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CAREER VALUES FOR LABOR MARKETS:
EVIDENCE FROM ROBOT ADOPTION

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ABSTRACT

Career progression is important for people's lives and economic decisions. We develop an empirical measure of an occupation's local "career value"—the long-run value of the earnings that will result from working in that job and following the career ladder associated with it. We then document that career values have been stagnating over the 2000-2016 period, in spite of growing wages, due to a deterioration in career mobility. We estimate the effect of robot automation on career values over the same time period and find that one additional industrial robot per 1,000 workers lowered local career values by about 1.5 percent. The reason is that robotization reduces transitions into better-paid occupations and redirects workers toward similar- or lower-paid jobs. The impact is largest in high-manufacturing areas, for mid-experience workers, and for males. Demotions from management jobs that result from robotization are more likely for less-educated workers and for women, who are more likely to respond by upskilling. Declines in career values led to a reduction in housing construction and college enrollment, and an increase in Republican vote shares in 2016, which highlights how the career effects of automation shape forward-looking household decisions.

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1 Introduction

Career progression is important for people's lives. When people decide to take a new job, choose the right education, or move to a new place to live, they often consider not only their current earnings but also the expected evolution of these earnings over time and the opportunities for moving to better-paying occupations. Understanding how career trajectories evolve and the forces that shift these trajectories is, therefore, essential but remains significantly understudied in the literature. To get a better picture of one's lifetime career progression and opportunities, one needs a combined measure of wages and occupational trajectories. Moreover, understanding the impact of technological change on labor markets requires understanding how it impacts careers.

In this paper, we start from the premise that every occupation has a "career value"—the long-run value of earnings that will result from working in that job and following the career ladder associated with it. This measure of career value is a theoretical concept that considers the expected future payoff from holding a given occupation, taking into account the probability of transitions to other occupations and wages in these occupations. To create measures of career trajectories and to estimate career values, we use data from Burning Glass Technologies (BGT), containing more than 18 million resumes for workers in the United States from 2000-2017. This dataset consists of data on individual resumes available on the internet from more than 3000 online job boards, such as LinkedIn, Monster.com, etc., yielding 247 million sequential worker-year observations. Our measure allows us to understand the trends in upward mobility and differentiate the degree of change coming from the growth of wages vs. change in workers' likelihood of moving across jobs. We describe how career values changed over the period of 2000 to 2016, and suggest that technological changes – specifically, robot adoption – affected the change in career trajectories, career values, and job-related upward mobility.

We use career values as a single index to capture expected job transitions and their quality, measured from an income perspective. We define the career value of a (6-digit) occupation as an average expected income flow corresponding to an occupation, taking into account the probabilities of transitions from this occupation to future occupations. To construct empirical proxies for these expected career values, we estimate transition probabilities from the resume data and combine them with the wages corresponding to these occupations at the state level and the prevalence of different occupations in each commuting zone.[1]

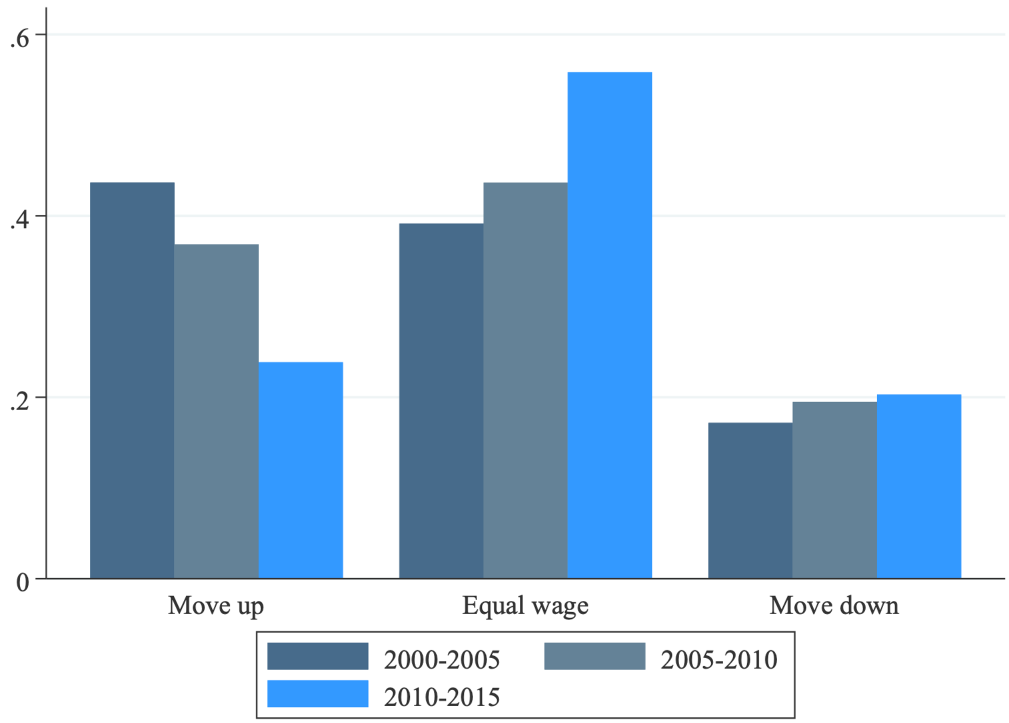
We begin by documenting a set of empirical patterns in job-to-job transitions. First, the incidence of upward occupational moves–defined as transitions to better-paying jobs or into occupations with greater responsibilities, such as those in management, architecture, and engineering–has declined since 2000. Over the same period, the transitions to lower- and same-income jobs have increased: Figure 1 shows that workers have become less likely to find themselves 5 years later in a job that pays a substantially higher real wage if we compare periods starting in 2000, 2005, and 2010.[2] We show that career value

[1]We weight the transition matrix to make it representative of the U.S. population, based on BLS data on the age structure of employment.

[2]See Figure A.3 in the Online Appendix for evidence of a similar pattern in real wage changes conditional on switching occupations.

growth has been declining over time, especially after 2008 and the Great Recession. We then study how technological changes affect career values and, thus, expected upward mobility. We follow the approach in Acemoglu and Restrepo (2020) to study the impact of robotization, using industry-level robot adoption in Europe as an instrument for exposure to robots in U.S. labor markets.

Figure 1: 5-year Transitions to Better- / Worse-Paid Jobs by Time Period



Notes. The figure depicts the share of all workers in our resume sample that transition to better-paid, worse-paid, and (approximately) equal-pay jobs over 5-year time periods between 2000 and 2015. We define a move up in wages as a 10% or larger increase in real wages for the occupation-by-state that the employee is in between the first year of the period and the last year. Analogously, a move down is a 10% or larger decrease in real wages over the same time period, and "equal wage" indicates a change in real wages in between the two thresholds. The shares are computed as a percentage of all workers in the sample at both the beginning and the last year of each period.

Second, we show that automation and robotization affected both transitions and career values. Higher robot adoption led to more transitions to similar- and lower-wage jobs and fewer transitions to higher-wage jobs, and more so in high-manufacturing commuting zones (i.e., commuting zones with above-median manufacturing employment). [3]

Third, we investigate the heterogeneous effects of robot adoption by education and worker experience. We decompose the effects of robotization on career values by wage and career path separately for each sub-population of interest. For education, we find numerically smaller effects for those with higher levels of education. We also examine the differential career trajectories at the individual level. We find that individuals with higher education are less likely to experience demotions in response to robotization.

[3] When we look at the within-firm and across-firm transitions, we find that most of the career value decline comes from the transitions to other firms.

Workers at all experience levels face career value and wage declines, but we see a U-shaped relationship between the years of experience and effects of robotization on occupational mobility: the least and the most experienced workers are shielded and see lower declines in movement towards higher-wage occupations.

Fourth, we also estimate heterogeneity in career value effects by gender. While both men and women face comparable wage losses, for men, the losses due to changes in their career path are 3 times higher than those of women. Combining the career path effects with the wage effects, men's career values decline by 1.5 times as much as those of women as a result of robotization. Individual career trajectories suggest one reason why this could be the case: even though women are more likely to get demotions from managerial roles as a result of robot adoption, they are nevertheless more likely to acquire additional education in places more affected by robotization, mitigating the career losses they experience due to robotization.

Fifth, we look at the impact of robot adoption on career value inequality in the US. To compute inequality in career values, we rank all individuals in our data from the lowest to the highest career values and estimate the change due to robotization in various high-to-low percentile career value ratios, such as P75/P25 and P90/P10. We document a sizable impact of robotization on career value inequality. These findings complement those from Acemoglu and Restrepo (2022), who find that automation is a significant driver of the growing wage inequality in the U.S.

Finally, to understand the implications of observed changes in career values and upward mobility, we explore the relationship between higher expected career values and long-term investments that individuals make–such as investments in housing and schooling–, as well as their political behavior. We instrument career values using wages and occupational transitions in commuting zones located more than 100 miles from the focal commuting zone. We find that higher career values have positive effects on new home construction and the share of individuals pursuing higher education, as well as a negative effect on the vote shares of the Republican party candidate in the 2016 presidential election.

Overall, our results suggest that between 2000 and 2016, there was a decline in economic opportunities–specifically, in upward occupational mobility–and that robot adoption contributed to this decline. This decline in career prospects due to robotization was more pronounced for the low-skilled as well as male workers. The reduction in opportunities led individuals to adjust their long-term investment decisions, such as those related to housing and educational investment, and also shifted their voting behavior.[4] We further document the effect of robot adoption on career value inequality.

Our paper contributes to several strands of literature. The literature on upward mobility (Solon, 1999; Black and Devereux, 2011; Chetty et al., 2014, 2016, 2017) consistently reports high levels of heterogeneity and a decline in intergenerational mobility across community zones in the U.S. over time. Putnam (2015) similarly highlights the diminishing opportunities available to children. We contribute to this body of work by documenting declining rates of occupational upward mobility–as measured by transitions to better-paying jobs or higher career values–in the U.S. between 2000 and 2016. Furthermore, we show that technological change, in particular robotization, contributed to this decline. However, we also find

[4] In a related paper, we also document that politicians, in turn, adjusted their political stance and campaign behavior to respond to the labor market changes stemming from robotization (Petrova et al., 2025).

that other sources of upward mobility, such as increased access to higher education, help mitigate the negative effects of robotization.

Second, we contribute to the literature on the economic consequences of automation, robotics, and artificial intelligence (AI) for jobs, wages, and society more broadly (Frank et al., 2019). Acemoglu and Restrepo (2019) and Furman and Seamans (2019) argue that the growth of automation could lead to the creation of new jobs and occupations due to productivity gains, even if it displaces some labor. Therefore, a decline in employment may not ex ante be the predicted effect. Alekseeva et al. (2021) also find that demand for AI skills in the labor market increased dramatically between 2010 and 2019, suggesting that some job creation is occurring in response to new technologies. Battisti et al. (2023) show that automation reduces firms' demand for routine jobs relative to abstract, task-based jobs. Despite some evidence of creative destruction, Acemoglu and Restrepo (2020) document that the adoption of robots led to job losses in the U.S. between 1990 and 2007. Graetz and Michaels (2018), in a study of 17 countries, find evidence of increased productivity growth resulting from higher rates of robot adoption. Faber et al. (2019) show that robotization affects migration and, independently of our work, document spillover effects of automation and robotization. Cockriel (2023) finds that, historically, artisan shoemakers lost lifetime earnings due to the shift toward factory-based shoe production. Paolillo et al. (2022) compute job robotization risks and discuss workers' available alternatives. Cortes et al. (2021) examine whether technological change reduces the gender wage gap. We contribute to this literature by studying the impact of robot adoption on future career opportunities, as well as the implications of our forward-looking measure of lifetime income on long-term individual decisions and other outcomes.

Third, there is a body of literature on growing income inequality and economic changes that contribute to it, e.g., trade and globalization (Helpman et al., 2017; Antràs et al., 2017), capital intensity of the economy (Piketty, 2014; Piketty and Zucman, 2014), colonial origins (Acemoglu et al., 2001; Alvaredo et al., 2021), housing expenditures (Dustmann et al., 2021), and robot adoption (Faia et al., 2022; Cortes et al., 2023). Our findings suggest that technological change—and, in particular, robotization—has contributed to the growing inequality in opportunities for moving to better occupations.

Finally, we contribute to a growing body of research that estimates the impact of economic shocks related to technology and globalization on the political fortunes of politicians in the U.S. (Autor et al., 2020, 2016; Che et al., 2022; Heins, 2023; Frey et al., 2018), Europe (Colantone and Stanig, 2018; Anelli et al., 2021), the U.K. (Gallego et al., 2022), Germany (Dippel et al., 2015), and France (Malgouyres, 2017). We contribute to this literature by studying the impact of forward-looking economic expectations on electoral preferences.

The rest of the paper is organized as follows. Section 2 describes the data on job employment histories and summarizes the basic patterns in job transitions over time. Section 3 describes the theoretical framework, defines career values, and introduces local labor market career values. Section 4 presents the empirical strategy that allows us to study the effects of robotization and describes its effects on local labor market career values in addition to breaking the effects by heterogeneous characteristics of individuals. Section 5 studies the implications of changes in career values for long-term decisions. Section 6 concludes.

2 Job Transitions Data

Employment History and Individual Characteristics Data We use data from Burning Glass Technologies (now operating as Lightcast), one of the largest repositories of resumes available online in the United States. The data set combines resumes of over 18 million individuals with location and career history, collected from nearly 3,000 job boards, such as monster.com, LinkedIn, Yahoocareers, and similar sites. The data contains information about the job titles candidates have (mapped into the standard occupational classification codes, or SOCs) for each job an individual holds. The data also lists the companies that candidates worked at, the job start and end dates, their education, certificates held, skills, and location at a zip-code level, and is parsed to create a personal career history, starting from the first reported job to the most recent occupation that they hold. The education history is recorded as the number of years in school. The skill data are binary-coded and recorded according to the following classification. First, *baseline* skills are generic skills like leadership, project planning, and building effective relationships. *Software* skills are software-specific skills, and *specialized* skills are domain or industry-specific skills.[5] For the years 2000-2016, we can observe individuals coming from 379 out of 388 Metropolitan Statistical Areas in the United States. Table 1 provides the summary statistics of the data.

