Industrial Automation and Intergenerational Income Mobility in the United States

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Abstract

This article examines how the automation of jobs has shaped spatial patterns of intergenerational income mobility in the United States over the past three decades. Using data on the spread of industrial robots across 722 local labor markets, we find significantly lower rates of upward mobility in areas more exposed to automation. The erosion of mobility chances is rooted in childhood environments and is particularly evident among males growing up in low-income households. These findings reveal how recent technological advances have contributed to the unequal patterns of economic opportunity in the United States today.

1 Introduction

In past decades, the U.S. labor market has experienced pervasive job polarization, as formerly well-paid jobs for the middle class have disappeared (Autor, Levy, and Murnane, 2003; Neckerman and Torche, 2007; Visser, 2019). Although there is scholarly disagreement about the relative contribution of factors such as globalization, industry deregulation, or union decline, there is evidence that automation is one key

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driver behind these developments (Autor, 2015; Huber and Stephens, 2014; Meyer, 2019; Powell and Snellman, 2004; VanHeuvelen, 2018). Many observers believe that we are living through a "fourth industrial revolution" where automation technologies are transforming the nature of work to the same extent as the rise of the factory, the assembly line, and computer technologies did in the past (Frey, 2019; Ruggles, 2015). Despite extensive work on the effects of recent automation on incumbent workers (Autor, 2015; Acemoglu and Restrepo, 2020; Parolin, 2021), we know surprisingly little about how it impacts on the economic attainment of children who grow up in deindustrializing communities.

In this paper, we analyze the relationship between automation and intergenerational income mobility in the United States by linking local income mobility to differences in exposure to robot adoption across 722 commuting zones: ecologically meaningful units that span the U.S. mainland (Tolbert and Sizer, 1996). We focus on industrial robots as a shock specifically to the manufacturing industry, once a cornerstone of the U.S. economy that upheld its prospering middle class. Industrial robots have in recent decades displaced workers and exacerbated wage inequality, as less-educated men in particular saw their advantages in the labor market deteriorate (Acemoglu and Restrepo, 2020). To analyze how these disruptions affect the next generation, we measure exposure to automation for each commuting zone by combining historical differences in industrial specialization with data on the adoption of industrial robots by industry from the International Federation of Robotics. We then link this information to data on income attainment for children born in the early 1980s from Chetty et al. (2014), focusing both on relative mobility and upward mobility out of the bottom of the distribution.

Our findings suggest that community-level exposure to automation erodes chances for upward mobility, perpetuating the transmission of economic status across generations. To understand what explains these results, we distinguish two mechanisms: diminished job prospects for cohorts entering the labor market and early life-course consequences of community job loss. In fact, we show that mobility deficits associated with automation appear already in children's educational attainment and increase with the proportion of childhood spent in an area more exposed to automation. This allows us to rule out that labor market prospects alone drive the relationship. We also show that these effects are largely concentrated among sons rather than daughters, while patterns by race are more complex: Blacks appear less disadvantaged by automation but part of this is explained by their lower mobility chances to begin with. Taken together, our results provide new evidence on how the disruption brought about by recent technological advances has shaped patterns of intergenerational opportunity in the United States.

2 Background

Early work on intergenerational mobility posited that with technological change, allocation to social positions would follow increasingly meritocratic criteria (Blau and Duncan, 1967; Lipset and Bendix, 1959; Treiman, 1970). As children were pushed away from their parents' footsteps, the labor market and public institutions would ensure access to new opportunities, reducing the inheritance of economic status. Today, this logic seems outdated in its optimism. Economists have documented the pervasive negative impact of recent automation on employment and earnings (Acemoglu and Restrepo, 2020). Qualitative work testifies to the wide-reaching consequences of deindustrialization for affected workers, families, and communities (e.g., Goldstein, 2017). There is also a large literature on the consequences of layoffs for children of displaced workers (Brand, 2015; Gassman-Pines et al., 2015). Although the potential harms of technological job loss are well recognized, there has been little work documenting its implications for intergenerational mobility.

What are the theoretical effects of automation for intergenerational mobility? When jobs in declining sectors disappear, there is a mechanical sense in which mobility increases: by pushing children away from following in their parents' footsteps. However, whether that change is for the better depends on how equipped society is to prepare its young for the future. A large literature shows how involuntary job loss can harm children's health (Bubonya, Cobb-Clark and Wooden, 2017; Lindo, 2011; Schaller and Zerpa, 2019), behavioral skills (Johnson, Kalil, and Dunifon, 2012; Peter, 2016), and academic progress (Brand and Thomas, 2014; Kalil and Wightman, 2011; Rege, Telle, and Votruba, 2011). Results for children's income attainment are mixed (Bratberg, Nilsen and Vaage, 2008; Hilger, 2016; Oreopoulos, Page, and Stevens, 2008). Nevertheless, we expect that industrial upheaval may exacerbate the intergenerational persistence of status.

Intergenerational economic persistence increases either when children of low-income households do worse, or when children of high-income households do better. In principle, it is possible to expect automation to reduce mobility through either mechanism. As for bottom incomes, automation is likely to push children of manual workers into more precarious employment, such as that found in low-skilled service jobs (Autor and Dorn, 2013). As for top incomes, decompositions of the rising skill premium have found it to be concentrated among occupations such as engineers, engineering managers, and computer and systems analysts (Liu and Grusky, 2013)—professions that are to a high degree inherited (Jonsson et al., 2009). We distinguish between these mechanisms by studying persistence in both the bottom and the top of the income distribution. However, we find that consequences appear concentrated in the bottom of the distribution and therefore focus on upward mobility from the bottom throughout most of our analysis.

Automation could harm the economic attainment of disadvantaged children in two ways. The first is by depriving cohorts recently entering the labor market of industrial jobs that used to offer stability and good pay in the past. A second possibility is that children's attainment is harmed by job destruction earlier in the life course, by eroding the ability of families and communities to invest in the young (Ananat et al., 2017; Gassman-Pines et al., 2015). We test for the latter mechanism in two ways. First, we compare children who through family moves spent a different amount of their childhood in a given area (Chetty and Hendren, 2018). If detrimental effects of automation on mobility work solely through opportunities in the labor market, we would expect similar effects for those who live in a given area when entering adulthood, regardless of where they grew up. On the other hand, if adverse effects of automation are rooted in childhood experiences, it should be stronger the larger the proportion of childhood spent in a given area.

