heterogeneous country. We therefore expect the effect of technological adoption on population health to vary systematically across places. In the analysis below we consider three aspects of local context that may moderate the relationship between

automation and working-age mortality: social safety net policies, labor market policies, and prescription opioid supply.

A. Social Safety Net Policies

Recent evidence suggests that cross-state variation in the generosity of social safety net programs is an important determinant of spatial patterns in population health (Montez 2017; Montez et al 2020). In the context of this analysis, we might expect social safety net program generosity to moderate the relationship between automation and mortality by blunting the social and economic hit to workers, families, and their communities. Our measures of program generosity are taken from Fox et al (2020), who create summary indices for each social program that are based on program generosity, eligibility requirements, and administrative burdens to accessing benefits.⁶ In addition to a composite measure capturing the overall generosity of state social safety net policies, we consider two specific programs that exhibit substantial variation across state lines: Medicaid and Unemployment Insurance (UI). We use measures from the earliest year available (2000) in their data.

Our prior is that the generosity of state Medicaid programs is the most likely to moderate the relationship between automation and mortality; during our study period there was considerable cross-state variation in Medicaid income eligibility thresholds for working-age adults. Previous

⁶ For example, the Medicaid generosity index combines multiple measures of generosity (based on coverage of optional benefits, e.g., dental, vision, psychologists), eligibility requirements (i.e., income eligibility thresholds for children, pregnant women, parents, and non-parents), and administrative burdens (e.g, presence of asset tests, face-to-face interviews, presumptive eligibility, continuous enrollment). They combine these measures to create an index ranging from 0-100 which is increasing in generosity - see Fox et al (2021) for details. Fox et al also construct indices for the Temporary Assistance for Needy Families (TANF) and Supplemental Nutrition Assistance Program (SNAP). However, we did not consider these programs in our analysis given either the limited scope of the program (TANF) or relative lack of cross-state variation in generosity during the study period (SNAP).

research finds variation in Medicaid policy impacted spatial patterns in both all-cause and drug overdose mortality (Sommers, Baicker & Epstein 2012; Venkataramani & Chatterjee 2019; Miller, Johnson, Wherry 2021). While generosity of (and eligibility for) UI varies across state lines, it is a time-limited social benefit. Even so, recent work by Kuka (2020) finds a causal association between unemployment insurance generosity and health insurance coverage and utilization, particularly during periods of high unemployment. She also finds UI generosity is associated with higher self-rated health. Similarly, Cylus, Glymour and Avendano (2014) find that more generous UI benefits at the state level are associated with lower suicide rates, particularly during periods of high unemployment. Moreover, evidence suggests that UI program generosity is associated with improved job matching for unemployed workers (Farooq, Juggler & Muratori 2020), which may both reduce despair and improve material outcomes for workers in ways that benefit health.

B. Labor Market Policies

Beyond the social safety net, there is substantial variation in state labor market policies. We consider two: minimum wage rates and ‘right to work’ laws. Evidence on the effect of state minimum wage rates on health outcomes of the working-age population is mixed, with most studies finding no discernable effects (see Leigh, Leigh and Du 2019 for a review). There is, however, growing evidence linking higher minimum wage rates to reductions in mortality from suicide among working-age adults (Dow et al. 2020; Gertner, Rotter and Shafer 2019). Moreover, correlational analyses find reports of unmet medical needs among low-skilled workers are lower in states with higher minimum wages, net of individual and contextual covariates (McCarrier et al 2011). In our conceptual framework, higher minimum wages laws may moderate the effect of automation on mortality by mitigating the wage loss associated with a decline in manufacturing

employment. In the analysis below, we test for effect heterogeneity as a function of the state minimum wage rate in nominal dollars in the year 2000 (obtained from UKCPR 2021).

We also consider the potential moderating effect of state ‘right-to-work’ (RTW) laws. Right-to-work laws are state-level prohibitions on unions requiring non-members who benefit from union-negotiated benefits to contribute to the cost of union representation. The empirical evidence on the effects of RTW laws on labor market indicators such as aggregate employment and wages is mixed and inconclusive (see Collins 2012 for a review), although there is evidence RTW laws reduce labor organizing (Ellwood and Fine 1987) and private sector unionization rates (Eren and Ozbeklik 2015). To the extent these laws shape the quality and/or quantity of jobs available to displaced workers they may moderate the association between automation and working-age mortality. We explore this using a binary indicator for whether the state had a RTW law as of 2000 with data taken from Caughey and Warshaw (2016).