Table 1: Summary of the Job Characteristics

	Mean	SD	Min	Max	N
Female	0.509	0.500	0.000	1.000	16,526,192
Age	29.199	8.232	16.000	94.000	19,084,971
College Degree	0.156	0.363	0.000	1.000	19,084,971
First Year Data	2004.854	4.998	2000.000	2017.000	19,084,971
Last Year Data	2014.053	4.183	2000.000	2017.000	19,084,971
Years of Work	9.580	5.488	1.000	18.000	19,084,971
Average Number of Occupation Changes (Weighted)	1.742	1.799	0.000	16.122	19,084,971
Average Number of Occupation Changes	5.324	9.909	0.000	1669.000	19,084,971
Average Number of Occupation Changes per Year (Weighted)	0.198	0.189	0.000	1.000	19,084,971
Average Number of Occupation Changes per Year	0.584	0.928	0.000	156.000	19,084,971
Average Number of Moves Up (wage-wise) (Weighted)	0.516	0.833	0.000	9.000	19,084,971
Average Number of Moves Down (wage-wise) (Weighted)	0.394	0.719	0.000	7.750	19,084,971
Average Number of Same Pay Moves (Weighted)	4.546	5.012	0.000	17.000	19,084,971
Number of Unique Occupations (per worker)	2.641	1.453	1.000	16.000	19,084,971
Number of Unique Firms (per worker)	3.75	2.21	1.00	23.00	19,084,971
	Total				
Number of Unique Workers	19,084,971				
Number of Unique Occupations	1,091				
Number of Unique Firms	27,275,851				

Notes: The statistics are calculated using resume data from Burning Glass Technologies (BGT) for the period 2000–2017. Age is imputed using the formula: Age = Years of Experience + Years of Education + 6, with a minimum of 12 years assumed for education (i.e., high school). An occupation change is defined as a transition between different occupations across a 1-year interval. For weighted metrics, each transition occurring between year t and $t+1$ is weighted by the inverse of the number of distinct occupations the worker holds in the destination year, $t+1$. This method gives less weight to transitions for individuals holding multiple jobs simultaneously. Wage-based moves (Up, Down, Same Pay) are determined by comparing the state-level average wage for each occupation-year and include instances where a worker remains in the same occupation.

Working with a large and detailed resume data set provides us with some advantages, most impor-

[5] Please see Table C.1 in the Appendix for example skills under each category.

tantly, being able to see the movement of an individual across occupations and industries. There are also some concerns related to working with this data set. First, some positions, such as blue-collar jobs, may not hire based on individual resumes, and the data set may overrepresent the jobs from some industries and underrepresent those from others. Figure A.1 in the online appendix compares the share of resumes in the BGT data relative to the shares reported by the Bureau of Labor Statistics. Relative to the BLS shares, we see that the data oversamples from white-collar occupations including finance/marketing, IT/engineering, and management. Schubert et al. (2021) also show that these occupations are substantially overweighted in the BGT data. Data underrepresent construction/transportation and hospitality/tourism sectors, where some occupations can be seasonal. Occupations in other industries seem to have shares comparable to those of the BLS data.

Second, occupations that require resumes from applicants may be more concentrated in urban areas. Figure A.2 in the online appendix demonstrates the distribution of the resume sample across counties. The figure demonstrates that the coverage is better in some locations than others, but the majority of the highly populated areas of the U.S., and most commuting zones, are well represented in the data.

A third concern is the possibility of false reporting of career history, in particular in an effort to hide damaging records. Most typically, individuals may not truthfully report job start and end dates in an effort to hide a gap in employment. For our study, exact dates of job start and end are not essential, but truthful reporting of the jobs held matters. Since occupational history is often verified before employment, we believe false reporting of employment history is less likely to be an issue. While empirical evidence on resume accuracy is scarce, the limited studies that we are aware of do not show high rates of resume fraud.[6] Moreover, even in the case of misrepresentations, the fact that workers *claim* a job to be consistent with their work history still constitutes evidence that the stated career transitions are plausible, which is what we are trying to measure.

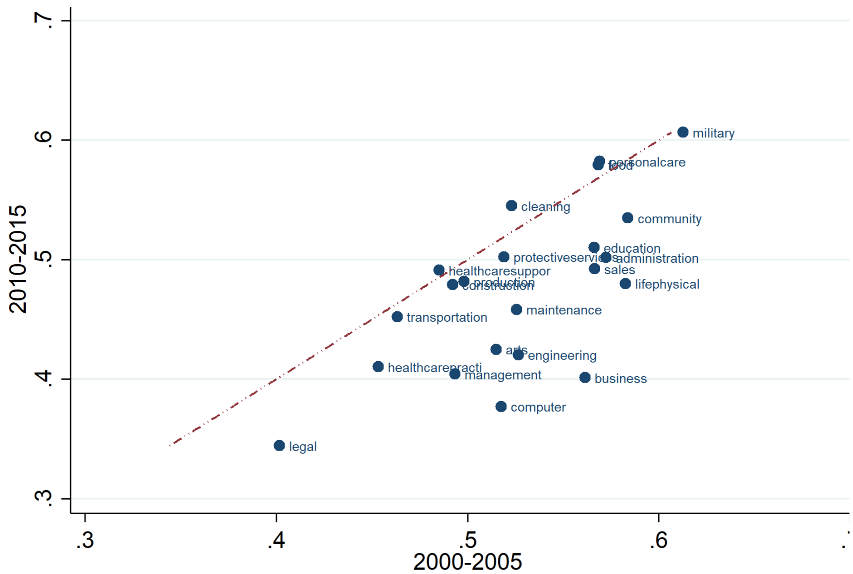
Fourth, there may be concerns about the representativeness of the BGT resumes for different demographic groups of workers. Schubert et al. (2021) show that the resume data set is close to being representative of the overall labor force in terms of gender balance. Moreover, while the raw data overweight younger workers, we explicitly correct for this by computing occupational mobility only after reweighting observations to adjust for the relative prevalence of different ages in our sample relative to the U.S. labor force. The BGT resumes also overrepresent workers with a college degree relative to the population.

These and other potential demographic imbalances do not represent a serious issue for our analysis, as we use the data mainly to compute occupational mobility, not to construct representative composition statistics at the labor market level. While the overall sampling of the BGT resumes may overweight some occupations (e.g., those with higher education requirements) relative to others, we only require the data to be representative of worker mobility conditional on starting in each occupation. Moreover, we adjust occupational transitions by the local prevalence of different occupations in data from the American

[6]For example, Nosnik et al. (2010) found that only 7% of the publications listed by a sample of urology residency applicants on their resumes could not be verified – and truly fraudulent listings have to be a subset of these. For a more detailed discussion of this and other concerns regarding the BGT data, see the online appendix to Schubert et al. (2021).

Community Survey (ACS). Finally, the fact that the BGT data set has more than an order of magnitude more data points compared to other data sources, such as the Current Population Survey, and does not rely on the consistent coding of occupations by surveyors means that our occupation-level transition measures are likely to have substantially lower measurement error.[7]

Figure 2: Probabilities of Transition out of 2-digit Occupation Groups, 2000-2015



Notes. For any time period, the probability of transition out of an occupation is the number of individuals who work in that sector at the beginning of the period and whose occupations at the end of the period are different, over the number of individuals who work in that sector at the beginning of the period. Occupations for individuals are reported based on 2-digit Standard Occupation Codes and there are 23 unique occupations. Individuals with missing occupational values are dropped from the calculations. The transitions reported in this figure are calculated over 5 years, where the x-axis corresponds to the probability for the 2000-2005 period and the y-axis corresponds to the 2010-2015 period.

Preliminary observations In this subsection, we present some graphical analysis with a description of the transitions observed in the labor market over the course of 15 years.[8] As Figure 2 suggests, occupational transitions seem to have slowed during 2010-2015 relative to the 2000-2005 period.[9] These transitions may be upward—moving toward a better-paying or higher-prestige position—or downward. Figure 3 illustrates transitions from the “production” occupation group (in the center)—the group to which most manufacturing occupations belong—to any other occupation group, separately for the years 2004 and 2016 on the left and on the right, respectively. Each circle connected with an arrow indicates the occupation group workers transition to, and the size of the circle indicates the probability of transitioning to the group. Comparing the left and the right figures, the probability of transitions from production to “management” and “architecture and engineering” occupation groups—which likely represent upward

[7]See Appendix Section A.3 for related references and details on how our data compares to the CPS.

[8]For the empirical method details, see Section 3. The trends presented are based on the BGT data.

[9]The latter period may also include the long-term consequences of the 2008 economic recession. However, since the recession resulted in job losses, transitions out of occupations are more likely to intensify in this period rather than slow down.

transitions—seems to have declined between 2004 and 2016. Appendix figures A.4 and A.5 repeat this exercise for the construction and installation groups, respectively, and show a similar pattern of reduced mobility towards management and architecture and engineering jobs.

Figure 4 complements the earlier figures by depicting the trends in transitioning out of production occupations and into management occupations. The figure shows the numbers normalized by the total number of transitions to correct for natural variation caused by business cycles. As shown, the first type of transitions appears to be increasing over time, while the second type appears to be decreasing.

As we briefly discuss in the introduction, we can also distinguish between the upward and downward transitions based on information about the average wage of an occupation. In Figure 1, we summarize changes in terms of transitions to better-paid, worse-paid, and to (approximately) equal-payment jobs over 5-year time periods. Comparing 2000-2005 with 2010-2015, transitions to worse-paid jobs increased, while transitions to better-paid jobs decreased.[10] Overall, the descriptive analysis of occupational transitions presented in this subsection suggests a decline in upward mobility between 2000 and 2015.

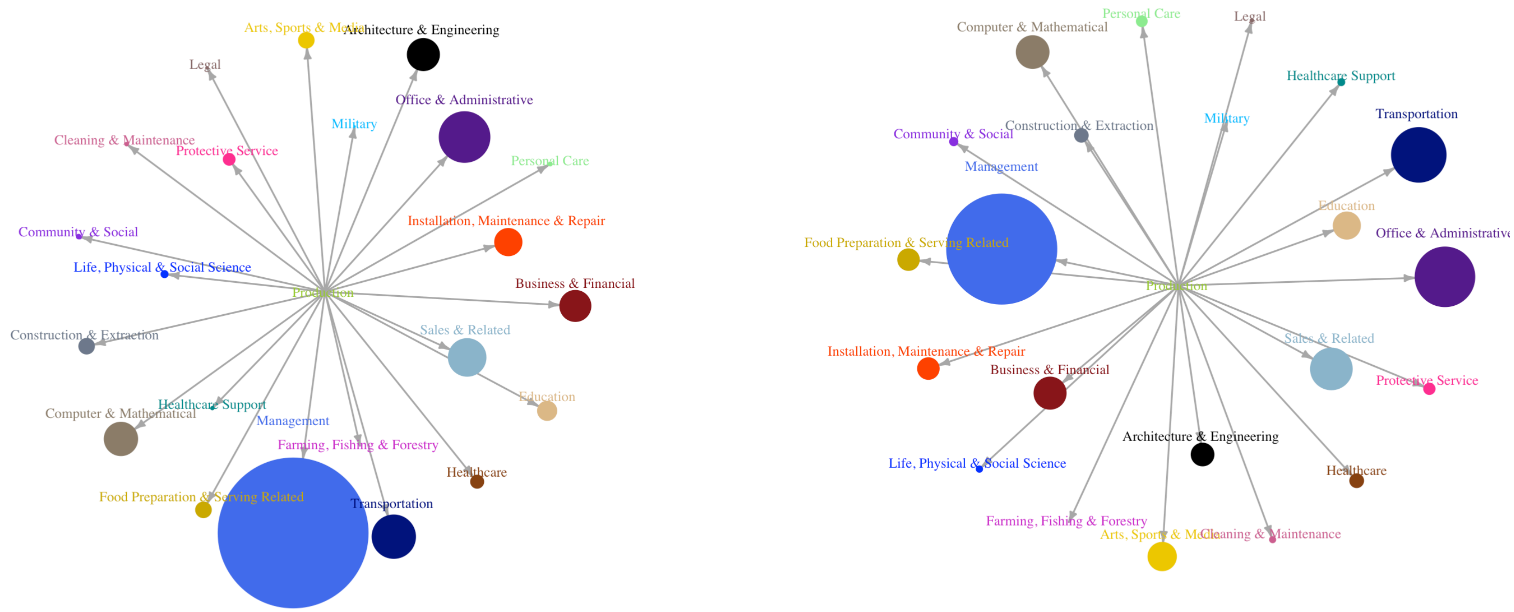
Comparison to CPS mobility patterns. While the pattern of declining mobility and increasing likelihood of occupational transitions to lower-wage jobs is quite striking in our main data set (Figures 1 and 2), there may be a concern that this pattern is a function of our particular data source. While the ability to compute long-horizon career progress for workers is a key advantage of resume data over short-run survey data, we can at least directionally confirm that similar patterns hold in commonly used representative data sources. To confirm that this pattern of declining mobility is robust, we therefore compute similar measures of mobility from Current Population Survey (CPS) data, which is a much smaller sample than our resume data (and therefore less suitable for the detailed geographic and demographic breakdowns we are interested in), but is designed to be nationally representative and is commonly used for studying short-run occupational mobility in the aggregate (e.g., Moscarini and Vella, 2008).

There are many reasons why the CPS data might show different 1-year mobility patterns than our longer-horizon measure, both related to measurement issues in the CPS and to the conceptual difference that long-run career and wage progress depends not just on short-run transition probabilities, but also on how sequential career moves are correlated. As detailed in Appendix A.3, we find that, similar to the resume data, the CPS data show a clear decline in overall occupational mobility between the early 2000s and the 2010s, broadly similar to the pattern seen in Figure 2. We also find that CPS data show a decline in the likelihood of moving up in real wages by 2% at a 1-year horizon between the early 2000s and the 2010s, and an increase in the chance of seeing declining real wages. These findings of declining 1-year occupational mobility in CPS data are also supported by several recent papers that find declining occupational mobility since the 1990s in CPS data (Moscarini and Thomsson, 2007; Xu, 2018; Vom Lehn et al., 2022).[11] Overall, these results confirm that the mobility trends in the resume data are qualitatively

[10] A period of unemployment may result in transitions to temporary, low-wage occupations to "make ends meet." To avoid temporary positions, we consider only occupations held for a minimum of six months. However, such temporary jobs are less likely to be reported on resumes, as applicants may view them as irrelevant or even damaging to their careers.