Second, we test whether consequences are rooted in childhood experiences by looking at educational outcomes. With the erosion of living standards that job loss brings, parents will be worse placed to provide a nurturing environment, access to good neighborhood or schools, or pay for their children's way through college (Ananat et al., 2017; Schneider, Hastings, and LaBriola, 2018). Such detrimental effects can propagate beyond the families immediately affected and extend to whole communities, through local economic decline, and decreased public investments or social cohesion (Alvarado, 2018; Gassman-Pines et al., 2015; Mayger, Hochbein, and Dever, 2017). Thus, diminished access to education is a key potential mediator between automation and mobility.

We expect the prospects of men from low-income homes to be especially harmed. The jobs replaced by robots are mostly in routine manual, assembly, and other blue-collar work that is traditionally male-typed. This would affect boys more than girls, certainly through labor market prospects but also potentially through early-life mechanisms where boys may suffer more from fathers' unemployment (Buchmann and DiPrete, 2006; Lei and Lundberg, 2020). As discussed above, automation may also enhance the earnings of male-typed occupations at the high end of the class spectrum (Aksoy, Özcan, and Philipp, 2021). For this to improve mobility, however, these sectors would have to recruit from former industrial communities, which seems less likely. Meanwhile, gender norms may discourage men from seeking higher education (Buchmann, DiPrete, and McDaniel, 2006), or from going into the emerging service economy where many occupations are female-typed (Levanon and Grusky, 2016; Yavorsky and Dill, 2020).

We examine race differences by distinguishing between Blacks, Hispanics, and non-Hispanic Whites. The popular perception is that automation struck hardest among white men whose stable employment would have offered them life-long security a generation ago. Theoretical expectations with regard to race are not self-evident, however. Ananat et al. (2017) report that community job loss has more harmful consequences for the attainment of Blacks. The loss of industrial jobs is also a prominent theme in the work of Wilson (1987, 1996) on urban Black poverty, and the "spatial mismatch" hypothesis became a popular explanation for racial disparities in the 1990s (Mouw, 2000). As Cherlin (2014, p. 7-9) points out, a larger proportion of Black than white men were working in manufacturing at the peak of industrial employment. However, our earliest income measurements are from the late 1990s, after the suburban exodus of industrial employers. This, along with the particular shock that we study, makes it plausible that detrimental effects will be especially apparent among non-Hispanic white families.

3 Data and measures

Figure 1 displays the rise of industrial robots from 1982 to 2011, measured as the total number of units in operation U.S.-wide. The U.S. remains a relative laggard in the adoption of industrial robots relative to its Asian and European counterparts—for example, while the U.S. stock of robots per thousand workers hovered between 1 and 2 in the first decade of the new millennium, it rose from 3 to 5 in Germany during the same period (Acemoglu and Restrepo, 2020). Whereas the adoption of robots in the U.S. is still relatively limited, it has been heavily concentrated to certain sectors. We use this sectoral variation together with local industrial composition to study variation at the level of U.S. commuting zones—rural and urban labor markets delineated based on commuting patterns (Tolbert and Sizer, 1996). Combining differences in the adoption of robots across industries with initial differences in industrial specialization uncovers significant local variation in the susceptibility to automation that allows us to study how automation affected intergenerational mobility for children born in the early 1980s.

3.1 Intergenerational mobility

Intergenerational mobility data come from the Equality of Opportunity Project (Chetty et al., 2014), which has estimated a range of mobility metrics using individual federal tax records from the Internal Revenue Service (IRS). Most mobility metrics pertain to cohorts born in 1980–1982 and their parents, with children assigned to the commuting zone where they resided at age 16. Child income is measured as mean family income in 2011–2012 when children are approximately 30 years old, while parent income is measured by mean family income between 1996–2000 (Figure 1). In some analyses,

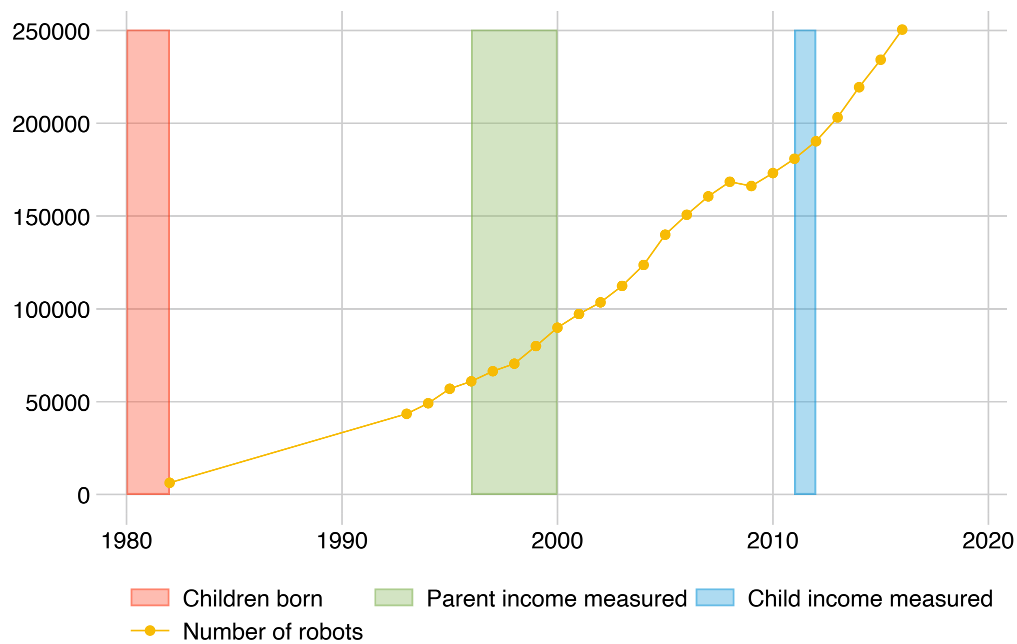


Figure 1: Automation and measurement of parent and child income in our data.

we also inspect children's individual income separately, measured in the same years. While family income is the more encompassing measure of living standards, individual incomes are useful to disentangle the separate implications for men and women's labor market prospects.