C. Prescription Opioid Supply

Several recent studies find a positive association between local area prescription opioid supply and drug overdose rates (see, e.g., Currie & Schwandt 2020; Ruhm 2019; Monnat 2019). We therefore also consider the possibility that the local opioid supply may moderate the effect of automation on mortality. Specifically, we hypothesize that any effect of robot adoption on drug overdose mortality is likely to be higher in local areas with relatively greater supply of prescription opioids. To examine this, the study team amassed data on the prevalence of oxycodone scripts across counties in the U.S. as reported to the Automated Reports and Consolidated Ordering System (ARCOS), maintained by the U.S. Department of Justice which collects information on controlled substance transactions from manufacturers and distributors. We used these data to

calculate the (logged) milligram equivalent of morphine (MME) of oxycodone prescribed per working-age adult between ages 20-64 in each county in 2000.

DATA

Data for our main exposure, commuting-zone level exposure to automation, was obtained from AR (2020). The measure captures the *predicted* increase in industrial robots per 1,000 workers over the period 1993-2007. The measure is constructed using 1970 U.S. commuting zone-level data⁷ on employment shares across 19 different industries combined with data on the growth in industrial robots in each of these industries for 5 European countries (Denmark, Finland, France, Italy, and Sweden). The use of data from these countries, who adopted industrial robots sooner than the U.S. did, instead of data from the U.S., allows AR 2020 to limit bias from endogenous commuting-zone labor demand factors that may have jointly influenced automation and our outcomes of interest (e.g., worsening health leading both to firms adopting automation technologies and increased working-age mortality, e.g. Currie et al. 2018; Krueger 2017). This type of measure is known as a “shift-share instrument” in the econometrics literature (Goldsmith-Pinkham, Sorkin and Swift 2020). **Figure 1** maps the predicted change in automation across commuting zones between 1993 and 2007 as estimated by AR2020.

We constructed county-specific, age-adjusted mortality rates by age group, sex, and cause using restricted-access death certificate data obtained from the U.S. National Center for Health Statistics (National Center for Health Statistics - Centers for Disease Control and Prevention, 2018) and annual age-sex specific population estimates for the U.S. Census Bureau. We examine

⁷ AR (2020) use 1970 values to address potential bias from mean reversion in industrial employment shares in the 1980s.

sex-specific mortality rates for the 20-29, 30-44, 45-54, and 55-64-year-old age groups given evidence of heterogeneous impacts by age and sex in other work. For each group, we compute mortality rates from all-causes as well as from drug overdoses, suicides, homicides, cardiovascular diseases, respiratory illnesses, cancers, and unintentional injuries (excluding drug overdoses, see **Appendix Table 1** for relevant ICD-9 and ICD-10 codes; See **Appendix Table 2** for mortality rates by age and sex in 1993). To best match the automation data, we compute changes in mortality rates for each demographic group and cause (per 100,000) between 1993 and 2007. For each baseline and endline year, we use the surrounding three-year average for mortality rates to improve the precision of measurement (Venkataramani et al 2020; Woolf and Schoomaker 2019).

ANALYTIC STRATEGY

To estimate the impact of automation on working-age mortality we estimate versions of the following first differences model:

$$\Delta Y_{i,j,r,t1-t0} = \alpha_1 \times \Delta Automation_{j,r,t1-t0} + \beta \times BaselineChar_{j,r,t0} + \theta_r + e_{i,j,r,t} \quad (1)$$

where i indexes the county, j indexes the commuting zone, and $t1$ and $t0$ index 2007 and 1993, respectively. $\Delta Y_{i,j,r,t1-t0}$ represents the change in mortality 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. This specification corresponds to the “long-difference” model used by AR (2020).