[11] The decline may have been preceded by increases in occupational mobility from the 1970s to the 1990s (Kambourov and Manovskii, 2009).

Figure 3: Probabilities of Transitioning out of Production Occupations, 2004 vs 2016

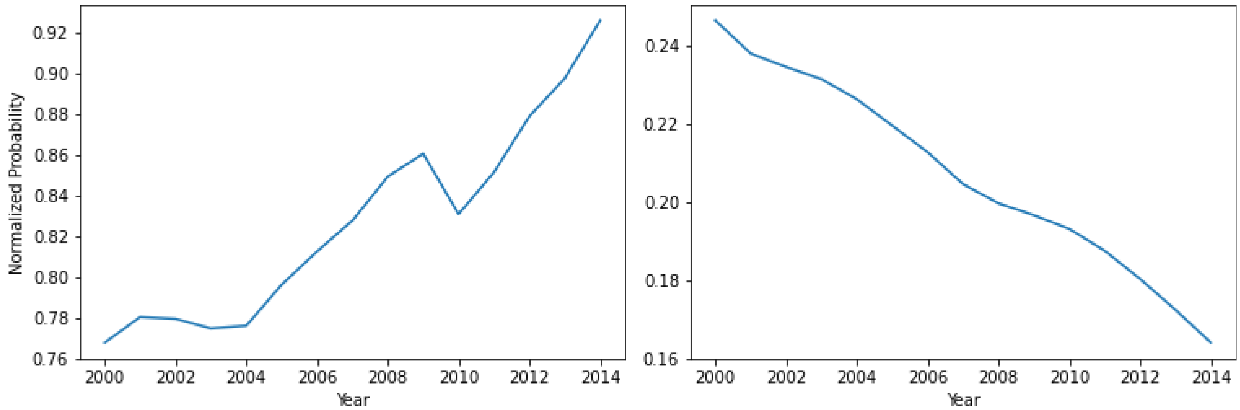


(a) 2004

(b) 2016

Notes. Figures show the normalized probabilities of transitioning from production occupations to various other occupation groups. Panel (a) shows the transitions for the year 2004 and panel (b) shows the transitions for 2016. The size of each bubble indicates the likelihood of transition to the labeled occupation group. Annual job transition probability out of occupation o is calculated as the share of individuals in the BGT data employed in occupation o in period t and in any occupation other than o in period $t+1$. Transition to occupation o is calculated by taking all the individuals changing occupations between time period t and $t+1$ in the BGT data, and calculating the share employed in occupation o in period $t+1$. Normalization is carried out by dividing the transition probabilities between specific occupations by the overall probability of transitioning between any two occupations between period t and $t+1$. Occupations held for less than 180 days are excluded. Plotted probabilities are moving averages over 3 years around the year of interest.

Figure 4: Transitions from Production Occupations and Transitions into Management Occupations



(a) Move from production occupations

(b) Move to management occupations

Notes. Panel (a) shows the probability of transitioning from the "production" two-digit occupation group to any other occupation. Panel (b) shows the probability of moving from any occupation into management occupations. Annual job transition probability out of occupation o is calculated as the share of individuals in the BGT data employed in occupation o in period t and in any other occupation than o in period $t+1$. Transition to occupation o is calculated by taking all the individuals changing occupations between time period t and $t+1$ in the BGT data, and calculating the share employed in occupation o in period $t+1$. Both panels plot the normalized series where normalization is carried out by dividing the transition probabilities by the overall probability of transitioning between periods t and $t+1$. Occupations held for less than 180 days are excluded. Plotted probabilities are moving averages over 3 years around the year of interest.

very similar to those in the nationally representative CPS data and are not an artifact of our resume sample.

One of our key propositions is that current wages and the probability of one-time occupational transitions do not fully capture the potential lifetime career trajectory and gains enabled by a particular career move. For instance, individuals may choose to move to a lower-paying occupation if it offers better opportunities for upward mobility later. To understand the expected lifetime gains associated with choosing each occupation and to compress all the multidimensional information from individual job histories into a tractable measure, we will formally define the concept of "career values" in the following section. We will then describe trends in career values in the U.S. and demonstrate a recent decline, partly driven by reduced occupational mobility. Finally, we will discuss robotization as one contributing factor to this decline.

3 Methodology

3.1 Combining Transitions and Wages: Identifying Career Values

To talk about an individual's sequence of upward and downward transitions over their lifetime, ideally, we want to have a single first-approximation index of an individual's lifetime income given the job that they currently have. We introduce a measure of *career value* at the worker-occupation level. Specifically, for a given worker, we can think of the present monetary value of their lifetime income C_{vt} in time period

t as the sum of current and future wages W along their career path v, discounted by a factor β:

$$C_{vt} = \sum_{j=1}^{T} \beta^{j-1} W_{v,t-1+j}. \tag{1}$$

Neither the worker nor the econometrician can observe the future career value of an individual perfectly. Instead, for an individual in occupation o in period t, we can estimate the present value of one's career by considering the probabilistic path of occupations they are likely to hold in periods $t+1, t+2, \ldots$ and the wages these future occupations pay. Specifically, we define *expected* career value C_{ot} for each occupation o by summing over the average current probabilities and (expected) wages of different occupational sequences following o, for all occupations $\{o, p, q, r, \ldots N_{Occ}\}$:

$$\begin{aligned} C_{ot} &= W_{ot} + \beta \sum_{p \in N_{Occ}} \pi_t^{o \to p} \left(W_{pt} + \beta \sum_{q \in N_{Occ}} \pi_t^{p \to q} \left(W_{qt} + \beta \sum_{r \in N_{Occ}} \pi_t^{q \to r} \left(W_{rt} + \ldots \right) \right) \right) & (2) \\ &= W_{ot} + \beta \sum_{p \in N_{Occ}} \pi_t^{o \to p} C_{pt}, & (3) \end{aligned}$$

where $\pi_t^{o \to p}$ denotes the probability of transitioning from occupation o to p, $\pi_t^{p \to q}$ denotes the probability of transitioning from occupation p to q, and so on. W_{ot} is the wage in occupation o in time period t and β is the discount rate. The right-hand side includes the occupation that the worker is currently in, as there is some probability $\pi^{o \to o}$ that she does not switch occupations.

Expected C_{ot} values can be calculated as a function of wages and probabilities by assuming that a worker can reason through higher-order transitions between occupations. This captures the idea that workers are able to learn about what careers are associated with different starting positions by observing the trajectories of workers around them. Let $\mathbf{C_t}$ represent the present value of careers, $\mathbf{W_t}$ represent the vector of wages, and $\mathbf{\Pi_t}$ represent the probability transition matrix for all occupations in time period t. Then we can rewrite Equation (3) by stacking occupations as:

$$\begin{aligned} \mathbf{C_t} &= \mathbf{W_t} + \beta \mathbf{\Pi_t} \mathbf{C_t} \\ &= \mathbf{W_t} + \beta \mathbf{\Pi_t} \mathbf{W_t} + \beta^2 \mathbf{\Pi_t}^2 \mathbf{W_t} + \beta^3 \mathbf{\Pi_t}^3 \mathbf{W_t} \ldots \\ &= (\mathbf{I} - \beta \mathbf{\Pi_t})^{-1} \mathbf{W_t} \\ &= \mathbf{\Psi_t} \mathbf{W_t}, \end{aligned}$$

where each element of the matrix $\mathbf{\Psi_t}$ represents the discounted probabilities that a worker starting in any occupation o is expected to move to any other occupation p over their entire career. The diagonal of matrix $\mathbf{\Psi_t}$ captures the importance of the current occupation for the value of a worker's future career path and off-diagonal elements represent the weight attached to other occupations that the worker might move into. Intuitively, for each occupation, the diagonal values subtracted from one would indicate the discounted lifecycle probability of moving to other occupations.

We can empirically compute $\mathbf{C_t}$ from data on wages and occupational transition probabilities under some assumptions. We compute the transition probabilities using BGT data and contemporaneous transitions as a proxy for expected future transitions. For an average worker, the best predictor of the distribution of potential occupational transitions in the future is likely the current observed distribution of occupational transitions. For the expected wages $\mathbf{W_t}$ after transitioning into another occupation, we use the most recent wages as a proxy.

The assumption that future transition probabilities and wages can be proxied by today's values is justifiable if workers form career expectations based on recent observations, rather than relying on a sophisticated model to forecast the evolution of the U.S. labor market. In other words, we assume that, in the absence of perfect foresight into future labor market conditions, workers use their most up-to-date information to form beliefs about future earnings.[12] [13] Additionally, we assume that workers can anticipate the transitions that follow an immediate occupational move. This is a realistic assumption, as Table 1 shows that the average number of occupational transitions per worker is only 2.89.

To compute occupational transitions, we approximate the share of workers moving from occupation o to occupation p with the share of all workers observed in occupation o at any point in year t who are observed in occupation p at any point in year $t+1$, dropping jobs lasting less than 6 months. We only focus on transitions between occupations from one year to another and exclude any other possible transitions, including those into/from unemployment, which are usually not recorded on resumes.[14] This unconditional occupational transition probability is our proxy for $\pi_{o \to p}$:

$$\pi_t^{o \to p} = \frac{\text{Number of workers in occ } o \text{ in year } t \text{ who are observed in occ } p \text{ in year } t+1}{\text{Number of observed in occ } o \text{ in year } t \text{ still observed in } t+1}.$$

We use full-time jobs and their 6-digit Standard Occupational Classification (SOC) codes defined by the BLS. To reduce noise in our estimates, we average wages and transition probabilities over the adjacent years before and after t, centering around the year of interest. For instance, our estimate of 2004 transition probabilities uses data from the 2003–2005 period.[15]

The above transition probabilities treat all local labor markets the same in terms of *how likely* it is for a worker to obtain a job in another occupation. This is unrealistic, because local careers are constrained by the occupations that exist in local industries, and, as geographic mobility tends to be small, occupations in other locations are likely of little relevance for most workers. To account for the local market variation, we adjust the occupational transition probabilities by the relative prevalence of occupations in the local labor market. This reflects the intuition that in a location where another occupation is twice as prevalent as the national average, that occupation should also be twice as likely to be the next career step—relative

[12] Experts with advanced degrees often disagree about labor market growth trends (e.g., Graetz, 2020), so we presume that workers also lack perfect foresight.

[13] We also assume that workers base their career expectations on wages in their local labor market, rather than in other regions–implicitly assuming that geographic moves are considered unlikely to factor into their calculations.

[14] Note that as long as expectations of transitions into unemployment do not vary substantially *between* occupations, they do not affect the *relative* career values of different occupations. Introducing a constant probability π_u of entering unemployment simply rescales the transition matrix to $(1 - \pi_u)\Pi$. The additional unemployment term adds the same constant to every occupation's value, leaving all relative comparisons unchanged.

[15] Our methodology for estimating the job transitions from BGT data is similar to Schubert et al. (2021), Section 2.

to the average national tendency to move into that occupation. Local career transition probabilities in market c are captured by the matrix $\mathbf{\Pi}_{ct}$, where each element (o, p) of $\mathbf{\Pi}_{ct}$ is defined as

$$\pi_{ct}^{o \to p} = \frac{\frac{s_{p,ct}}{s_{p,t}} \pi_t^{o \to p}}{\sum_{j \in N_{Occ}} \frac{s_{j,ct}}{s_{j,t}} \pi_t^{o \to j}}.$$

Here, $s_{p,ct}$ represents the local and $s_{p,t}$ represents the national employment share of occupation p, so that each element of $\mathbf{\Pi}_{ct}$ scales the corresponding element of $\mathbf{\Pi}_t$ by the local prevalence and then renormalizes each row to sum up to one, considering all occupations j.

To adjust the transition probabilities for the local prevalence of occupations, we use ACS microdata on occupation shares in each CZ relative to the national employment share, and fill in occupations not contained in the ACS data by computing the analogous ratio of the occupation share for the majority state of the CZ from BLS Occupational Employment Statistics (OES) data, again relative to the national average. If data from neither source is available, we assume that the occupation does not exist locally and set its share to zero.