The literature on economic mobility has generated a variety of measures, of which the most common is the intergenerational elasticity of incomes. This statistic, which simply reflects the derivative of expected log child income with respect to log parent income is usually estimated using ordinary least squares, where the elasticity becomes the regression coefficient (Mitnik et al., 2019). Sensitivity to marginal distributions and the ages at which income is measured has led recent research to prefer the rank-order correlation (Bloome et al., 2018; Chetty et al., 2014), which represents a similar derivative where each variable has instead been transformed to percentile ranks. Letting intercept and slope vary by commuting zone j, we have:

$$Y_{ij}^{C} = \alpha_j + \beta_j Y_{ij}^{P} + \varepsilon_{ij},$$

where Y_{ij}^{C} and Y_{ij}^{P} represent child and parent income ranks in the national income distribution. The main parameter of interest here is β_j which represents how strongly income rank is transmitted from parent to child. We use the term "rank correlation" to refer to this parameter, although national ranks may deviate from a uniform distribution at the commuting-zone level.

Rank correlations are uninformative about whether mobility is driven by persistence at the bottom, top, or somewhere in between. As the impact of automation has mainly been felt in low- and middle-income jobs (Acemoglu and Restrepo, 2020; Autor et al., 2003; Graetz and Michaels, 2017), a single parameter may not be enough to capture the complexity of mobility patterns. In a next step we therefore inspect transition probabilities for the full 5×5 mobility table between quintiles of parent and child income. That is, we define a set of measures:

$$P_{pq,j} = Pr(Q^C_{ij} = q \,|\, Q^P_{ij} = p), \qquad \forall p, q = 1, \ldots, 5,$$

where Q^C and Q^P represent child and parent income quintiles, and j indexes the commuting zone as before. This, in turn, allows us to define more specific mobility patterns such as "rags-to-riches" mobility $[Pr(Q^C = 5 \,|\, Q^P = 1)]$, poverty persistence $[Pr(Q^C = Q^P \,|\, Q^P = 1)]$, elite persistence $[Pr(Q^C = Q^P \,|\, Q^P = 5)]$, or downward mobility from the middle class $[Pr(Q^C < Q^P \,|\, Q^P \in \{2, 3, 4\})]$. In practice, we find that much of the consequences of automation are located in the bottom half of the distribution. A useful summary measure is therefore what Chetty et al. (2014) term "absolute upward mobility," defined as the income rank expectation for a child born into the bottom half of the distribution—which, given the approximate linearity of the rank-rank relationship, is equivalent to the predicted rank of children born to parents at the 25th percentile:

$$A_j = E(Y^C_{ij} \,|\, Y^P_{ij} < 50) = \alpha_j + 25\beta_j.$$

This measure also offers an expedient way to look at racial differences which are not well captured by the rank correlation (Chetty, Hendren, Jones, et al., 2020). We use upward mobility for the 1980–1982 birth cohorts when studying the whole population, but expand the window to 1978–1983 birth cohorts to overcome small cell sizes when studying mobility separately by race, and 1980–1986 birth cohorts for the age-specific effects that we describe next.

To test our hypothesis that the link between automation and income attainment is rooted in childhood events rather than mere labor market prospects, we use estimates from a specification comparing children who move at different ages (Chetty and Hendren, 2018). These estimates net out time-constant variation across commuting zones and use only variation in the length of childhood spent in a given area. The intuition is as follows. Consider all children of a given cohort who reside in commuting zone j at the time they turn 16. Some of those children will have lived their whole life there, others have moved there with their families at any time between age 0 and

16. The fixed-effects specification discards the population of permanent residents and compares only the outcomes of children who have moved to the area, depending on when they arrived. To the extent that earlier arrivals achieve a lower level of income we attribute this to experiences before the age of 16, since local labor market prospects are the same for all children regardless of when they arrived. These estimates are scaled to reflect the expected percentage decrease (or increase) in adult income from spending one additional year of childhood in a given commuting zone. Because of the later birth of these cohorts (1980–1986), income is here measured at age 26.

Finally, we look at the probability of completing various educational transitions conditional on childhood income: high school, at least some college, and a four-year college degree. Information on educational attainment is from decennial Censuses or the 2005–2015 American Community Survey (ACS) that have been linked to the IRS data underlying the income mobility estimates (Chetty, Friedman, et al., 2018). Educational attainment is as reported by the child, with priority given to more recent ACS data if available, and excluding all respondents younger than age 24 at the time of questionnaire completion. High school degree holders include those with a General Educational Development (GED) certificate, the next level includes those who report "at least some college credit" or higher, while four-year college completion is defined as having at least a Bachelor's degree.

3.2 Exposure to automation

A central challenge in identifying the impacts of automation is a lack of data on the diffusion of technology. Most studies have consequently adopted an indirect occupation- or task-based approach (Autor et al., 2003; Frey and Osborne, 2017; Fernández-Macías and Hurley, 2017; Parolin, 2021). By identifying tasks that are technologically feasible to automate, these approaches estimate the share of occupations or tasks that are susceptible to automation. Instead, we study the spread of industrial robots that provide a rare opportunity to directly observe the spread of an automation technology.[1] We obtain these data from the International Federation of Robotics (IFR) that provide industry-level information on the use of industrial robots in 13 manufacturing industries and six broad non-manufacturing sectors for a number of countries including the United States.[2] Notably, the industries that saw the most rapid increase in the adoption of

[1]The IFR follows the International Organization for Standardization in defining an industrial robot as an "automatically controlled, reprogrammable multipurpose manipulator programmable in three or more axes" (see: https://ifr.org/industrial-robots).

[2]In manufacturing, there are consistent data on the use of robots for 13 industries: food and beverages; textiles; wood and furniture; paper; plastic and chemicals; glass and ceramics; basic metals; metal products; metal machinery; electronics; automotive; other vehicles; and other manufacturing industries. Outside of manufacturing, we construct the data for the use of robots in six broad

robots were not those with a high share of routine jobs, which have been designated as more susceptible to automation in the previous literature (Acemoglu and Restrepo, 2020).

Our interest is in the *local* exposure to automation, however, which requires mapping the aggregate industry-level data from the IFR to the level of commuting zones through the distribution of local employment across industries. To measure local industrial composition, we rely on individual-level data from the 1980 Census that includes information about individuals' place of residence and employment by industry.[3] By collapsing the individual-level Census data, we can then simply calculate employment shares by industry for each individual commuting zone, which in turn can be linked to the IFR data on robot use in each industry listed above.