α_1 , which captures the association between exposure to automation and mortality, is our parameter of interest. This parameter captures health impacts accruing from both the material and despair pathways, i.e., the effects of automation-led job and benefit loss, diminished wages among

still-employed workers (Elser et al. 2019), reduced physical exertion and injury risk among still-employed workers (Gihleb et al 2020; Gunadi and Ryu 2021), reduced economic opportunities and future expectations (Venkataramani et al. 2020), and the effects of shifting social factors (e.g., changes to marriage markets, destruction of social capital) (Cherlin 2014; Wilson 1996). Our research design and data limitations do not allow us to assess the specific contribution of each of these pathways, and we flag this as an important area for future research.

Shift-share instrumental variables may be 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 et al. 2020). To address this concern, we follow AR (2020)’s preferred specification and adjust rich set of baseline characteristics (denoted by the vector $BaselineChar_{j,r,t0}$) measured in 1990, 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), given regional patterns in the evolution of automation and our main outcomes (**Figure 1**). We estimate the above model for mortality outcomes separately by age-sex groups and cause. In all analyses, we cluster standard errors at the state level to account for potential geographic correlation in the exposure and outcomes, and weight by appropriate (sex-age group) population size. Clustering at the commuting zone level produces substantively identical results (see **Appendix Table 3**).

We test for potential contextual moderators by estimating models that include an interaction term between our contextual measure (e.g., state minimum wage rate) and the

automation measure. We also include in our models all of the interactions between the focal contextual measure and the full set of covariates, in order to reduce possibility that the interaction effects of interest are confounded by other interactions between the contextual measure and observable characteristics that are potentially correlated with our automation measure. Specifically, we estimate versions of the following equation:

$$\Delta Y_{i,j,r,t1-t0} = \gamma_1 \times \Delta Automation_{j,r,t1-t0} + \gamma_2 \times \Delta Automation_{j,r,t1-t0} \times StateContext_{j,r} + \gamma_3 \times StateContext_{j,r} + \delta \times BaselineChar_{j,r,t0} + \vartheta \times BaselineChar_{j,r,t0} \times StateContext_{j,r} + \theta_r + \theta_r \times StateContext_{j,r} + u_{i,j,r,t} \quad (2)$$

The key parameter of interest here is γ_2 , which captures the interaction between the focal contextual measure ($StateContext_{j,r}$) and our automation instrument. We estimate this model specifically for men and women ages 45-54, for whom increases in mid-life mortality have been most prominent and for whom we find large impacts of automation on all-cause mortality in our main analyses. For the ease of interpretation, we report marginal effects of automation on mortality evaluated at high and low values of the contextual measure $StateContext_{j,r}$ (we report estimated coefficients on the interaction term in Appendix Tables 9-14).

RESULTS

Impacts of Automation on Mortality

Main Findings

Figure 2 plots estimated coefficients of the effects of automation on mortality by cause for males in four age categories (**Appendix Table 3** reports the coefficients and standard errors).

Across all four age categories, the estimated effect of automation on all-cause mortality is positive and substantial in magnitude; however, only for males aged 45-54 is the point estimate statistically distinguishable from zero at conventional alpha levels ($p < .05$). Among 45–54-year-old men, an increase of 1 robot per 1,000 workers was associated with a statistically significant 8 additional deaths per 100,000 persons (relative to a scenario where there was no increase in industrial robots). This is a sizable relative increase in mortality, notably among the exact demographic subgroup identified by Case and Deaton (2017) as suffering from increased deaths of despair. The average increase in automation over the study period (2 robots per 1,000 workers) was thus associated with 16 additional deaths per 100,000 persons, equivalent to roughly 25% of the overall secular decline this age group observed between 1993-2007 (64 deaths per 100,000).

Disaggregating by cause, we find evidence that increases in robot penetration led to significant increases in drug overdose mortality across all four age categories. The average increase in automation across commuting zones of 2 robots per 1,000 workers can account for 13.5% of the overall increase (14 deaths per 100,000) in drug overdose deaths between 1993-2007 among 20–29 year old men ($p < .05$); 20.1% of the overall increase (11 per 100,000) among 30-44 year old men ($p < .05$); 8.2% of the overall increase (22 per 100,000) among 45-54 year old men ($p < .10$); and 12.0% of the overall increase (11 per 100,000) among 55-65 year old men ($p < .10$). To place these findings in context, we note that the relative share of drug overdose deaths explained by automation is somewhat smaller than the share explained due to local exposure to international trade. For example, Pierce and Schott (2019) note that local economic shocks resulting from the U.S. granting permanent trade relations with China could account for ~40% of the growth in drug overdose mortality in the early 2000s.