We combine the transition probabilities with annual wages by occupation and state, using data provided by the BLS Occupational Employment Statistics survey, thus we use localized (not national-level) wages. We adjust all wages for inflation according to the urban consumer price index (CPI) to be expressed as real wages in constant year 2000 dollars, and we set the discount factor to $\beta = 0.85$.[16] [17]

3.2 Career Values, Wages, and Automatability

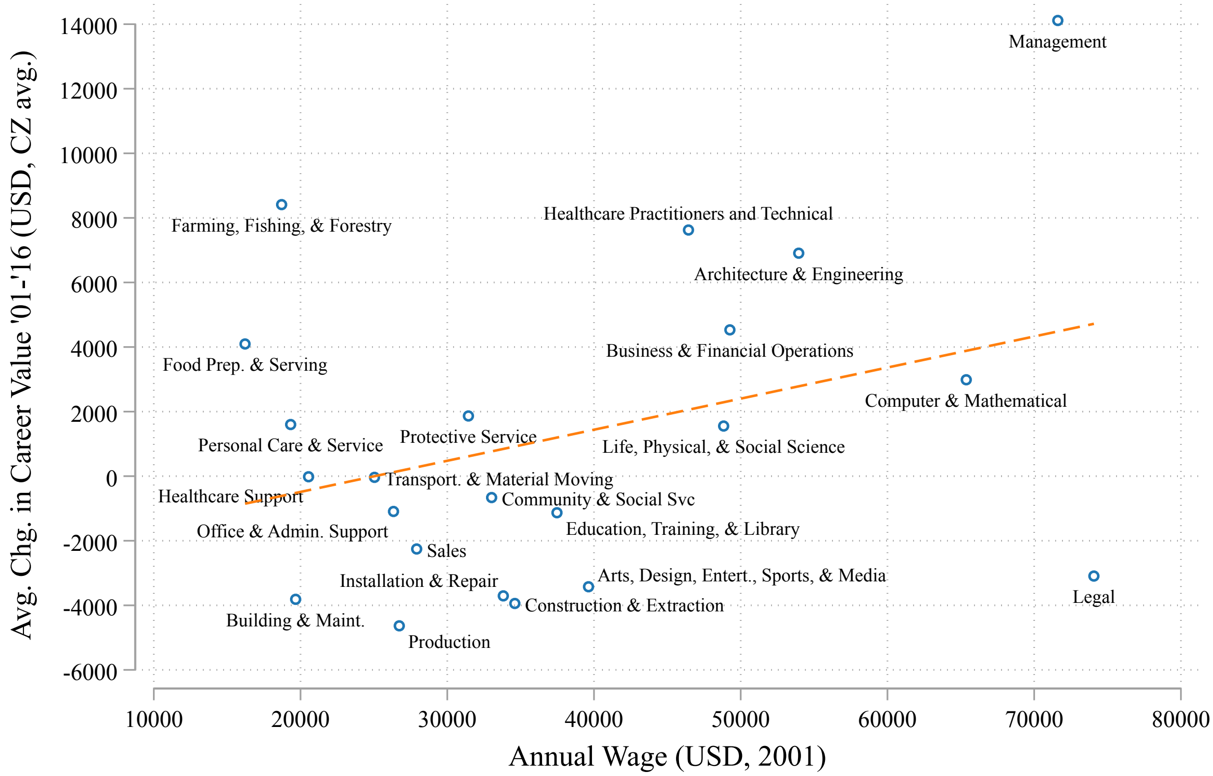
Figure 5 shows the average change in career values between 2000 and 2016 vs. the average starting annual wage between 2000 and 2002 for each occupation group. This figure shows that career value changes are correlated with the initial wages, but there is substantial variance: for some occupations, career values increased substantially, while for others they stayed the same or even declined. In contrast, if we plot changes in wages versus initial wages, the dots in the graph seem to be well aligned along a linear prediction (Figure 6). The comparison of Figures 5 and 6 suggests that occupations are different not only in their wage gains, but also in the career mobility opportunities they offer, and the career values of occupations in Figure 5 are more dispersed.

In appendix Figure A.10, we show that the change in occupational career values between 2000 and 2016 is correlated with the automatability of an occupation, a computerization measure introduced by Frey and Osborne (2017) using a combination of expert opinions and machine learning. We find a clear negative relationship between automatability and the career value of the occupation groups. According

[16]This value is consistent with experimental estimates of discount factors applied in economic decisions (Coller and Williams, 1999; Newell and Siikamäki, 2015; Patnaik et al., 2022). It is on the lower end of values exogenously imposed in discrete choice models in the literature (e.g. in Dix-Carneiro (2014)), as we wanted to be conservative in the degree to which we assume that future career moves matter to workers.

[17]While the derivations above allow for short-term (less than a year) transitions to unemployment, they remain focused on ongoing job-to-job transitions. While a low probability, a share of workers may transition to unemployment for periods longer than a year. For completeness, we also carried out an exercise where we explicitly include transitions to and from unemployment. Our main qualitative findings remain similar throughout the paper when we include unemployment. The details of this analysis can be requested from the authors.

Figure 5: Average Career Value Change Between 2000 and 2016 vs. Starting Wage, by 2-digit SOC



Notes. The figure depicts the average change in career values between 2000 and 2016 vs. the starting wage of an occupation, where the latter is calculated by averaging the wages in an occupational group for the years 2000 to 2002. Career values are calculated using the transition probabilities from BGT data and annual wage data from the BLS Occupational Employment Statistics survey. All wages are adjusted for inflation according to the urban consumer price index (CPI). The discount factor in the calculation of the career values is set to $\beta = 0.85$.

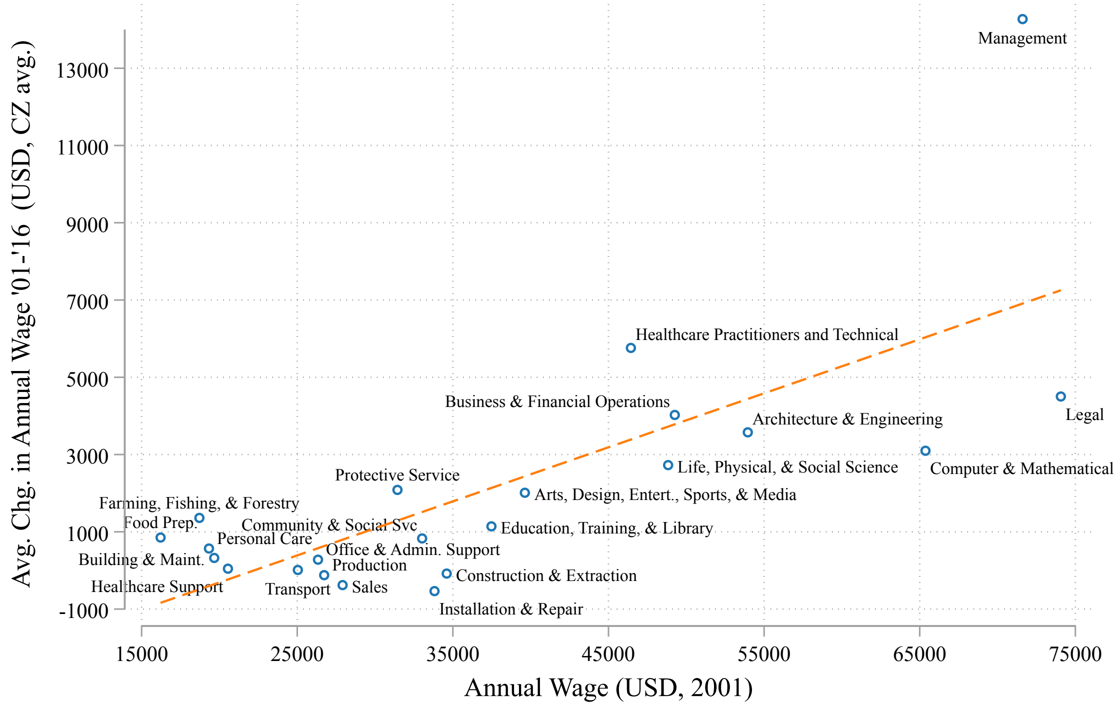
to the figure, an approximate 0.2 unit increase in the automatability score is associated with a $2,500 smaller increase in career value between 2000 and 2016. We explore the role of automation effects more formally in Section 4, where we estimate the effect of robot adoption on career values.

Local Market Career Values. To study the changes in career values at the local labor market level, we estimate the "local market career value" ($LMCV_{ct}$) which represents the aggregate career values of all local occupations weighted by their local employment shares in CZ c in time period t:

$$LMCV_{ct} = \sum_{o \in N_{Occ}} \lambda_{cot} C_{cot}, \tag{4}$$

where λ_{cot} is the share of employees holding occupation o in market c in period t, C_{cot} is the career value of occupation o in period t in local market c. Here, $LMCV_{ct}$ has a straightforward interpretation: it measures the present discounted value of expected lifetime earnings for a randomly selected worker in labor market c. We focus on CZs as the unit of local labor markets in line with Autor et al. (2013) and Acemoglu and Restrepo (2020). For employment shares in CZs, we rely on data from the American

Figure 6: Average Wage Change Between 2000 and 2016 vs Starting Wage, by 2-digit SOC



Notes. The figure plots the average change in wages over the period 2000 to 2016 vs. the starting wage calculated by averaging the wages in the occupational group for the years 2000 to 2002. Annual wage data is gathered from the BLS Occupational Employment Statistics survey. All wages are adjusted for inflation based on the urban consumer price index (CPI) and are in constant year 2000 dollars.

Community Survey (ACS).

The change in $LMCV_{ct}$ can be decomposed into changes due to the composition of local labor market employment opportunities and career value changes:

$$\Delta LMCV_{ct} = \underbrace{\sum_{o \in N_{Occ}} \Delta\lambda_{cot} C_{co,t-1}}_{\text{Market composition change}} + \underbrace{\sum_{o \in N_{Occ}} \lambda_{co,t-1} \Delta C_{cot}}_{\text{Career value change}} + \underbrace{\sum_{o \in N_{Occ}} \Delta\lambda_{cot} \Delta C_{cot}}_{\text{Interaction: Market comp.} \times \text{CV}},$$

where the first term "market composition" refers to the changes in a local market due to the shifts in the employment shares of occupations ($\Delta\lambda_{cot}$), holding the probability of transitions between occupations and the wages fixed. The local market career value could increase, for instance, due to composition changes if the shares of high-value occupations increase in a region. The second term "career value" captures the changes in a region due to the shift in career values, fixing the job composition. This term describes the changes that occur either due to shifts in the probabilities of transitioning between occupations or due to changes in the anticipated wages of future occupations while holding the current distribution of occupations in the local labor force constant. The last interaction term encompasses changes that occur in tandem due to the interaction between shifts in market composition and changes in career value.

The changes in career value can further be decomposed into changes in occupation o in location c due to changes in career path *mobility* and changes in *wages*, as follows:

$$\Delta C_{cot} = \underbrace{\sum_{o \in N_{Occ}} \Delta \psi_t^{o \to p} W_{cp,t-1}}_{\text{Career path chg.}} + \underbrace{\sum_{o \in N_{Occ}} \psi_{t-1}^{o \to p} \Delta W_{cp,t}}_{\text{Wage changes}} + \underbrace{\sum_{o \in N_{Occ}} \Delta \psi_t^{o \to p} \Delta W_{cp,t}}_{\text{Interaction: Wage} \times \text{Path}}$$

where the $\psi_t^{o \to p}$ represents the career mobility weights of the occupation p that individuals transition to from occupation o, i.e., the (o, p) element of the matrix $\mathbf{\Psi_t} = (\mathbf{I} - \beta \mathbf{\Pi_t})^{-1}$.

Table 2 summarizes the changes in career values and their components over the years, averaging across all CZs. The results imply that career values grew in the 2000-2008 period, while there was some decline in the 2008-2016 period. Decomposition into wage and occupational path changes indicates that wages continued to grow in both periods, albeit at a lower rate in the later period. However, there was a loss in career values from the occupational mobility component in both periods, which implies a decline in transitions into higher-paying occupations.

According to these numbers, between 2000 and 2008, overall, the average LMCV increased by $2,100; whereas from 2008 to 2016, it declined by $200. The average local market career values were $230,957 in 2000, $233,025 in 2008, and $232,874 in 2016. Thus, from 2000 to 2008, there was an approximate 0.9% increase in lifetime career value, and from 2008 to 2016, there was an approximate 0.09% decline, on average. The direct effect of wages on the average LMCV was a $16,100 (7%) increase between 2000 and 2016. The direct effect of occupational mobility on the average LMCV was a $12,500 (5.5%) decline in the same period. In the discussion which follows, we will look at the effects of robotization on career value declines, and show that the effects of the latter are more dramatic for regions undergoing a higher rate of robotization.

Table 2: Average Local Market Career Value Changes: Decomposition

	2000-2008	2008-2016	2000-2016
Local Mkt. CV Change	2.1	-0.2	1.9
Mkt Composition	0.4	1.4	1.0
Occ. Career Values	2.8	-0.7	1.4
Career Path chg.	-5.8	-7.0	-12.5
Wage chg.	9.0	6.9	16.1
Own occ. wage chg.	1.8	1.8	3.5
Other occ. wage chg.	7.2	5.1	12.6
Interaction: Path x Wages	-0.4	-0.5	-2.3
Interaction: Comp. x Occ. CV	-1.1	-0.9	-0.4

Notes: All terms are in units of $1,000 of net present career value in constant year 2000 dollars, at a discount factor of 0.85.

3.3 Identifying Effects of Robot Adoption

Throughout the paper, we aim to study the impact of robotization, an important factor of economic transformation that has been taking place during our time period (2000-2016). In most specifications, we follow Acemoglu and Restrepo (2020) and Faber et al. (2019) and focus on a measure of exposure in CZs, weighted by earlier industry shares for each industry potentially affected by robotization. CZs differ in their exposure to robots because they are composed of different industries, and workers across CZs are exposed to robot adoption at different rates. Our empirical strategy consists of estimating regression specifications of the form:

$$\Delta Outcome_{c,(t_0,t_1)} = \beta_1 + \beta_2 Exposure\_to\_robots_{c,(t_0,t_1)} + \beta \mathbf{X}_c + \varepsilon_{c,(t_0,t_1)}, \tag{5}$$

where $\Delta Outcome_{c,(t_0,t_1)}$ stands for the aggregate change in labor market outcomes of interest between periods t_0 and t_1 in CZ c. $\mathbf{X}_c$ stands for controls for c, including the log of population, share of males (in total population), share of population above 65 years, share of population with high school, some college, college and postgraduate education, share of whites, African Americans, Hispanics, and Asians (in total population), share of employment in manufacturing, construction, and mining, and share of female workers in manufacturing employment, following the list of controls used in Acemoglu and Restrepo (2020) and Faber et al. (2019) for 1990. In addition, for some specifications, we include share of employment in manufacturing, share of female employment in manufacturing, share in light manufacturing (textile industry and the paper, publishing, and printing industry), share of employment in routine occupations and change in exposure to imports from China from 1990 to 2007 using data from the American Community Survey and County Business Patterns.

For the industrial robots in stock, we use data provided by the International Federation of Robotics (IFR). The dataset covers 38 industry codes with the International Standard Industrial Classification (ISIC) code. While the data contain information about the operational stock of industrial robots in about 50 countries between 1993 and 2016 (corresponding to about 90% of the industrial robots market), the industry breakdown of the robot stocks starts in 2004. Therefore, we focus on the data after 2004 to calculate automation exposure in the U.S. For more details on this dataset, please see appendix C.