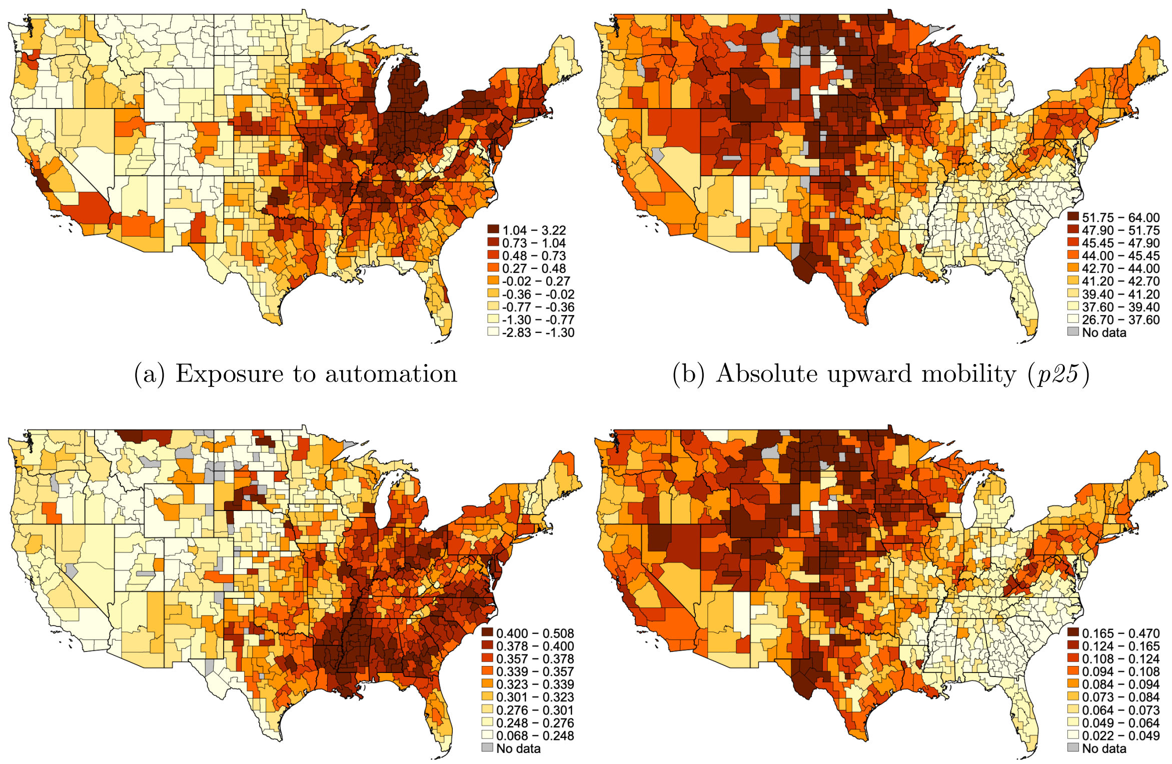
Formally, after pairing the industry-level data from the IFR and the commuting-zone level industrial shares we define the exposure to automation between 1980 and 2011 for each commuting zone j as follows:

$$Exposure_j = \sum_{k \in K} Industry^k_{j,1980} \times \left(\frac{Robots^k_{US,2011}}{Workers^k_{US,2011}} \right),$$

where $Industry^k_{j,1980}$ corresponds to the share of a commuting zone's workers employed in industry k in 1980 computed from the 1980 Census, and $Robots^k_{US,2011}/Workers^k_{US,2011}$ denotes the national level of robot usage per thousand workers in that industry in 2011 based on data from the IFR and the 2011 ACS. Intuitively, this measure reflects differences in exposure to robots across commuting zones driven by variation in automation across U.S. industries in 2011 and initial differences in industry specialization across commuting zones in 1980, which predates the measurement of both child and parent income in all our main mobility measures (Figure 1). In other words, a higher level of exposure to automation is thus driven by local specialization in industries that experienced a subsequent greater penetration of robots. To reduce the skewed distribution of robot exposure across commuting zones, we enter this variable in logged form and standardize it to have a mean of zero and standard deviation of one throughout the empirical analysis. Figure 2a displays the geographical distribution of our baseline exposure measure, documenting the significant spatial variation in exposure to automation across U.S. commuting zones and that the highest levels of exposure are heavily concentrated to the Rust Belt, as we would expect.

industries: agriculture, forestry, and fishing; mining; utilities; construction; education, research, and development; and other non-manufacturing industries (e.g., services and entertainment).

[3]To preserve confidentiality, the Census reports individuals' place of residence for "county groups" that in some cases span multiple commuting zones. In cases where individuals are enumerated in such county groups, we use a probabilistic-weighting approach to assign them to commuting zones (Dorn, 2009).



(a) Exposure to automation

(b) Absolute upward mobility (*p25*)

(c) Relative mobility (rank-rank slope)

(d) Rags-to-riches mobility

Figure 2: Exposure to automation and intergenerational mobility metrics across commuting zones.

One important caveat is that detailed data on the use of industrial robots is limited throughout the 1980s (see Figure 1). However, we know that the number of robots by 1982 was as low as 6,300 nationwide (Office of Technology Assessment, 1984), which allows us to establish that robot use in the early 1980s was negligible. This means that our measure of robot exposure can be interpreted as capturing over-time change in exposure. To corroborate this interpretation, we also calculate the actual change in exposure until 2011 using the starting points of 1982 (Office of Technology Assessment, 1984) and 1993, respectively—the latter being the first year in which data are available from the IFR. Because robot use is not disaggregated by industry for these years, we allocate robots to industries based on the observed industry shares in the early 2000s. Reassuringly, using these alternative data sources to estimate changes in robot exposure between 1982–2011 and 1993–2011 yields nearly identical results and they are both highly ($r > 0.99$) correlated with our baseline measure.

Another concern is that the spread of industrial robots may partly be driven by local factors also shaping mobility prospects. The main empirical strategy partly alleviates such concerns by focusing on differences in the *exposure* to automation, rather than the actual adoption of industrial robots that is likely more endogenous. However, to further address such concerns we deploy the instrumental variable strategy from Acemoglu and Restrepo (2020). Their strategy uses variation in the adoption of robots in five European countries (Denmark, Finland, France, Italy, and Sweden) that are ahead of the U.S. in robotics. Importantly, the rate of robot adoption in European industry is unlikely to be driven by factors that shape mobility outcomes across local labor markets in the United States. The instrument is constructed as the interaction between changes in industry-level robot adoption in European countries between 1993-2010 based on the IFR data and historical shares of industrial employment across commuting zones from the 1970 Census, which predates the year when the children in our sample are born. Differences in robot exposure based on adoption patterns in European industries strongly predict variation in our main measure of exposure to automation, which solely relies on variation across U.S. industries and commuting zones.