Estimates for other causes of death depend strongly on the age group of interest. Among 30-44-year-old men, we find evidence that automation led to increases in homicide deaths. Among 45-54-year-old men, we find evidence of impacts on suicide mortality rates, with the average increase in robot penetration of 2 per 1,000 workers accounting for 51% of the overall increase in suicide deaths (4.91 deaths per 100,000) in this age group over the study period. In addition to increasing deaths of despair, we also find evidence that automation is associated with elevated risk of cardiovascular mortality, particularly among males aged 55-64 where we find each additional robot per 1,000 workers was associated with an additional 5 deaths per 100,000.⁸ This finding is consistent with an emerging literature linking area-level economic prosperity with cardiovascular disease outcomes.

Figure 3 presents the corresponding analysis for females. Here the estimated effect sizes are generally smaller but follow a similar pattern: automation is associated with an increase in all-cause mortality among working-age females, with statistically significant effects among those aged 20-29 ($p < .05$) and aged 45-54 ($p < .01$). In the latter group, the average increase in automation led to a relative increase in mortality equal to about 59% of the overall decline in all-cause mortality observed over the study period (12.77 deaths per 100,000). As with men, drug overdose mortality among women aged 20-29 increases with automation. Among women ages 30-44 we find that automation is associated with higher cancer mortality rates.⁹ As with men, we find the

⁸ In absolute terms, this is largest effect for a specific cause of death across all age-sex groups. However, given that the baseline rates for cardiovascular disease mortality are an order of magnitude larger than for other disease (with the exception of cancer), these effects are in fact smaller in relative (e.g., percent increase) terms than, for example, the automation-driven increase in drug overdose deaths among men in any age group.

⁹ Given small sample sizes, we follow standard practice aggregate cancers from all causes into a single statistic for the purposes of this analysis.

largest absolute impact is on cardiovascular mortality for women aged 55-64, with each additional robot per 1,000 workers associated with an increase of just under 4 deaths per 100,000.

Taken together, our findings reveal a direct link between the rise of automation and the mortality among adults aged 45-54, operating largely through increasing deaths from drug overdose and suicide. We also find evidence that automation led to a relative increase in overall mortality among younger females and, for certain age-sex groups, increased mortality from causes as varied as cancer and cardiovascular disease.

Robustness Checks

Following AR (2020) we checked that our findings were not being driven by a subset of commuting zones where adoption of industrial robots distinctly outpaced the rest of the U.S. We re-estimate our models after removing these “outlier” commuting zones and find similar substantive effects (**Appendix Table 4, Col 1**).¹⁰ We also examined the effect of automation in areas with high levels of manufacturing employment, defined as counties in the top quartile of the share of residents employed in manufacturing in 1980 (**Appendix Table 4, Col 2**). Notably we find the estimated effect of automation on drug overdose mortality and suicide mortality to be substantially larger (and statistically different) when we restrict our sample to communities in which manufacturing workers tended to live, consistent with the fact that automation affected these workers the most (Acemoglu and Restrepo 2020).

¹⁰ We also note that AR (2020) find that the bulk of the effects of automation on labor market outcomes are unlikely to explained by migration, and that migration in general appears to play a minor role in other studies examining the link between economic opportunity and health (Autor et al. 2019; Schwandt and von Wachter 2020; Venkataramani et al. 2020a; Ganong & Shoag 2017)

A key threat to inference in our research design is pre-existing trends in the outcome of interest. Namely, areas with greater adoption of industrial robots over the study period may have already experienced worsening mortality. We address this possibility by estimating models regressing changes in cause-specific mortality rates between 1981-1992 on automation between 1993-2007 (conditional on the same covariates in our main specification). Large, positive estimates on automation in these models would be consistent with upward biasing pre-existing trends. As seen in **Appendix Table 4, Col 3**, we find no evidence of pre-existing trends of increasing mortality rates. If anything, some of the estimates suggest pre-trends in the opposite direction. To correct for this, we estimate versions of our main model for each cause of death adjusting for the 1981-1992 pre-trends; our results are substantively unchanged by inclusion of this covariate (**Appendix Table 4, Col 4**).