Exposure to robots in CZ c in period (t_0, t_1), $Exposure\_to\_robots_{c,(t_0,t_1)}$, is constructed as a shift share instrument, summing over the product of local industry employment share weights (l_{ci}) from year 1990 and the change in the robot stock impacting a particular industry code as in Acemoglu and Restrepo (2020) and Faber et al. (2019):

$$Exposure\_to\_robots_{c,(t_0,t_1)} = \sum_{i \in \iota} l_{ci} APR_{i,(t_0,t_1)}, \tag{6}$$

where $APR_{i,(t_0,t_1)}$ is the change in the adjusted penetration of robots in an industry i in all industries in the set ι between t_0 and t_1. Because adoption of robots in any industry is likely to be jointly determined with labor market outcomes through a host of correlated unobservables—that is, $Cov(\varepsilon_{c,(t_0,t_1)}$, $Exposure\_to\_robots_{c,(t_0,t_1)}) \neq 0$—, we might not be able to isolate the changes in local labor market conditions due to automation shocks if the above-mentioned robot exposure measures are calculated using data from the U.S.[18] To alleviate this problem, we use a Lasso-based IV approach (Chernozhukov et al., 2015), which chooses the set of countries C for which the adjusted penetration of robots linearly best predicts the U.S. robot adoption measure $APR_{i,(t_0,t_1)}$.

The identification of causal effects of automation exposure on labor market outcomes requires that (1) the instrument based on exposure to European robot adoption predicts exposure to the U.S. variation in robot adoption, and (2) the local exposure to industries with growing robot adoption in Europe is uncorrelated with unobservable shocks driving local labor market dynamics in the U.S. That is, intuitively, we can think of the IV Lasso procedure as constructing a first-stage predicted variation in local robot exposure given by

$$\overline{Exposure\_to\_robots}_{c,(t_0,t_1)} = \sum_{j \in \mathbf{C}} \beta_j^{\text{Lasso}} \left(\sum_{i \in \iota} l_{ci} \overline{APR}^{j}_{i,(t_0,t_1)} \right), \tag{7}$$

where $\mathbf{C}$ is the set of European countries selected by the first stage of an IV Lasso procedure, and β_j^{Lasso} are the corresponding weights on the exposure to each country's robot adoption. The exclusion restriction requires $Cov(\varepsilon_{c,(t_0,t_1)}, \overline{Exposure\_to\_robots}_{c,(t_0,t_1)}) = 0$, conditional on the included control variables. This approach is similar to other shift-share approaches in the literature where the identification requires exogeneity of the exposure shares—here, the local industry structure—with regard to the *changes* in unobserved local shocks. The econometrics of this approach are detailed in Goldsmith-Pinkham et al. (2020).

How plausible is the assumption of exogenous industry shares? Acemoglu and Restrepo (2020) already address a number of potential concerns, such as possible pre-trends in regions more exposed to industries that are adopting robots at a faster pace. In addition, Goldsmith-Pinkham et al. (2020) suggest that controlling for coarser industry structures (e.g., manufacturing shares) may help to address confounders related to overall economic structure. We address this issue by splitting the sample into high and low manufacturing share areas in subgroup analyses to establish that the effects hold even within the sample of high manufacturing areas that would be expected to bear the brunt of automation effects. In addition, our baseline analyses include a rich set of demographic control variables and census division-level fixed effects that capture differences between the broad U.S. regions (e.g., "Rust Belt" vs "New England").

3.4 Other Data

In addition to BGT transitions data, wage data from the BLS Occupational Employment Statistics, and robotics data, we also employ a number of reasonably standard datasets to construct control variables and additional economic outcomes.

[18] To deal with this issue, Acemoglu and Restrepo (2020) use an average penetration measure from a subset of European countries which are well ahead of the United States in their adoption of industrial robots. Using robot penetration of European countries thus allows to "isolate the source of variation coming from global technological advances (rather than idiosyncratic U.S. factors)" (pg.13 Acemoglu and Restrepo, 2020). They calculate the adjusted penetration value using data from Denmark, Finland, France, Italy, and Sweden. For the time period in our analysis, the same five countries are no longer necessarily ahead of the United States in automation. As a result, their adoption patterns might become less predictive of which industries in the U.S. should see an increase in robot adoption.

Current Population Survey We use data from the Current Population Survey (CPS) to compute estimates of occupational mobility that can be compared with estimates from the BGT data. We use individual-level data on current and previous year occupations from the Employee Tenure and Occupational Mobility Supplement of the CPS for the years 1995-2022, available via IPUMS. The sample is composed of employed male workers, aged 20-64, who are employed at the time of the survey. The data uses 2000 SOC occupation codes, which we crosswalk to their 1990 counterparts. We also include data from the basic monthly survey for March of each year to study changes in wages by occupation.

Bureau of Labor Statistics Occupational Employment and Wage Statistics The Bureau of Labor Statistics (BLS) Occupational Employment and Wage Statistics (OEWS) data, accessed through the BLS website, is used to compare the share of employment in different occupations in 2016. Occupations are defined based on 2-digit SOC codes.

Robot Stock Data. Data on the robot stock and robots in operation are from the International Federation of Robotics data, reported for various countries annually. For more details on these data, please see Acemoglu and Restrepo (2020) and online appendix C.

Political Outcomes We study political outcomes such as voter shares. Data on electoral outcomes are from Dave Leip's Atlas of the U.S. Presidential Elections, referred to as the Election Atlas.

4 Empirical Results

The previous section has shown that measuring career values and occupational mobility provides a new lens on recent labor market dynamics. We use this new approach to empirically study the effects of one of the key technological trends of recent decades: exposure to automation and robotization.

The analysis estimates the effect of robot exposure on forward-looking labor market characteristics—in the form of expected career trajectories and the present value of career income.

Robot Adoption and Local Market Career Values

In what follows, our objective is to understand whether important contemporary technological changes, e.g. automation and robotization, played a role in the observed decline in career values. We start by reporting how robotization exposure influences career values in a typical commuting zone, estimating equation (5) with the change in local market career values, $\Delta LMCV_{c,(t_0,t_1)}$, as an outcome.

Table 3 reports this relationship across different years using OLS (column 1) and IV Lasso (column 2). The OLS coefficient is slightly smaller than the IV coefficient, which may point to measurement-error bias, but since the coefficients are nearly identical, bias appears to be small and toward zero. The coefficient in column (2) suggests that higher exposure to robots resulted in a decline in the expected LMCVs, and the magnitudes imply that a one-unit increase in robotization exposure (1 additional robot per 1000 workers) decreased the average local market career value by $3.36K between 2000 and 2016.

This value corresponds to about 1.45% of the average career value in 2000 ($230,957). Table A.8 in the Appendix replicates this result but includes the share of employment in routine occupations and the change in the exposure to imports from China from 1990 to 2007 as controls.

Table 3: Exposure to Robots and Labor Market Career Value Change (OLS and IV Lasso)

	Δ Local Market Career Value	
	(OLS)	(IV)
	(1)	(2)
U.S. Robot Exposure '04-'16	-0.317***	-0.336***
	(0.041)	(0.037)
Mean of D.V.	-0.238	-0.238
F-stat.		62.936
Census Division FE	Yes	Yes
A&R Controls	Yes	Yes
Observations	722	722

Notes. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Robust standard errors are in parentheses and clustered by state. All columns include census division dummies as well as controls for demographic characteristics of commuting zones in 1990 identical to those in Acemoglu and Restrepo (2020) (log population; the share of females; the share of population above 65 years; the shares of population with no college, some college, college and professional degrees, and masters and doctoral degrees; the shares of Whites, Blacks, Hispanics, and Asians; the share of employment in manufacturing; the share of female employment in manufacturing; and the share of employment in light manufacturing, namely, textile industry and the paper, publishing, and printing industry). U.S. Robot Exposure is instrumented using robot exposure in Denmark, Italy, Sweden, Finland, France, Germany, Spain and the UK in the same time periods. Observations are weighted by commuting zone population. Local market career values are divided by 10,000.

Changes in LMCV from automation can be due to changes in market composition, changes in occupation career value, or both. As discussed, the former measures the changes in career values due to the changes in local market job composition, fixing the probabilities of job transitions and wages. The latter measures the changes in the LMCV due to changes in career values, fixing the labor market composition. We further decompose the change in career value into changes due to 'career path' (ψ) and 'wages' (W) and also report the interactions of these effects.

Table 4 summarizes how the results of this decomposition depend on robot exposure, using the IV Lasso framework. The IV results for all CZs (column 1) indicate that the LMCV does not change substantially due to the market composition, with our confidence intervals allowing us to rule out an effect of up to $83.5 for a mean dependent variable of $2,147, i.e., it is a precisely estimated zero. This suggests that migration that potentially changes the mix of local workers, though important (Faber et al., 2019), is unlikely to explain our career values results. So the decline in LMCV is almost entirely due to the changes in occupation-level career value (column 2), with approximately two-thirds of the effect ($2,030 decline) being due to the decline in wages, and one-third of the effect ($1,170 decline) being due to the decline in career paths, i.e., a decline in upward transitions if we hold wages fixed (both numbers are for 1 additional robot per 1000 workers), rounding off the small interaction coefficients (columns (5) and (6)). Repeating the analysis separately for the high-manufacturing and low-manufacturing commuting zones (2nd and 3rd panels), we see that the estimated effects are mostly coming from the former, albeit in line with intuition, the implied first stage for the IV Lasso procedure tends to be weaker for low-manufacturing commuting zones.

Table 4: Exposure to Robots and Disaggregated Changes of Labor Market Career Values, IV Lasso

	Δ CC	Δ CV	$\Delta CV:\ \Delta W$	$\Delta CV:\ \Delta\psi$	$\Delta CV:\ \Delta\psi \times \Delta W$	Δ CC $\times$ CV
	Mkt. Compos. (1)	Occ. Career Values (2)	Wage (3)	Career Path (4)	(5)	(6)
Panel A: All Commuting Zones						
U.S. Robot Exposure '04-'16	0.005	-0.333***	-0.203***	-0.117***	-0.013*	-0.008**
	(0.004)	(0.039)	(0.044)	(0.021)	(0.008)	(0.003)
Mean of D.V.	0.220	-0.356	1.067	-1.239	-0.183	-0.103
F-stat.	1.048	77.107	57.972	20.214	6.924	6.787
Observations	722	722	722	722	722	722
Panel B: High-Manufacturing Commuting Zones						
U.S. Robot Exposure '04-'16	0.003	-0.351***	-0.216***	-0.119***	-0.016	-0.006**
	(0.008)	(0.031)	(0.034)	(0.024)	(0.010)	(0.003)
Mean of D.V.	0.235	-0.730	0.674	-1.249	-0.154	-0.077
F-stat.	0.212	68.033	48.855	15.983	4.493	4.174
Observations	362	362	362	362	362	362
Panel C: Low-Manufacturing Commuting Zones						
U.S. Robot Exposure '04-'16	0.251	0.389	0.418	0.050	-0.079	0.358*
	(0.298)	(1.804)	(1.114)	(1.198)	(0.352)	(0.187)
Mean of D.V.	0.204	0.021	1.462	-1.229	-0.213	-0.128
F-stat.	1.545	0.137	0.373	0.005	0.119	13.865
Observations	360	360	360	360	360	360
Census Division FE	Yes	Yes	Yes	Yes	Yes	Yes
A&R Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Robust standard errors are in brackets and clustered by state. All columns include census division dummies as well as controls for demographic characteristics of commuting zones in 1990 identical to those in Acemoglu and Restrepo (2020) (log population; the share of females; the share of population above 65 years; the shares of population with no college, some college, college and professional degrees, and masters and doctoral degrees; the shares of Whites, Blacks, Hispanics, and Asians; the share of employment in manufacturing; the share of female employment in manufacturing; and the share of employment in light manufacturing, namely, textile industry and the paper, publishing, and printing industry). U.S. Robot Exposure is instrumented using robot exposure in Denmark, Italy, Sweden, Finland, France, Germany, Spain and the UK in the same time periods. Commuting zones are classified as high manufacturing zones if the share of population employed in the manufacturing sector is greater than the median share of employment in manufacturing in the country. Low manufacturing zones have below median share of employment in manufacturing. Observations are weighted by commuting zone population.

Table A.2 in the online appendix further decomposes the changes in career values into those from an employee's current (own) occupation and from other (future) occupations. In regions with higher robot exposure, both the lifetime earnings from one's own occupation and other occupations declined more steeply. However, the point estimate of the $ decline from other occupations (-$2,920) from one additional robot per 1000 workers is about 6 times that for the current occupation (-$430). The decline in the current occupations' contribution to one's career value is due to the decline in wages (column 3), whereas the decline in other occupations' contribution to career value is associated with both the losses in wages (column 6) and the reduced job mobility (column 7).

4.1 Automation Exposure and Transitions to Higher and Lower Wage Occupations

To better understand the results in Table 3 and Table 4, we look into the impact of exposure to robots on job transitions only, using the same general framework of equation (5). We normalized the number of job transitions in each category to have a mean of zero and a standard deviation of 1, to make the numbers comparable across different columns.

In particular, we focus on transitions to better-paid occupations, same-, and lower-wage occupations, using the same data as in Figure 1. These results are summarized in Table 5. As one can see, transitions to same-pay (column 1) and lower-pay (column 3) jobs increased and transitions to higher-pay jobs decreased overall (column 2). These effects are in the same direction in high-manufacturing commuting zones (columns 4, 6, and 8), but there are no significant changes in the low-manufacturing regions (columns 5, 7, and 9). The magnitudes imply that one additional robot per 1000 workers leads to on average a 7.4% increase in the normalized probabilities of transitions to similar pay jobs (column 1), a 6.3% decrease in the normalized probabilities of transitions to better-paid jobs (column 2), and a 5.7% increase in the normalized probabilities of transitions to lower-paying jobs (column 3). For high-manufacturing commuting zones, the corresponding estimates are a 17.0% increase in the similar-pay jobs (column 4), a 6.3% decline in transitions to higher-pay jobs (column 6), and a 10.2% increase in transitions to lower pay jobs (column 8). Table A.9 in the Appendix replicates these results but includes the share of employment in routine occupations and change in exposure to imports from China from 1990 to 2007 as controls.