3.3 Control variables

Automation is, however, only one of the major shocks that have hit local labor markets and an important question is to what extent it is conflated with other variables. We address this by controlling for a range of other demographic and structural characteristics. As basic commuting zone controls, we include the log of population size, the log of average household income, and whether the commuting zone intersects a metropolitan statistical area. To adjust for local demographic composition, we further control for the share of Black residents, the share of population in four different age

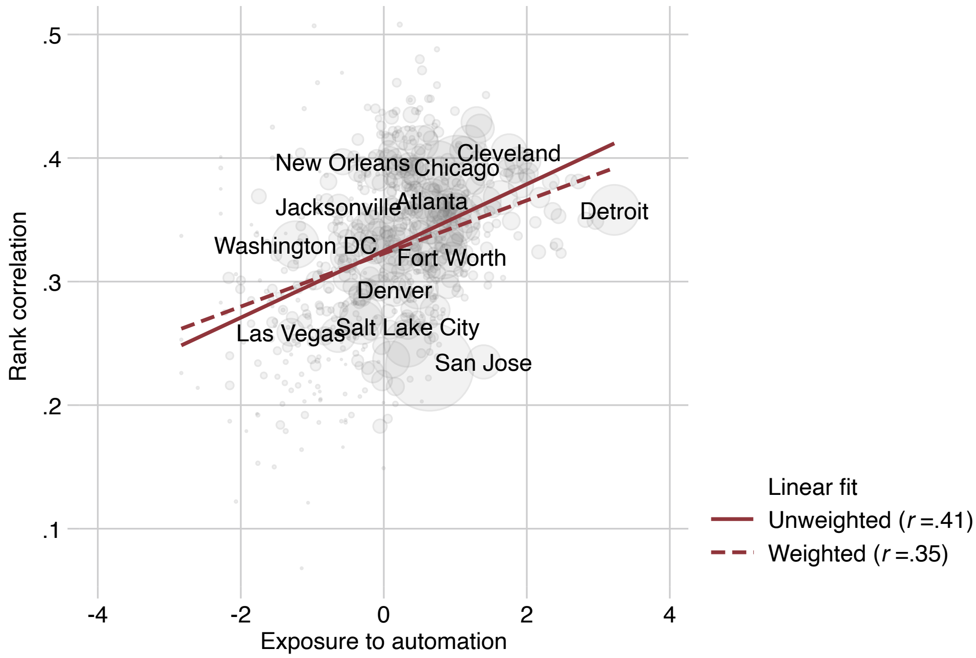


Figure 3: Automation and intergenerational persistence in income rank across commuting zones.

bins (below 15, age 15–24, 25–64, and 65 or above), and the share female. In a further step we add a control for the share of college educated. Thereafter we control for initial differences in employment composition, measured as the share of workers employed in manufacturing in 1980. Finally, in a last step we include controls for Census region and division as a set of fixed effects (U.S. Census Bureau, n.d.). To avoid conditioning on posttreatment variables, all these measures are observed at baseline in the 1980 Census.

4 Results

4.1 Intergenerational income persistence

To analyze the link between automation and intergenerational mobility across U.S. commuting zones, we first examine the bivariate association between exposure to automation and the intergenerational rank correlation β_j in Figure 3. Recall that the rank correlation is a measure of persistence, so higher values indicate that mobility is lower. The correlation between automation and persistence in income rank is sizeable

Table 1: Intergenerational mobility and exposure to automation (OLS/2SLS).

	Panel A. Outcome: Relative mobility (rank-rank slope)						
	OLS (1)	OLS (2)	OLS (3)	OLS (4)	OLS (5)	OLS (6)	2SLS (7)
Exposure to automation	0.021**	0.026**	0.024***	0.015***	0.010*	0.000	0.012
	(0.004)	(0.006)	(0.002)	(0.003)	(0.004)	(0.006)	(0.014)
Mean of outcome	0.333	0.333	0.333	0.333	0.333	0.333	0.333
First-stage F-stat							15.44
Observations (CZs)	693	693	693	693	693	693	693
	Panel B. Outcome: Absolute upward mobility ($p25$)						
	OLS (1)	OLS (2)	OLS (3)	OLS (4)	OLS (5)	OLS (6)	2SLS (7)
Exposure to automation	-0.884	-0.987	-1.274**	-1.229*	-1.543*	-1.159*	-1.517*
	(0.441)	(0.468)	(0.365)	(0.431)	(0.505)	(0.441)	(0.643)
Mean of outcome	41.624	41.624	41.624	41.624	41.624	41.624	41.624
First-stage F-stat							15.44
Observations (CZs)	693	693	693	693	693	693	693
	Panel C. Outcome: Rags-to-riches mobility						
	OLS (1)	OLS (2)	OLS (3)	OLS (4)	OLS (5)	OLS (6)	2SLS (7)
Exposure to automation	-0.009*	-0.011*	-0.012**	-0.011*	-0.012**	-0.008	-0.010*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)
CZ controls	No	Yes	Yes	Yes	Yes	Yes	Yes
CZ demographics	No	No	Yes	Yes	Yes	Yes	Yes
CZ education	No	No	No	Yes	Yes	Yes	Yes
CZ manufacturing	No	No	No	No	Yes	Yes	Yes
Census region FE	No	No	No	No	No	Yes	Yes
Mean of outcome	0.081	0.081	0.081	0.081	0.081	0.081	0.081
First-stage F-stat							15.41
Observations (CZs)	712	712	712	712	712	712	712

Note: Standard errors are given in parentheses and are clustered at the Census division level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

and of the expected sign: 0.41, or 0.35 when weighted by population size. Notably, this association is comparable to that of several key mobility correlates (Chetty et al., 2014).