Contextual Moderators

To test for potential contextual moderators of the effect of automation on mortality we estimate versions of our core model that additionally include interaction terms between the contextual measure and automation (as well as interactions between the contextual measure and each of the covariates, see estimating equation 2). For safety net and labor market policies, we focus on outcomes for males aged 45-54 where the effect of robots on mortality is largest (for corresponding analysis for females aged 45-54 see **Appendix Table 8**). For opioid supply, we examine all-cause and drug overdose mortality for all working-age males and females.

A. Safety Net Programs

We examine effect heterogeneity using a composite index of the overall generosity of state social safety net programs as well as indices of the generosity of two specific programs that vary across state lines: Medicaid and Unemployment Insurance. Note our policy generosity variables are measured in 2000; as this time point falls in the middle of the study period, estimates on interaction terms cannot be interpreted causally if program generosity was responsive to economic shocks. Even if they were not, program generosity may be correlated with other policy choices or state-level factors. Consequently, we consider this exercise to be descriptive.

Table 1 presents estimates from our safety net policy heterogeneity models. 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 overall safety net program generosity as well as specifically for Medicaid and UI program generosity. Estimates of the interaction term between automation and safety net programs, which effectively test whether the differences between effects in low versus high program generosity areas are statistically significant, are presented in Appendix Tables 9-11. Focusing on coefficient magnitudes, unemployment insurance generosity does appear to moderate the effect of automation on all-cause mortality for men aged 45-54. Point estimates indicate that in states with relatively less generous UI benefits, 1 additional robot per 1,000 workers is associated with an increase in all-cause mortality of about 16 deaths per 100,000 compared to only about 10 deaths per 100,000 in states with relatively more generous UI programs. However, these differences are not statistically significant (Appendix Table 11).

Turning to cause-specific mortality, we find strong evidence that state safety net generosity, overall and for both UI and Medicaid in particular, moderates the effect of automation on suicide mortality (with estimates on the key interaction term between automation and program

generosity being statistically significant – Appendix Tables 9-11). We also find evidence that state Medicaid program generosity substantially mitigates the effect of automation on drug overdose mortality, an interaction effect which is precisely estimated (Appendix Table 10) and consistent with prior work. Notably we find no evidence these programs moderate the effect of automation on other causes of death. Taken together, these findings suggest that social safety policies may play a uniquely important role in blunting the effect of automation on drug overdose and suicide deaths.

B. Labor Market Policies

We next examine state labor market policy, specifically RTW laws and minimum wage rates. Estimates presented in the right panel of Table 1 reveal the effect of automation on middle-aged male all-cause mortality is higher in states with a ‘right to work’ law relative to states without such a law on the books (with the interaction between automation and RTW being statistically significant for all-cause mortality at the 10% level – Appendix Table 12). Point estimates suggest that every additional robot per 1,000 workers is associated with an increase of 28 deaths per 100,000 in right to work states compared to only about 9 deaths per 100,000 in the rest of the country. This appears to be driven in part by higher rates of suicide mortality in right to work states in response to automation. We see a similar pattern when we examine state minimum wage rates: the effect of automation on suicide mortality is higher in states with relatively lower minimum wage rates (Appendix Table 13). This again provides suggestive evidence that public policy, specifically state labor market policies, may play an important role in blunting the effect of automation on suicide deaths.

C. Local Supply of Prescription Opioids

Finally, **Table 2** examines heterogeneity in the effect of automation on all-cause and drug overdose mortality as a function of the county-level prescription opioids (logged millequivalents of morphine per capita) for the year 2000. Here we find that for both males and females of working-age, the effect of automation on drug overdose mortality is higher in areas with relatively greater local supply of prescription opioids. However, this interaction effect is not statistically significant (see Appendix Table 14). The direction of this finding suggests that opioid supply and economic demand may have worked interactively to produce the opioid crisis, a finding that warrants further exploration in contexts where there may be greater statistical power to detect true differences.