Table 5: Exposure to Robots and Job Transitions. IV Lasso

	Probability of transitions to: equal wage occupations	Probability of transitions to: higher wage occupations	Probability of transitions to: lower wage occupations	Probability of transitions to: equal wage occupations: high-manuf.	low-manuf.	Probability of transitions to: higher wage occupations: high-manuf.	low-manuf.	Probability of transitions to: lower wage occupations: high-manuf.	low-manuf.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
U.S. Robot Exposure '04-'16	0.074**	-0.063***	0.057**	0.170***	1.669	-0.063***	-0.159	0.102***	0.400
	(0.031)	(0.010)	(0.025)	(0.019)	(1.055)	(0.024)	(0.221)	(0.018)	(0.335)
Mean of D.V.	0.007	0.008	0.008	0.256	0.073	0.259	0.073	0.258	0.074
F-stat.	29.125	90.359	15.583	169.764	32.425	35.512	1.026	43.806	4.847
Census Division FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
A&R Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	722	722	722	362	360	362	360	362	360

Notes. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Robust standard errors are in brackets and clustered by state. All columns include census division dummies as well as controls for demographic characteristics of commuting zones in 1990 identical to those in Acemoglu and Restrepo (2020) (log population; the share of females; the share of population above 65 years; the shares of population with no college, some college, college and professional degrees, and masters and doctoral degrees; the shares of Whites, Blacks, Hispanics, and Asians; the share of employment in manufacturing; the share of female employment in manufacturing; and the share of employment in light manufacturing, namely, the textile industry and the paper, publishing, and printing industry). All columns include controls for the potential transition to equal, high or lower wage occupations for the years 2004 and 2016 depending on the outcome variable. In columns (4)-(9), these controls are for the high and low manufacturing zones exclusively. U.S. Robot Exposure is instrumented using robot exposure in Denmark, Italy, Sweden, Finland, France, Germany, Spain and the UK in the same time periods. Commuting zones are classified as high manufacturing zones if the share of population employed in the manufacturing sector is greater than the median share of employment in manufacturing in the country. Low manufacturing zones have below median share of employment in manufacturing. Observations are weighted by commuting zone population.

Table A.3 in the online appendix provides estimates for the effect of robotization on the probability of transitioning *from* manual, cognitive, routine, and non-routine occupations among the individuals transitioning to another occupation, using classifications based on the classification in Autor et al. (2003). The table demonstrates that in regions with higher exposure to robotization, the likelihood of moving away from routine and non-routine manual occupations (columns 1, 5, and 6) and manufacturing occupations (column 9) increased significantly, while no significant changes were recorded for the cognitive occupations (columns 2, 7, and 8).[19]

4.2 Heterogeneity in Effects of Robotization

Our results so far suggest that between 2004 and 2016, the growth in expected lifetime incomes slowed down, while opportunities for upward mobility steadily declined. Tables 3, 4 and 5 imply that robotization is one reason for that. In this subsection, we analyze whether education as a source of upward mobility and other workers' characteristics can mitigate the negative effect of robot exposure.

Heterogeneity by Education. One of the principal sources of upward mobility is education. Obtaining higher education vastly improves workers' career options, and the college premium effects are well-documented in the literature. We start our analysis by computing career values separately for different levels of education to see whether exposure to robots affects high- and low-skilled workers differently. Following the convention in the literature, we define high-skilled workers as those with at least college-level education.[20]

Table 6 summarizes these results. Column (1) shows the results of the estimation of equation (5) for the change in occupational composition, column (2) presents the baseline effect for career values, disaggregated by education, columns (3) and (4) show how the components of career values change in response to robotization, focusing on the changes in wages, holding career transitions constant (column 3) and the changes in career paths, holding wages constant (column 4). Columns (5) and (6) show the results for the interactions.

On average, exposure to robots affects both below college and college and above workers negatively. Column (2) Panel A indicates that one additional robot per 1000 workers led to a significant decline of approximately \$3.78K in career values for those below college education, and Panel B shows a \$3.56K decline for those with college and higher level. 60-65%–nearly 2/3s–of these declines are due to lower wages for both groups (column 3), which are statistically similar for the two groups. At the same time, the magnitudes in column (4), the component of career value coming from fixing wages and looking at the change in career path, look more negative for the low-skilled workers. For low-skilled workers, the effect is -0.146, while for high-skilled workers it is equal to -0.119. This implies that education could partially mitigate the negative career mobility effects of robotization. We investigate the role of education in demotions in subsequent sections. Overall, the results in Table 6 suggest that robotization affects the

[19] These findings are related to the disappearing routine job phenomenon, discussed by Cortes et al. (2020).

[20] To compute career values separately, we split the resumes in the BGT data into 2 groups: those with college and above, and those with below college education. We compute transition matrices separately for these two groups. We then merge these data with wages by occupation and state for each group and obtain a measure of career values by education at both the occupation and the local labor market levels.

career prospects of less-educated workers more, which may contribute to the widening gap between highly and less educated workers, thereby exacerbating the inequality they face in the labor market.

Table 6: Exposure to Robots and Labor Market Career Values, by Education. IV Lasso

	Occ. Composition ΔCC (1)	Career Value ΔCV (2)	Wage $\Delta CV:\ \Delta W$ (3)	Career Path $\Delta CV:\ \Delta\psi$ (4)	Career Path x Wage $\Delta CV:\ \Delta\psi \times \Delta W$ (5)	Occ. Comp. x Career Value $\Delta CC \times \Delta CV$ (6)
Panel A: Below College						
U.S. Robot Exposure '04-'16	-0.007	-0.378***	-0.218***	-0.146**	-0.014*	-0.013***
	(0.008)	(0.080)	(0.041)	(0.060)	(0.008)	(0.004)
Mean of D.V.	0.295	-0.166	1.041	-1.020	-0.187	-0.265
Mean Career Value 2004	22.749	22.749	22.749	22.749	22.749	22.749
F-stat.	0.886	45.603	82.357	8.674	3.738	7.138
Observations	722	722	722	722	722	722
Panel B: College and Higher						
U.S. Robot Exposure '04-'16	-0.002	-0.356***	-0.238***	-0.119***	0.001	-0.009***
	(0.004)	(0.033)	(0.042)	(0.022)	(0.007)	(0.002)
Mean of D.V.	0.241	-0.243	1.118	-1.176	-0.186	-0.159
Mean Career Value 2004	23.832	23.832	23.832	23.832	23.832	23.832
F-stat.	0.001	82.760	76.878	19.626	0.821	9.081
Observations	722	722	722	722	722	722
Census Division FE	Yes	Yes	Yes	Yes	Yes	Yes
A&R Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Robust standard errors are in brackets and clustered by state. All columns include census division dummies as well as controls for demographic characteristics of commuting zones in 1990 (log population; the share of females; the share of population above 65 years; the shares of Whites, Blacks, Hispanics, and Asians; the share of employment in manufacturing; the share of female employment in manufacturing; and the share of employment in light manufacturing, namely, textile industry and the paper, publishing, and printing industry). The set of controls is more parsimonious so as to avoid taking the education split and its correlates into account twice. U.S. Robot Exposure is instrumented using robot exposure in Denmark, Italy, Sweden, Finland, France, Germany, Spain and the UK in the same time periods. Observations are weighted by commuting zone population.

Heterogeneity by Experience. Table 7 replicates Table 4 with respect to heterogeneity in years of job experience. The individuals in the resume data vary in experience, with the median employee in the sample having 9 years in the workforce. We regenerate the transition matrices for four experience groups, splitting individuals into 0-5, 6-10, 11-20, and 20+ years of experience. It is important to note that the occupations held by these experience groups and the rates of transitioning across jobs may change differently due to robotization.

While all four experience groups see varying degrees of negative effects from robotization on average, we observe an inverse U-shaped pattern across the experience tiers. The workers with the least and the most experience seem more shielded from the negative career path effects of robotization.

In particular, robotization results in significant declines in career values (column 2) and wages (columns 3). While the career value decline is greater for those with mid to senior (11-20 years) of experience (-0.450), the decline is least pronounced for the lowest experience group (-0.198). Column 4, however, indicates substantial heterogeneity in the effects of robotization on career paths. While for the least experienced group, the effect is insignificant, for the most experienced workers the effect is negative but smaller in magnitude compared to individuals in the mid-experience tiers (-0.05 vs. -0.14 or -0.21). Columns (5) and (6) are provided for completeness and do not exhibit substantial variation across experience groups.

Compositions of the jobs held by the four experience groups may also vary over time and across commuting zones. A decomposition, similar to the one carried out in Table 4, shows an opposite U-shaped pattern. Those with the lowest and the highest experience individuals see an increase in the share of high-value occupations between 2004 and 2016. However, the career values of the average occupation is shrinking at a greater rate than this growth. On the contrary, the share of high-career-value occupations is shrinking for the two mid-experience tiers.

Table 7: Exposure to Robots and Labor Market Career Values, by Experience. IV Lasso

	Occ. Composition ΔCC (1)	Career Value ΔCV (2)	Wage $\Delta CV:\ \Delta W$ (3)	Career Path $\Delta CV:\ \Delta\psi$ (4)	Career Path x Wage $\Delta CV:\ \Delta\psi \times \Delta W$ (5)	Occ. Comp. x Career Value $\Delta CC \times \Delta CV$ (6)
Panel A: Experience 0 to 5 years						
U.S. Robot Exposure '04-'16	0.046***	-0.198***	-0.239***	0.002	0.039***	-0.027***
	(0.016)	(0.066)	(0.033)	(0.075)	(0.015)	(0.007)
Mean of D.V.	0.495	0.242	1.033	-0.683	-0.107	-0.392
Panel B: Experience 6 to 10 years						
U.S. Robot Exposure '04-'16	-0.026***	-0.353***	-0.191***	-0.140**	-0.022	-0.029**
	(0.010)	(0.055)	(0.038)	(0.056)	(0.017)	(0.014)
Mean of D.V.	0.533	-0.043	1.134	-0.938	-0.239	-0.723
Panel C: Experience 11 to 20 years						
U.S. Robot Exposure '04-'16	-0.028***	-0.450***	-0.249***	-0.210***	0.010	-0.016**
	(0.009)	(0.047)	(0.041)	(0.050)	(0.009)	(0.008)
Mean of D.V.	0.451	-0.300	1.184	-1.235	-0.249	-0.545
Panel D: Experience more than 20 years						
U.S. Robot Exposure '04-'16	0.012*	-0.294***	-0.241***	-0.050**	-0.003	-0.008***
	(0.007)	(0.054)	(0.047)	(0.023)	(0.008)	(0.003)
Mean of D.V.	0.268	-0.069	1.088	-1.010	-0.147	-0.242
F-stat.	1623.985	1623.985	1623.985	1623.985	1623.985	1623.985
Observations	722	722	722	722	722	722
Census Division FE	Yes	Yes	Yes	Yes	Yes	Yes
A&R Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Robust standard errors are in brackets and clustered by state. All columns include census division dummies as well as controls for demographic characteristics of commuting zones in 1990 (log population; the share of females; the share of population above 65 years; the shares of Whites, Blacks, Hispanics, and Asians; the share of employment in manufacturing; the share of female employment in manufacturing; and the share of employment in light manufacturing, namely, textile industry and the paper, publishing, and printing industry). U.S. Robot Exposure is instrumented using robot exposure in Denmark, Italy, Sweden, Finland, France, Germany, Spain and the UK in the same time periods. Observations are weighted by commuting zone population.

While we cannot test for a single mechanism for why the mid-experience tiers face more negative career value declines, the literature provides some guidance about how to think about these effects. We can speculate about two potential forces consistent with the observed numbers. Experienced workers are reported to change careers less frequently (Neal, 1999). This is partly accounted by the fact that as workers continue job search through their years of work, they will find ideal occupations and become less likely to decouple from these jobs (Kambourov and Manovskii, 2009). Less experienced workers may be more willing or flexible to part with their existing jobs and move to other occupations. This desire may partially mask the negative career path effects, even if these workers' industries are impacted by robotization.

The most senior employees may similarly face less negative career value effects, but for a different reason. If human capital is a substitute resource to machine capital, senior-most workers hold the highest and most valuable human capital and are thus the least substitutable resource to machines. At the same time, top management occupations may be disproportionately held by this tier relative to other tiers. These occupations require leadership, decision-making, supervision, and social and communication skills (Deming, 2017), for which robotization may provide an imperfect substitute. These arguments together would support a moderate career value impact observed for this group. Later, in Table 9, we will turn to the changes in individual career trajectories, interacting robotization with various occupational skills. We find that generalized (baseline) skills, which are likely to grow with experience, mitigate the negative effects of robotization on the likelihood of being demoted from managerial roles.

Heterogeneity by Gender. Next, we move along to the heterogeneity with respect to gender of the workers. Robotization may make a different impact on male and female workers because the share of men in manual and routine occupations and manufacturing industries, which are more directly impacted by robotization, is higher than that of women (United States Census Bureau, 2022).[21] Moreover, women are closing the college education gap in the labor force, as noted by the literature and in our own sample (Goldin et al., 2006). Finally, women are reported to score higher on social and emotional intelligence dimensions relative to men (Deming, 2017), which are skills not directly substitutable by robotization. These differences may contribute to the differential effects of robotization on the two genders.

Table 8 splits our sample by gender and re-calculates career values separately by deriving a transition matrix and wages for each group. We find that for men, the losses in career value are about 1.5 times that of women (column 2). More importantly, while the losses due to declining wages are significant and of similar magnitude for both genders (column 3), there is a visible difference in the occupational mobility and men appear less able to move into better-paying occupations (column 4). While the coefficient for occupational mobility is negative for women, it is not significant (-0.044); for men, it is negative and significant (-0.148). Columns (5) and (6) do not show any significant interaction effects of career value and wage or occupational composition for either group.