We further examine this bivariate association in Table 1, panel A, where we estimate commuting-zone level regressions using the intergenerational rank correlation as the outcome with stepwise addition of the control variables described earlier. All regressions are weighted by population size with standard errors clustered at the Census division level. A one standard deviation difference in exposure to automation is associated with a 0.02-point higher rank correlation. This represents a 6% difference relative to the mean, or a correlation of 0.35 as shown in Figure 3. The association remains robust to controls for demographics and other commuting zone attributes throughout columns 2–4, but is reduced by controlling for the initial share of manufacturing employment and Census division, or when instrumenting for exposure to automation leveraging variation in robot adoption in European countries. Yet overall, these results suggest that income levels persist more strongly in areas heavily exposed to automation. However, they do not tell us where in the distribution that persistence is concentrated.

4.2 Upward and downward mobility

To examine whether the link between automation and mobility differs across the parental income distribution, we first inspect conditional transition probabilities throughout the full mobility table among parent and child income quintiles. In Figure 4, we plot each conditional probability in the 5×5 mobility matrix between quintiles of parent and child income predicted from a linear model. The linear probability model is tractable and has the added benefit that associations can be interpreted as average marginal effects (Mood, 2010). Here we standardize automation so that coefficients contrast the difference between areas one standard deviation below and above the mean of exposure. There is clearly higher persistence in the bottom two income quintiles in areas more exposed to automation, as well as lower rates of entry into the top from all other quintiles Q1–Q4. Interestingly, there are also signs of disproportional downward mobility from the three middle quintiles Q2–Q4 in areas with higher automation exposure, indicating a "downslide" from the middle class. In contrast, there is no association between automation and mobility for those who grow up in the top income quintile. Together, these results thus suggest that the consequences of automation for mobility are most marked in the bottom of the distribution.

To further probe whether automation may have reduced chances of upward mobility out of the bottom, we turn to panels B and C of Table 1 where we report commuting-zone level regressions using absolute upward mobility (the expected percentile rank for children born in the bottom half of the distribution) and rags-to-riches mobility (the probability that a child born to parents in the bottom income quintile ends up in the top quintile in adulthood) as the outcomes. Using both measures of upward mobility, there is a strong bivariate negative association between exposure to automation and mobility chances out of the lower end of the income distribution. Notably, these negative associations remain robust when adding additional commuting-zone-level controls, as well as Census division fixed effects.[4]

[4] Although the spatial overlap between exposure to industrial robots and trade competition, offshoring, and routine work is limited, one may be concerned that the estimated association between automation exposure and upward mobility is conflated with these factors. However, in additional specifications we also control for differences in exposure to Chinese imports between 1990-2007, the

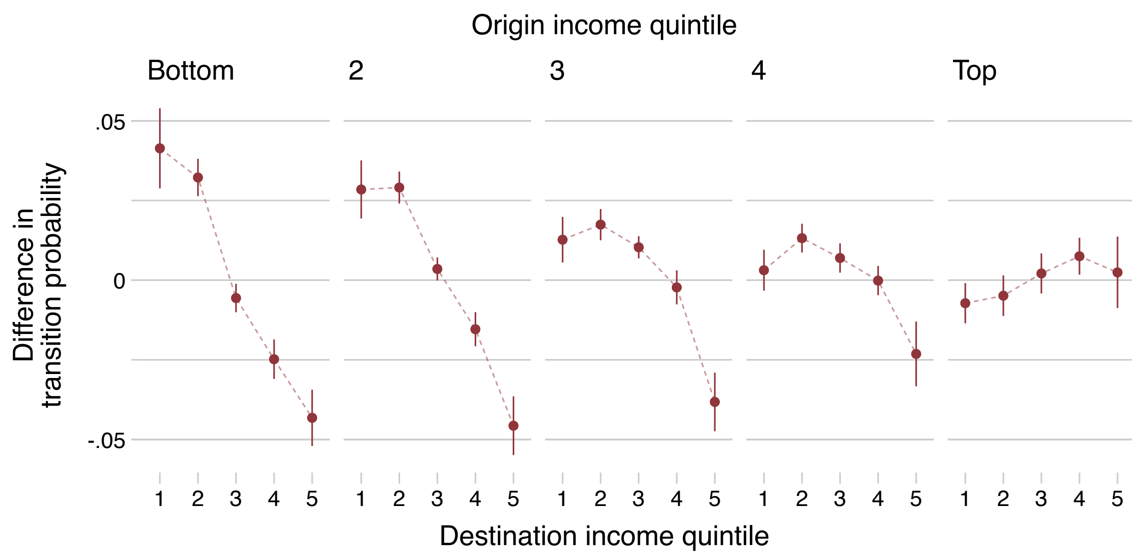


Figure 4: Automation and income quintile transition probabilities.

When instrumenting for exposure to automation using variation in robot adoption across European countries in column 7, the association remains negative though with a slightly larger absolute magnitude than in the OLS regressions. In the rest of our analysis below, we focus particularly on upward mobility and on models estimated under the full set of controls.

4.3 Upward mobility by gender and race

Although there is clear evidence of a negative association between exposure to automation and upward mobility chances, aggregate statistics may conceal significant heterogeneity across demographics. We next analyze whether the association between local exposure to automation and upward mobility differs across gender and racial groups. Table 2 shows regressions of absolute upward mobility separately by gender and race and this time we measure individual as opposed to household income in the child generation, as described above. As minorities are not represented in sufficient numbers in all commuting zones, the number of observations vary from 550 (Black males) to 722 (non-Hispanic whites). The results reveal that effects of automation are more pronounced among men, while the story for race differences is more complex.

share of offshorable jobs in 1990 (as in Autor and Dorn, 2013), and the share of routine jobs in 1990 from Acemoglu and Restrepo (2020). Adding the full set of these controls to the specification in Table 1, column 6 of panel B, results in a point estimate (s.e.) of -1.148 (0.482) that is very similar to our baseline estimate of -1.159 (0.441) reported in the table.

Table 2: Absolute upward mobility and exposure to automation (OLS): gender and race.