DISCUSSION & CONCLUSION

Technological change has led to increasing automation of routine tasks, a trend that is expected to continue in the coming decades. Since the 1990s, adoption of labor-displacing automation technologies in U.S. labor markets has coincided with rising rates of mortality, particularly among individuals with lower levels of education. Our study suggests a causal link between these trends, with (average) increases in automation accounting for a slowdown in mortality improvements equivalent to 25% of the overall decline in mortality among males aged 45-54 and 59% of the decline for females aged 45-54 observed during the study period, portending the stagnation and reversal in longevity observed in more recent years. We find this increase is driven in large part by increased mortality from so-called deaths of despair, including drug overdose and suicide. The effect of automation on despair mortality in turn appears to vary as a function of state safety net generosity, prevailing minimum wage rates and right to work laws, and the local level of prescription opioid supply.

Our findings have a number of implications for policymakers and researchers. First, they add causal evidence in support of the theory that declining economic opportunity—whether through automation or increased exposure to foreign trade—is a major driver of worsening population health and declines in expected longevity among working-age persons without a college degree (Seltzer 2020; Monnat 2019). Second, the mortality consequences of automation-led fading opportunity are heterogeneous by gender, age, and cause of death. For example, while the largest impacts were for 45-54-year-old men we also find important impacts on drug overdose, cancer, and all-cause mortality for younger women. This reveals that the impact of automation on mortality extends well beyond its direct effect on displaced workers to shape the population health of entire communities. This in turn motivates future research to identify and decompose potential indirect or ecological effects; for example, areas hit hard by the forces of deindustrialization face the double whammy of fewer high-quality jobs and the resulting deterioration in the wealth of tax bases used to fund the public sector.

Third, our findings also reveal that public policy plays an important role in mitigating the effect of deindustrialization on population health. Efforts to blunt the economic impacts of automation on workers through enhanced social safety net programs can make a difference. So can policies that improve local labor market opportunities and the quality of jobs available to workers (and ‘would be workers’) displaced by automation, such as higher minimum wage laws or rules that make it easier for workers to unionize. At the same time, constraining the supply of prescription opioids is critical to reducing the likelihood that the economic punch to individuals and communities from the arrival of industrial robots and reduction in manufacturing employment translates into higher rates of drug overdose mortality.

Deindustrialization driven by foreign competition and automation is expected to continue, perhaps even accelerate, in coming years. Counteracting these forces will require significant public sector investment in displaced workers. It will also require national investments in these distressed communities. To mitigate the negative health effects of this structural change to the economy, policymakers should consider targeting income support to this population, either by expanding eligibility or generosity of existing programs or introducing new transfer programs. At the same time, our findings suggest there may be real health gains to investing in industrial policies, i.e., policies designed to specifically increase the number of quality jobs and/or programs designed to help workers develop new skills and transition to new sectors (Katz et al 2020). Efforts to improve the economic wellbeing of workers displaced by structural shifts to the economy—from automation or foreign trade—will have substantial benefits for population health.

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Table 1. Heterogeneity in the impacts of automation on mortality rates among 45-54 year old men