Individual career trajectories

In this subsection, we study the heterogeneity of the effect of robot adoption on the typical career trajectories in the individual-level regressions. Specifically, we estimate the following equation

$$Outcome_{i,(t_0,t_1)} = \beta_1 + \beta_2 RbtEU_{i,c,(t_0,t_1)} * ind_i + \beta_3 ind_i + \gamma \mathbf{Y}_i + \mu_c + \varepsilon_{i,(t_0,t_1)}, \tag{8}$$

where $RbtEU_{i,c,(t_0,t_1)}$ is a variation of the expression in (7) but instead of Lasso, we use the average robot exposure in the five European countries adopted by Acemoglu and Restrepo (2020), Denmark, Italy, Sweden, Finland and France. This is an intent-to-treat specification. Here, ind_i is a dimension of heterogeneity for i, μ_c are the commuting zone fixed effect, and $\mathbf{Y}_i$ are individual-level controls.

[21] In our sample, controlling for education and commuting zone controls, women are 7.6 p.p. less likely to work in manufacturing occupations in the period before 2006.

Table 8: Exposure to Robots and Labor Market Career Values, by Gender. IV Lasso

	Occ. Composition ΔCC (1)	Career Value ΔCV (2)	Wage $\Delta CV:\ \Delta W$ (3)	Career Path $\Delta CV:\ \Delta\psi$ (4)	Career Path x Wage $\Delta CV:\ \Delta\psi \times \Delta W$ (5)	Occ. Comp. x Career Value $\Delta CC \times \Delta CV$ (6)
Panel A: Female						
U.S. Robot Exposure '04-'16	0.000	-0.242***	-0.203***	-0.044	0.005	-0.004
	(0.006)	(0.057)	(0.039)	(0.045)	(0.007)	(0.004)
Mean of D.V.	0.423	-0.119	1.051	-0.989	-0.181	-0.105
F-stat.	1623.985	1623.985	1623.985	1623.985	1623.985	1623.985
Observations	722	722	722	722	722	722
Panel B: Male						
U.S. Robot Exposure '04-'16	0.000	-0.357***	-0.216***	-0.148***	0.008	-0.004
	(0.006)	(0.061)	(0.045)	(0.044)	(0.010)	(0.005)
Mean of D.V.	0.509	-0.386	1.141	-1.304	-0.223	-0.260
F-stat.	1623.985	1623.985	1623.985	1623.985	1623.985	1623.985
Observations	722	722	722	722	722	722
Census Division FE	Yes	Yes	Yes	Yes	Yes	Yes
A&R Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Robust standard errors are in brackets and clustered by state. All columns include census division dummies as well as controls for demographic characteristics of commuting zones in 1990 (log population; the share of females; the share of population above 65 years; the shares of Whites, Blacks, Hispanics, and Asians; the share of employment in manufacturing; the share of female employment in manufacturing; and the share of employment in light manufacturing, namely, textile industry and the paper, publishing, and printing industry). U.S. Robot Exposure is instrumented using robot exposure in Denmark, Italy, Sweden, Finland, France, Germany, Spain and the UK in the same time periods. Observations are weighted by commuting zone population.

Note that here, we switch to the reduced form specification due to the inclusion of the interaction terms. While this estimation is conceptually similar to the IV specification, it is necessary to obtain precise estimates of the interaction term here.[22]

Table 9 contains the results from this specification for promotions to and demotions from management roles (based on 2-digit SOC codes) for subjects with employment data for both 2004 and 2016. We focus on management roles because these roles span a variety of positions requiring decision-making authority and supervision, almost universally exist in all industries and firms, and movements into such positions is a typical vertical transition. Specifically, a promotion is recorded if an individual does not have an occupation classified under the management code before 2006 but has one defined as such at some point between 2014 and 2018. Similarly, a demotion is recorded for an individual if they had a management occupation before 2006, but no longer held the occupation in or after 2014. Note that the commuting zone FEs absorb the average effect of the robot adoption shock, such that the table only shows the interaction terms that capture the differences in effect between demographic groups.

For promotions to management roles, we observe that in regions with higher degrees of robotization, promotions are more likely to be observed for people with more work experience (column 2). This finding is consistent with Dixon et al. (2021), who report fewer managerial roles in firms facing greater levels of automation. While work experience is a useful skill for moving to managerial roles, if such opportunities are shrinking in regions with higher levels of robotization, they may be allocated to those with higher levels of experience. The table also shows that people in regions with greater robotization are more likely

[22] These results are robust to using different sets of countries.

to get promoted to management roles if they hold baseline and software skills (columns 4 and 5), while people with specialized skills see a lower likelihood of promotion (column 6).

Looking at demotions in Panel B shows a different pattern. We find that individuals with higher levels of education were less likely to be demoted (column 1), consistent with the results from Table 6 where we show less negative effects of robotization for those with higher levels of education. Female workers were more likely to be demoted from management roles in regions that saw higher degrees of robotization (column 3). While this finding may seem to contradict those from Table 8, where we show less negative effects of robotization for women, this is not necessarily the case. The two tables together may suggest different and heterogeneous effects of robotization for men and women. While compared to men, women suffer less from career value losses with robotization when *all* occupations are considered, focusing on management roles, they are at a greater disadvantage and experience greater downward mobility out of management roles.

Table 9: Promotion and Demotion from Management: Interaction Terms

Panel A: Promotion	(1)	(2)	(3)	(4)	(5)	(6)
EU Instrument '04-'16 × Above College degree before 2006	0.0014					
	(0.0017)					
EU Instrument '04-'16 × Years of Experience in 2004		0.0004***				
		(0.0002)				
EU Instrument '04-'16 × Female			-0.0019			
			(0.0011)			
EU Instrument '04-'16 × Has a baseline skill				0.0014***		
				(0.0005)		
EU Instrument '04-'16 × Has a software skill					0.0021**	
					(0.0009)	
EU Instrument '04-'16 × Has a specialized skill						-0.0110***
						(0.0025)
Observations	2,640,823	2,640,823	2,640,823	2,602,991	2,602,991	2,602,991
R-squared	0.0034	0.0096	0.0034	0.0043	0.0033	0.0034
Panel B: Demotion						
EU Instrument '04-'16 × Above College degree before 2006	-0.0029*					
	(0.0016)					
EU Instrument '04-'16 × Years of Experience in 2004		0.0000				
		(0.0001)				
EU Instrument '04-'16 × Female			0.0040***			
			(0.0015)			
EU Instrument '04-'16 × Has a baseline skill				-0.0029*		
				(0.0015)		
EU Instrument '04-'16 × Has a software skill					-0.0013	
					(0.0012)	
EU Instrument '04-'16 × Has a specialized skill						0.0056
						(0.0118)
Observations	2,132,878	2,132,878	2,132,878	2,104,468	2,104,468	2,104,468
R-squared	0.0078	0.0083	0.0078	0.0077	0.0087	0.0077
Commuting Zone FE	Yes	Yes	Yes	Yes	Yes	Yes
Main Effect Included	Yes	Yes	Yes	Yes	Yes	Yes

Notes. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Robust standard errors are in brackets and clustered by state. All columns include commuting zone FE, controls at the individual level by gender, and having an above-college degree before 2006. The EU instrument is the average robot exposure in Denmark, Italy, Sweden, Finland and France during 2004-2016. All columns include the main effect of the interacted variable.

We explore these findings further in Table 10 by exploiting the fact that our resume data also allows us to observe the year in which education was obtained. In column 3, we find that females are significantly more likely to pursue schooling and obtain education, measured as completion of any educational degrees, in response to robot adoption. This may explain why, despite being more likely to be demoted from managerial roles, women experience a smaller decline in career values. Moreover, we observe that individuals who already possess higher levels of education are less likely to pursue additional education (column 1), possibly due to fewer opportunities for further advancement. Finally, we find that the effect of robot adoption on educational attainment is stronger for those with specialized skills (column 6). This finding is consistent with those in Table 9, where specialized skills were an impediment to workers' advancement into managerial roles. Additional education may help these workers broaden their skill sets from specialized to generalized ones to help increase their mobility in the labor market.

Putting the findings from the last three tables together, we see that while men's aggregate career paths suffer more due to robotization, the story at the individual level is more complex, with women facing specific downward pressures from management roles that they appear to counteract through greater investment in their educational capital.

Table 10: Attainment of Educational Degrees: Interaction Terms

Panel A: Get Any Education	(1)	(2)	(3)	(4)	(5)	(6)
EU Instrument '04-'16 × Above College degree before 2006	-0.0027**					
	(0.0010)					
EU Instrument '04-'16 × Years of Experience in 2004		-0.0000				
		(0.0001)				
EU Instrument '04-'16 × Female			0.0038***			
			(0.0013)			
EU Instrument '04-'16 × Has a baseline skill				-0.0006		
				(0.0009)		
EU Instrument '04-'16 × Has a software skill					0.0005	
					(0.0007)	
EU Instrument '04-'16 × Has a specialized skill						0.0060**
						(0.0025)
Observations	4,773,713	4,773,713	4,773,713	4,707,472	4,707,472	4,707,472
R-squared	0.0059	0.0201	0.0059	0.0067	0.0068	0.0060
Commuting Zone FE	Yes	Yes	Yes	Yes	Yes	Yes
Main Effect Included	Yes	Yes	Yes	Yes	Yes	Yes

Notes. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Robust standard errors are in brackets and clustered by state. All columns include commuting zone FE, controls at the individual level by gender, and having an above college degree before 2006. The EU instrument is the average robot exposure in Denmark, Italy, Sweden, Finland and France during 2004-2016. All columns include the main effect of the interacted variable.

In appendix Table A.10, we look at the effects of robotization on outcomes of promotions to management (Panel A) and demotions from management (Panel B), interacting robotization with job experience categories (10 years or less as the base category, 11-20 year and 20+ years), age categories (25 and younger as the base category, 26-40 and 40+), and the amount of training and preparation a job requires as classified by ONET, scaled from 1 to 5, with 5 (extensive preparation) requiring the highest amount of training and experience for the occupation. Panel A column (1) indicates that those with 11-20 years of experience see more promotions with robotization. Columns (2) and (3) indicate that, individuals above 25 or with jobs that require greater levels of training are more likely to see promotions to management roles with greater levels of robotization. Panel B shows few effects, but is generally consistent with Panel A. In column (3), we see that those with jobs requiring higher levels of preparation are less likely to be demoted as individuals when they are located in a region more exposed to robotization.

Robot Adoption and Inequality in Career Values Here, we further study the implications of robot adoption for the inequality in career values. More specifically, to compute different measures of inequality, we take all of our subjects with resumes and align them on the horizontal axis from the smallest to the largest, thus computing a predicted Lorenz curve. After that, we can compute different percentile measures of inequality in career values. Table 11 shows that higher robot exposure led to a significant positive change in the inequality in career values between 2000 and 2016, when comparing career values at the 75th percentile to those at the 25th percentile or at the 90th percentile to those at the 50th or 10th percentile. This effect seems to be concentrated in the upper part of the distribution. These findings are consistent with those from Acemoglu and Restrepo (2022), which state that automation is a significant source of growing wage inequality in the U.S. Our findings show that the effects of robotization are not only confined to growing wage inequality but also extend to inequality in occupational-mobility opportunities.

Table 11: Robot Adoption and Inequality in Career Values. IV Lasso

	Ratio of Career Values in 2016 for Percentiles			
	50 over 10	75 over 25	90 over 50	90 over 10
	(1)	(2)	(3)	(4)
U.S. Robot Exposure '04-'16	-0.001	0.004***	0.010***	0.010***
	(0.001)	(0.001)	(0.003)	(0.003)
Mean of D.V.	1.212	1.278	1.309	1.588
F-stat.	0.016	12.888	30.388	22.448
Inequality Measure '00	Yes	Yes	Yes	Yes
Census Division FE	Yes	Yes	Yes	Yes
A&R Controls	Yes	Yes	Yes	Yes
Observations	722	722	722	722

Notes. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Robust standard errors are in brackets and clustered by state. All columns include census division dummies as well as controls for demographic characteristics of CZs in 1990 identical to those in Acemoglu and Restrepo (2020) (log population; the share of females; the share of population above 65 years; the shares of population with no college, some college, college and professional degrees, and masters and doctoral degrees; the shares of Whites, Blacks, Hispanics, and Asians; the share of employment in manufacturing; the share of female employment in manufacturing; and the share of employment in light manufacturing, namely, textile industry and the paper, publishing, and printing industry). We control for the corresponding inequality measure in 2000 which is constructed similarly to the dependent variable; it is the ratio of the career values at different percentiles in the year 2000. U.S. Robot Exposure is instrumented using robot exposure in Denmark, Italy, Sweden, Finland, France, Germany, Spain and the UK in the same time periods. Robust standard errors are clustered by state. The dependent variables are the ratios of the career values of different occupations within a labor market at different percentiles. Observations are weighted by commuting zone population.

5 Career Values and Long-term Decisions of Individuals

Results in sections 4 suggest that automation affects future mobility and expected lifetime incomes. The decline in career values in a region can, on the one hand, motivate a desire to re-skill or obtain further training to start at a better-paying occupation and recover expected losses. On the other hand, better opportunities for upward transitions and better returns to education overall can increase people's willingness to undertake long-term investments in places with higher career values. To test which of these effects prevails, in what follows, we estimate the causal effects of expected career values, our measure of expected lifetime income, on schooling, housing, and voting.

Assessing the effect of a change in career values on these outcomes requires a different identification strategy than the one we introduced in Section 4. Here, to identify the effect of career values on college education, housing permits, and voting, we employ a different instrumental variables strategy because career values are an outcome of robotization. Specifically, we instrument the average market career values of a CZ using the career values from sufficiently similar but distant communities. We focus on the communities that are in states outside a 100-mile radius around the commuting zone of interest. That is, we are instrumenting for local career values using information from outside a 'donut' around the area of interest that is plausibly exogenous with regard to idiosyncratic local labor market shocks.