	Outcome: Absolute upward mobility ($p25$)					
	Panel A. Male			Panel B. Female		
	Black (1)	Hispanic (2)	White (3)	Black (4)	Hispanic (5)	White (6)
Exposure to automation	-1.093*	-1.617*	-1.552*	-0.356	-1.070*	-0.960
	(0.459)	(0.550)	(0.569)	(0.314)	(0.447)	(0.498)
CZ controls	Yes	Yes	Yes	Yes	Yes	Yes
CZ demographics	Yes	Yes	Yes	Yes	Yes	Yes
CZ education	Yes	Yes	Yes	Yes	Yes	Yes
CZ manufacturing	Yes	Yes	Yes	Yes	Yes	Yes
Census region FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean of outcome	38.894	47.540	49.265	41.382	40.850	40.431
Observations (CZs)	550	670	722	555	676	722

Note: Standard errors are given in parentheses and are clustered at the Census division level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

On the one hand, associations are nominally larger for non-Hispanic *and* Hispanic white men compared to their Black counterparts. However, this difference should be interpreted in light of the fact that Blacks as a group experience less upward mobility regardless of circumstances. When viewed in relation to their average mobility levels reported in Table 2, percentage differences for the three groups are more similar and only slightly higher among non-Hispanic (1.55/49.27 = 3.1%) or Hispanic white men (1.62/47.54 = 3.4%) as compared to Blacks (1.09/38.89 = 2.8%).

4.4 Exploring mechanisms: childhood environments and educational attainment

Automation could hamper income attainment via several mechanisms: through the opportunity structure children face when entering the labor market, or exposure to poorer environments earlier in life. In Table 3 we analyze results from the fixed-effects specification described above, where outcomes are only compared among children who moved to an area at different ages. We distinguish between family and individual income for both men and women and by parental income, with Panel A providing estimates for children from households below the median and Panel B for those above the median. Associations reflect the per-year percentage difference in adult income that results from spending a longer part of one's childhood in a given commuting zone. Table 3 reveals a differential impact of automation by length of childhood exposure for men but not women. For men in Panel A, moving to a commuting zone with a

Table 3: Childhood effects and exposure to automation (OLS).

	Panel A. Outcome: Childhood exposure effect on upward mobility ($p25$)					
	Family income			Individual income		
	All (1)	Male (2)	Female (3)	All (4)	Male (5)	Female (6)
Exposure to automation	-0.075*	-0.118**	-0.017	-0.079*	-0.107**	-0.024
	(0.025)	(0.031)	(0.031)	(0.031)	(0.031)	(0.030)
Mean of outcome	-0.072	-0.109	-0.056	-0.080	-0.107	-0.047
Observations (CZs)	702	676	673	702	676	673
	Panel B. Outcome: Childhood exposure effect on upward mobility ($p75$)					
	Family income			Individual income		
	All (1)	Male (2)	Female (3)	All (4)	Male (5)	Female (6)
Exposure to automation	-0.071	-0.077*	-0.080	-0.110	-0.094*	-0.054
	(0.032)	(0.030)	(0.048)	(0.060)	(0.037)	(0.114)
CZ controls	Yes	Yes	Yes	Yes	Yes	Yes
CZ demographics	Yes	Yes	Yes	Yes	Yes	Yes
CZ education	Yes	Yes	Yes	Yes	Yes	Yes
CZ manufacturing	Yes	Yes	Yes	Yes	Yes	Yes
Census region FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean of outcome	-0.025	-0.049	-0.033	-0.050	-0.075	-0.066
Observations (CZs)	702	676	673	702	676	673

Note: Standard errors are given in parentheses and are clustered at the Census division level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4: Educational transitions and exposure to automation (OLS).

Outcome:	Fraction of children attaining HS or college degree							
	All		Black		Hispanic		non-Hisp. White	
	Male	Female	Male	Female	Male	Female	Male	Female
Panel A. High school or GED	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposure to automation	-0.007	-0.008*	0.002	-0.005	-0.015*	-0.012*	-0.013	-0.011
	(0.003)	(0.003)	(0.005)	(0.002)	(0.005)	(0.005)	(0.007)	(0.005)
Mean of outcome	0.751	0.823	0.705	0.812	0.684	0.768	0.781	0.842
Observations	712	711	367	365	431	443	705	703
Panel B. At least some college	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposure to automation	-0.014*	-0.007	-0.008	-0.009	-0.016*	-0.012*	-0.018***	-0.009
	(0.004)	(0.005)	(0.006)	(0.006)	(0.006)	(0.004)	(0.003)	(0.006)
Mean of outcome	0.469	0.621	0.415	0.626	0.422	0.550	0.486	0.633
Observations	706	705	313	316	347	370	696	694
Panel C. Four-year college degree	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposure to automation	-0.008**	-0.011	-0.006	-0.010*	-0.008*	-0.016***	-0.013*	-0.017
	(0.002)	(0.006)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.008)
CZ controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CZ demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CZ education	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CZ manufacturing	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of outcome	0.155	0.234	0.111	0.204	0.110	0.176	0.166	0.247
Observations	706	705	313	316	347	370	696	694

Note: Standard errors are given in parentheses and are clustered at the Census division level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

one standard deviation higher automation exposure a year earlier in life results in a 0.12% penalty in adult family income. These effects are smaller among children from better-off homes (Panel B). In sum, these results suggest that the association between automation and mobility is stronger the earlier the onset of exposure.

If disadvantages among exposed children start before labor market entry, this points toward explanations rooted in life-course development, especially educational attainment. To test this mechanism, in Table 4 we show regressions of the fraction of children born in each commuting zone that attain a high school degree (or GED), some college, and a four-year college degree. Exposure to automation has detrimental effects on each transition among white men and women, and on college graduation for Black women. Some of the most pronounced effects, however, are found on the college entry of white men. A one standard deviation higher exposure to automation is associated with 1.8 percentage points lower probability of enrolling in college among non-Hispanic

Table 5: Educational transitions and exposure to automation: white males by childhood income (OLS).

	Outcome: Fraction of children attaining HS or college degree				
Parental income percentile:	$p1$	$p25$	$p50$	$p75$	$p100$
Panel A. High school or GED	(1)	(2)	(3)	(4)	(5)
Exposure to automation	-0.019	-0.013	-0.008	-0.005	-0.003
	(0.010)	(0.007)	(0.005)	(0.003)	(0.003)
Mean of outcome	0.671	0.781	0.855	0.908	0.942
Observations	705	705	705	705	705
Panel B. At least some college	(1)	(2)	(3)	(4)	(5)
Exposure to automation	-0.022**	-0.018***	-0.015***	-0.010**	-0.005
	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)
Mean of outcome	0.370	0.486	0.604	0.760	0.956
Observations	696	696	696	696	696
Panel C. Four-year college degree	(1)	(2)	(3)	(4)	(5)
Exposure to automation	-0.013*	-0.013*	-0.013*	-0.014	-0.015
	(0.004)	(0.004)	(0.004)	(0.006)	(0.012)
CZ controls	Yes	Yes	Yes	Yes	Yes
CZ demographics	Yes	Yes	Yes	Yes	Yes
CZ education	Yes	Yes	Yes	Yes	Yes
CZ manufacturing	Yes	Yes	Yes	Yes	Yes
Census region FE	Yes	Yes	Yes	Yes	Yes
Mean of outcome	0.111	0.166	0.247	0.399	0.806
Observations	696	696	696	696	696