	A. State Safety Net Generosity						B. State Labor Market Policies			
	Overall Generosity Index		Medicaid Generosity Index		UI Generosity Index		Right to work law		State minimum wage	
	Low	High	Low	High	Low	High	Low	High	Low	High
All-cause	9.62 (7.69)	5.66† (3.10)	3.23 (6.52)	3.20 (3.47)	15.87* (7.07)	10.45** (3.60)	8.86** (3.17)	28.36* (10.72)	13.54 (10.69)	6.83* (3.33)
Drug	1.75 (1.30)	0.47 (0.41)	2.48** (0.84)	0.17 (0.59)	-0.43 (1.54)	-0.19 (0.62)	0.88 (0.60)	1.09 (1.58)	0.74 (1.70)	1.01* (0.41)
Suicide	3.69*** (0.98)	1.18** (0.35)	2.82*** (0.71)	1.06* (0.47)	3.29** (1.17)	1.54** (0.50)	0.68† (0.36)	4.56** (1.54)	2.97** (0.83)	1.16** (0.38)
Homicide	-1.06* (0.49)	0.13 (0.19)	-0.67 (0.42)	0.03 (0.23)	-0.07 (0.42)	0.13 (0.25)	0.45 (0.31)	0.11 (0.54)	-0.57 (1.08)	0.33 (0.26)
Cardiovascular	1.73 (3.45)	0.51 (0.87)	0.77 (1.96)	0.08 (0.90)	5.59 (3.86)	2.61 (1.63)	-0.27 (0.81)	7.90 (6.98)	-0.40 (2.58)	1.38 (1.08)
Respiratory illnesses	-0.52 (0.67)	0.12 (0.30)	-0.53 (0.46)	-0.10 (0.31)	-0.09 (0.98)	0.13 (0.41)	0.12 (0.37)	0.12 (0.66)	-0.05 (0.94)	0.17 (0.30)
Cancer	1.60 (2.47)	-0.61 (0.97)	0.82 (1.82)	-0.98 (1.17)	1.82 (3.08)	0.06 (1.49)	-0.26 (0.99)	6.09† (3.61)	4.24 (3.27)	-0.38 (0.79)
Unintentional Injury (without drug)	0.36 (1.19)	0.64 (0.39)	0.89 (0.67)	0.20 (0.41)	0.59 (1.16)	0.93† (0.53)	1.28** (0.41)	0.85 (1.34)	-0.18 (1.36)	0.47 (0.36)
All other conditions	2.19 (3.60)	3.16* (1.20)	-2.91 (3.37)	2.60† (1.39)	4.82 (3.54)	5.02* (1.91)	5.88** (1.96)	7.65* (3.64)	6.90 (6.13)	2.68 (2.28)
N (clusters)	3,108 (48)		3,108 (48)		3,108 (48)		3,108 (48)		3,108 (48)	

Notes: Estimates from a first differences model regressing changes in mortality rates for 45–54-year-old men (per 100,000) 1993–2007 on automation, expressed as the change in the number of industrial robots per 1,000 workers between 1993 and 2007. Each set of rows reports the marginal effects (standard error) obtained from a separate regression model, with margins for Overall, Medicaid, and UI Generosity Indices evaluated at the 25th (low) and 75th (high) percentile of the national distribution of the heterogeneity variable and margins for state minimum wage evaluated at the 10th (low) and 90th (high) percentiles. Margins for right to work is evaluated at discrete levels – not having a RTW law (low) and having a RTW law (high). 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, census-division fixed effects, as well as interactions between all of these covariates and the heterogeneity variables of interest. Note that, for right to work and state minimum wage analyses, we use census region instead of census division fixed effects given the lack of variation in these outcomes within certain census divisions and, as a result, the inability to calculate marginal effects. Standard errors are clustered at the state level; † $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$.

Table 2. Impact of automation on mortality by gender, given oxycodone supply

Gender	All-cause		Drug	
	p25	p75	p25	p75
Male, ages 20-64	-0.40 (2.88)	-1.76 (6.70)	1.27* (0.53)	2.08† (1.05)
Female, ages 20-64	1.75 (1.16)	2.62 (1.94)	0.60† (0.32)	1.07† (0.60)
N (clusters)	3,058 (48)		3,058 (48)	

Notes: Estimates from a first differences model regressing changes in mortality rates for 20–64-year-old men and women (per 100,000) 1993–2007 on automation, expressed as the change in the number of industrial robots per 1,000 workers between 1993 and 2007. 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 county-level log milliequivalents of morphine (MME) supplied per capita in 2000. 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, and census-division fixed effects, as well as interactions between all of these covariates and the heterogeneity variables of interest. N = 3,058; 50 counties did not have outcome data. Standard errors clustered at the state level; †p < .10; *p < .05; **p < .01; ***p < .001.

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. Impacts of automation on mortality on males by age group

Notes: Estimates from a first differences model regressing changes in mortality rates (per 100,000) for each listed age-gender group, 1993–2007, 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 ($n=3,108$). 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. Standard errors clustered at the state level.

Figure 3. Impacts of automation on mortality among females by age group

Notes: Estimates from a first differences model regressing changes in mortality rates per 100,000 for each listed age-gender group, 1993–2007, 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 ($n=3,108$). 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. Standard errors clustered at the state level.