Note: Standard errors are given in parentheses and are clustered at the Census division level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

white men (Panel B, column 7).[5]

There could be several explanations for women's greater resilience in education shown in Table 4. Since the early 1980s, post-secondary education in the U.S. has followed a worrying trend where men's attainment remained stagnant while that of women increased (Mitnik et al., 2016; Roksa et al., 2007). Researchers have attributed this trend to boys' greater vulnerability to family hardship (Autor et al., 2019; Buchmann and DiPrete, 2006; Entwisle et al., 2007). Another possibility is that women may face better outside prospects in industries that require non-routine social skills, where there is a female advantage (DiPrete and Jennings, 2012). The shrinking

[5] Gender differences are reversed in the completion of a college degree, and significant for Black and Hispanic women. However, this needs to be seen in light of their much higher baseline probability of graduating from college than men, which means that the effect on a percentage scale is similar across genders.

of the gender wage gap since the 1970s has been attributed to technologies that put new emphasis on interpersonal skills (Bacolod and Blum 2010; Welch 2000), and the demand for such skills appears to be growing (Borghans, et al., 2014; Deming 2017).

Table 4 shows a deficit in college attainment in the bottom of the income distribution, especially pronounced among men. In Table 5, we ask how this disadvantage differs across the full income distribution by assessing non-Hispanic white men's attainment at five values of parental income: the bottom and top 1%, and percentiles 25, 50, and 75. The results confirm that the detrimental effects of automation are concentrated among the poor: the size of the penalty for "at least some college" decreases linearly with each step up the parental income ladder and is no longer significant at the top of the distribution. For high school and college degree, the results are less systematic but in the same direction. Thus, in line with our findings for income, educational attainment appears especially harmed among poorer white men.

5 Conclusions

Industrial automation has in past decades created new winners and losers by eroding the employment and earnings prospects of groups who used to enjoy great stability. Yet, existing work on the consequences of automation mainly focuses on its impacts on incumbent workers. We therefore have a limited understanding of the extent to which these disruptions also have intergenerational repercussions.

Our paper uses data on local labor markets in the United States to document that automation significantly has reduced the chances for upward mobility among children born in low-income families in the early 1980s. Mobility differs markedly across areas more and less exposed to industrial automation: a standard deviation higher exposure to industrial robots is associated with a 0.9–1.5-point reduction in upward mobility, the percentile rank that a child from the bottom half of the income distribution can expect to attain in adulthood. This difference corresponds to one tenth of the distance that separates a place like Charlotte from one like San Jose, representing the very bottom and top of the urban mobility hierarchy (Chetty et al., 2014).

To explain our results, we distinguished between two mechanisms. One concerns the prospects that children face in the labor market. The other is that automation impacts children's life course earlier on by eroding the ability of families to invest in their life-course attainment. Two findings point toward the latter explanation. First, mobility deficits associated with automation are rooted in childhood environments: each year of childhood spent in an area more exposed to automation accumulates to lower income in adulthood. Second, mobility deficits manifest themselves already in children's educational attainment. Thus, in circumstances where high education is increasingly a condition for upward mobility, low-income children are becoming less likely to attain it.

Our analysis is conducted at the ecological level as both mobility and industrial decline are social phenomena. In particular, the disappearance of work is a shock that extends beyond the individual or even family to send ripples throughout entire communities (Conger and Elder Jr., 1994; Jahoda et al., [1933]1971; Wilson, 1996). Future research should disentangle the exact pathways through which industrial disruption shapes children's mobility prospects, but existing literature offers some useful pointers. The workplace is an arena for communal engagement, the destruction of which can have negative consequences for social capital and collective efficacy (Brand, 2015). The decline of industry also tends to have downstream effects on employment in other sectors such as retail and personal services, as shown by Acemoglu and Restrepo (2020). Funding available for schools or other public goods will tend to diminish with the erosion of the local tax base (Gassman-Pines et al., 2015). Above all, the loss of industries can be a collective trauma that leaves local communities struggling to regain their sense of collective identity and purpose (Goldstein, 2017).

The analysis is not free of limitations. First, it is important to note that our results pertain to the impact of one particular automation technology—industrial robots. We have found that its adverse impacts on intergenerational mobility are concentrated among non-Hispanic white men. While our data provides a rare opportunity to observe the adoption of industrial automation technology, it does not capture the automation of a wide range of non-industrial (e.g., clerical) routine jobs. It is therefore possible that the more general automation of routine jobs may harbor equally or more harmful consequences for women and minorities. Indeed, the spread of industrial robots constitutes a distinct shock to local labor markets, only weakly correlated with the distribution of routine work and synchronous disruptions such as Chinese trade competition or offshoring (Acemoglu and Restrepo, 2020). Future work is needed to understand the extent to which the spatial incidence of such shocks has differentially affected the mobility prospects across both people and places.

Second, the variation we use is cross-sectional in nature and the observation window for parent and child incomes is limited. Arguably, this is more of a problem for the absolute level of intergenerational correlations than their geographic distribution (Mazumder, 2016). While our main results pertain to incomes attained by children in their early 30s, the fact that we document similar gradients in education suggests that, if anything, income differences might be larger had exposed cohorts been followed until old age. In other words, these results suggest that the impacts of industrial automation that we document will continue to have repercussions well into the 21st century.

Third, our analysis leverages variation across local labor markets within the U.S.

that exhibit significant variation in economic and social makeup. Yet an important question is whether these findings extend to other contexts. In particular, the labor-market impact of new technologies differs significantly across countries (Graetz and Michaels, 2018; Guschanski and Onaran, 2021), which suggests an important potential role for economic and social institutions in mitigating the negative impacts of automation. In line with this, research on Europe tends not to find the same harmful consequences for workers (Dauth et al., 2021), nor that male workers are particularly exposed (Aksoy, Ozcan, and Philipp 2020). In our view, an important avenue for future work is to examine whether the negative intergenerational impacts of automation we document are also evident in more encompassing welfare states such as Scandinavian countries or Germany.

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