For each occupation-by-CZ cell, we compute the unweighted mean $\widehat{C_{o,s,t}^{c+100m}}$ of the predicted career values for the same occupation in sufficiently distant states, where s indexes states other than those containing CZ c, and the superscript indicates observations more than 100 miles from zone c. In the next step, using the local employment shares in each CZ, we aggregate these predicted career values into predicted labor market career values $\widehat{\text{LMCV}_{c+100m,t}}$ for each CZ that use only wage levels and the resulting career values in *other states'* commuting zones.

The first-stage equation is then given by:

$$\Delta\text{LMCV}_{c,t_1,t_0} = \alpha_0 + \alpha_1 \widehat{\Delta\text{LMCV}_{|c+100m|,t_1,t_0}} + \alpha_2 X_{t_0} + \varepsilon_{t_1,t_0}$$

where $\Delta LMCV_{c,t_1,t_0}$ is the actual change in the local market career value of CZ c between year t_0 and t_1. We use the predicted local market career values in the 2SLS estimation for long-term outcomes and find that an increase in career values is predictive of investment in college education, housing, and voting, as detailed next.

First, we consider the effect of career values on education. The choice to invest in higher education (here defined as obtaining a college degree) is affected by the local returns to human capital, which are likely positively impacted by higher career values.

Second, we look at how career values affect housing investment. Expectations about future employment and earnings may influence long-term financial investment decisions, which can influence household demand for housing. Moreover, higher career values might affect beliefs about future housing demand. In what follows, we look at the logged housing construction permits times 100 per capita (based on 2000 population) and investigate their association to career values.

Next, we examine political behavior by testing for shifts in voting. The decline in career values and, overall, worsened opportunities for upward mobility can lead to a higher probability of voting for populist candidates. For instance, Panunzi et al. (2020) argue that unmatched expectations make people more risk-loving and more willing to support populist candidates like Donald Trump. Furthermore, Guiso et al. (2017) and Di Tella and Rotemberg (2018) argue that income loss and feelings of betrayal can generate anti-elite preferences and, as a consequence, higher support for more populist candidates.

Table 12 summarizes these results, with the first stage reported in column (1). As shown in columns (3), (5), and (7), career values have significant effects on long-term decisions in the predicted direction. Columns (2), (4), (6) report the results for OLS estimation for comparison. Numerically, higher career values led to a higher share of people obtaining education over the corresponding time period, with one standard deviation increase in career values leading to a 1.08 p.p. increase in the share of those getting higher education. In a similar vein, the coefficient in column (5) implies that a one standard deviation increase in career values led, on average, to a 22.8% increase in the number of new housing permits per capita.[23] Columns (6) and (7) demonstrate that in regions where the local market career values were lower, Trump vote shares were higher in the 2016 Presidential Election, controlling for the GOP vote share in the 2012 Presidential Election. Numerically, one standard deviation increase in career values led to a 0.67 p.p. decrease in Trump's vote share in 2016.

Table 12: Career Value Effects on Change in College Education, Housing Permits per Capita, and Voting

	Δ LMCV, 04-16	Δ College % 00-15		Δ ln(Housing Permits p.c.)		GOP Vote Share 2016	
	First-Stage	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Predicted Δ LMCV '04-'16	3.485***						
	(0.308)						
Δ LMCV '04-'16		0.303***	0.714***	7.219***	13.602***	-0.061	-0.445**
		(0.068)	(0.136)	(2.074)	(4.683)	(0.129)	(0.227)
Mean of D.V.	-0.238	4.805	4.805	-68.623	-68.623	65.368	65.368
KP F-stat.			128.331		126.873		129.536
R-Squared	0.570	0.586	0.527	0.296	0.277	0.982	0.982
Census Division FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
A&R Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
GOP Vote Share 2012						Yes	Yes
Observations	722	722	722	669	669	722	722

Notes. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Robust standard errors are in brackets and clustered by state. All columns include census division dummies as well as controls for demographic characteristics of commuting zones in 1990 identical to those in Acemoglu and Restrepo (2020) (log population; the share of females; the share of population above 65 years; the shares of population with no college, some college, college and professional degrees, and masters and doctoral degrees; the shares of Whites, Blacks, Hispanics, and Asians; the share of employment in manufacturing; the share of female employment in manufacturing; and the share of employment in light manufacturing, namely, textile industry and the paper, publishing, and printing industry). Columns (6) and (7) also include the share of votes won by the Republican candidate in the 2012 Presidential elections as a control. The change in local market career values is instrumented using the mean change in local market career values in commuting zones farther than 100 miles. Observations are weighted by commuting zone population.

6 Conclusion

In this study, we document changes in the growth of career values between 2000 and 2016. Career values are a projection of one's ability to move across occupations and earnings potential, and as such, capture a longer-term view of one's economic future. We find that the average local labor market career value grew

[23]To get this number, we multiplied the coefficient, 13.602 with one standard deviation of career values change, 1.51. Noting that the dependent variable was scaled by 100 and is a log change, we derive the result exp(13.602*1.51/100) - 1= 0.224 = 22.8%.

by $2,100 between 2000 and 2008, which corresponds to a 0.9% increase relative to the average expected lifetime career value in 2000, compared to a $200, or a 0.09%, decline in the local market career values between 2008 and 2016. Wage growth slows on average, but an important factor in the stalling of the growth of career values is reduced upward occupational mobility. The reduction in career value due to the reduced upward mobility (holding wages constant) was as large as $12,500 between 2000 and 2016.

We test and show that automation and robotization are contributing factors to the reduced growth of career values. We find that a one unit increase in the number of robots per 1000 workers decreases career values by $3,360, or 1.45% of the average career values in 2000. The negative effects of automation are concentrated in the manufacturing-intensive local markets. Low-skilled workers suffered more from robot adoption, with their opportunities for upward mobility declining the most.

In recent years, artificial intelligence (AI) technologies were also on the rise. Our identification strategy does not allow us to study the effects of AI precisely. However, based on what we learn about robots, we hypothesize that as some white-collar jobs get replaced by AI, it would exacerbate inequality, diminish upward transitions due to reduced demand for middle level managers, and erode the middle class.

Overall, our findings highlight that it is essential to think about the effects of automation from a broader perspective—looking beyond directly affected industries and beyond workers' immediate occupations. Automation and robotization affect both workers' wages and occupational mobility, and expectations regarding future wages and mobility may influence individuals' long-term investments, perceptions, and political behaviors today. Our study documents these effects.

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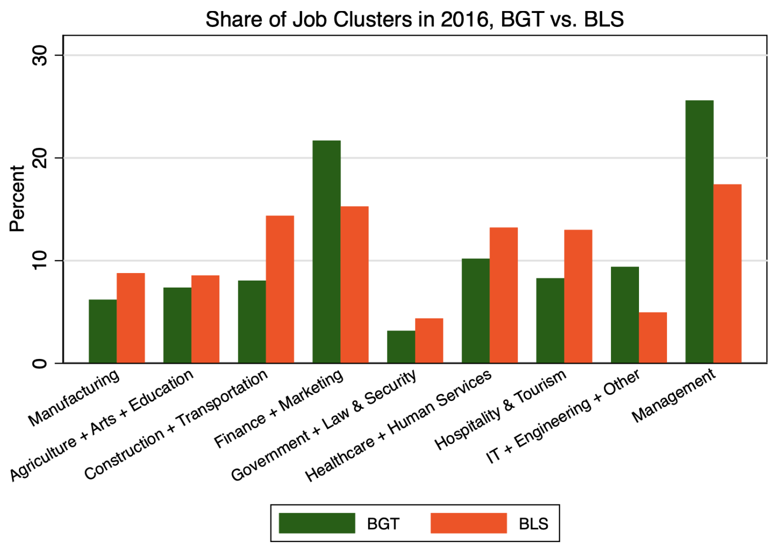
A ONLINE APPENDIX: Additional Figures & Tables (Not for Publication)

A.1 BGT Data Characteristics

FigureA.1 plots the share of occupations in different industries listed in the Burning Glass Technologies sample vs. the shares reported by the Bureau of Labor Statistics (BLS).

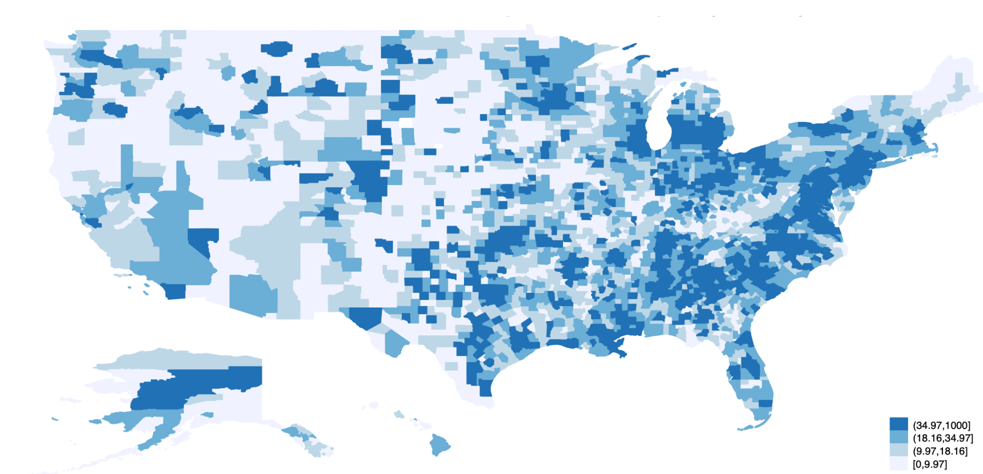
Figure A.2 maps the shares of resumes per 100 people in each county in the BGT data for the period between 2004 and 2016.

Figure A.1: Comparison of BGT and Bureau of Labor Statistics Share of Occupations



Notes. Figure represents the share of occupations in various industries in the Burning Glass Technologies sample vs. the shares reported by the Bureau of Labor Statistics (BLS) in 2016.

Figure A.2: Density of Resumes in BGT Data per County



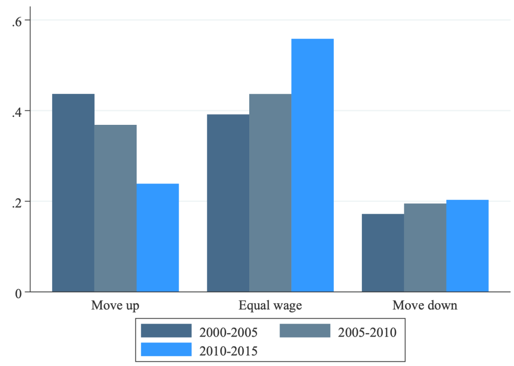
Notes. The figure represents the share of resumes in the BGT dataset per 100 people in each county. County population data is obtained from American Community Survey 5-yearly estimates. Only candidates with a job between 2004 and 2016 are plotted in the figure.

A.2 Occupational Transitions

Figure A.3 replicates Figure 1, but conditions the sample on workers who change occupations during the time period.

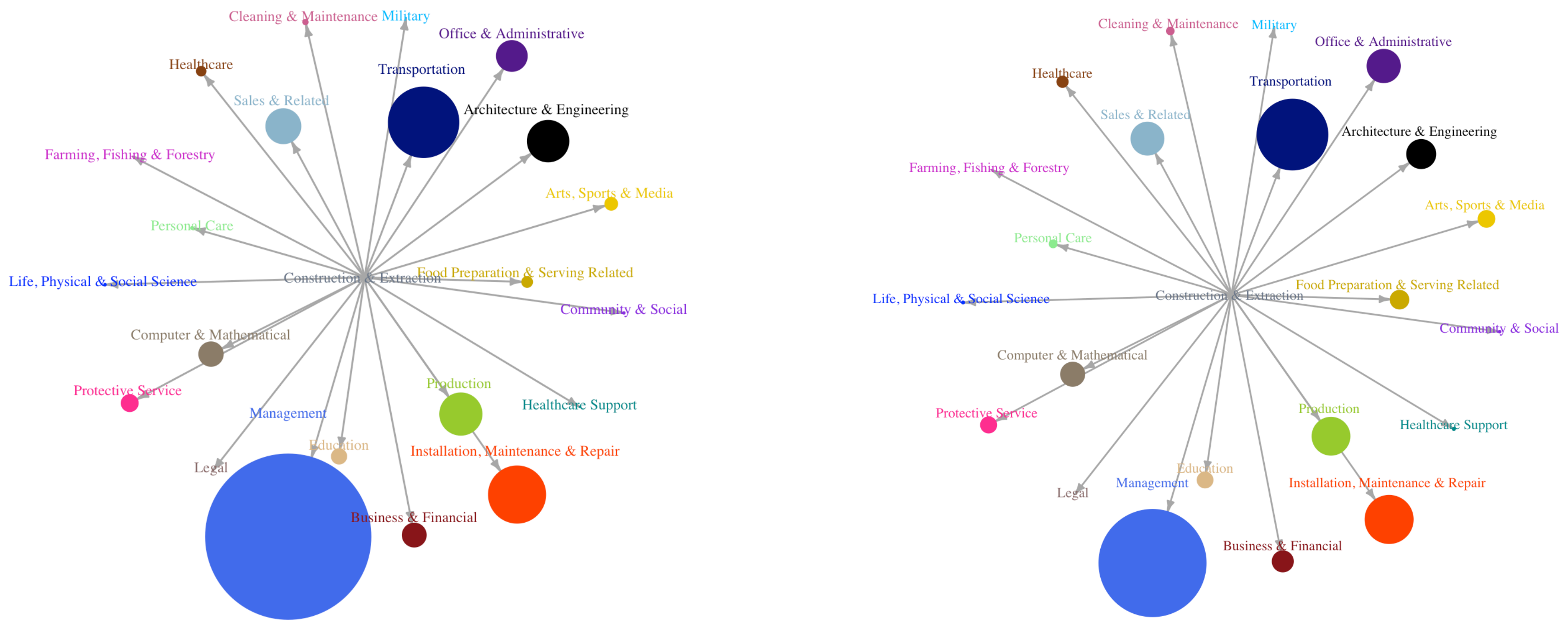
Figures A.4 and A.5 replicate Figure 3 of the paper for construction and installation occupations, respectively, based on the BGT sample.

Figure A.3: 5-year Transitions to Better- / Worse-Paid Jobs by Time Period, Conditional on Changing Occupations



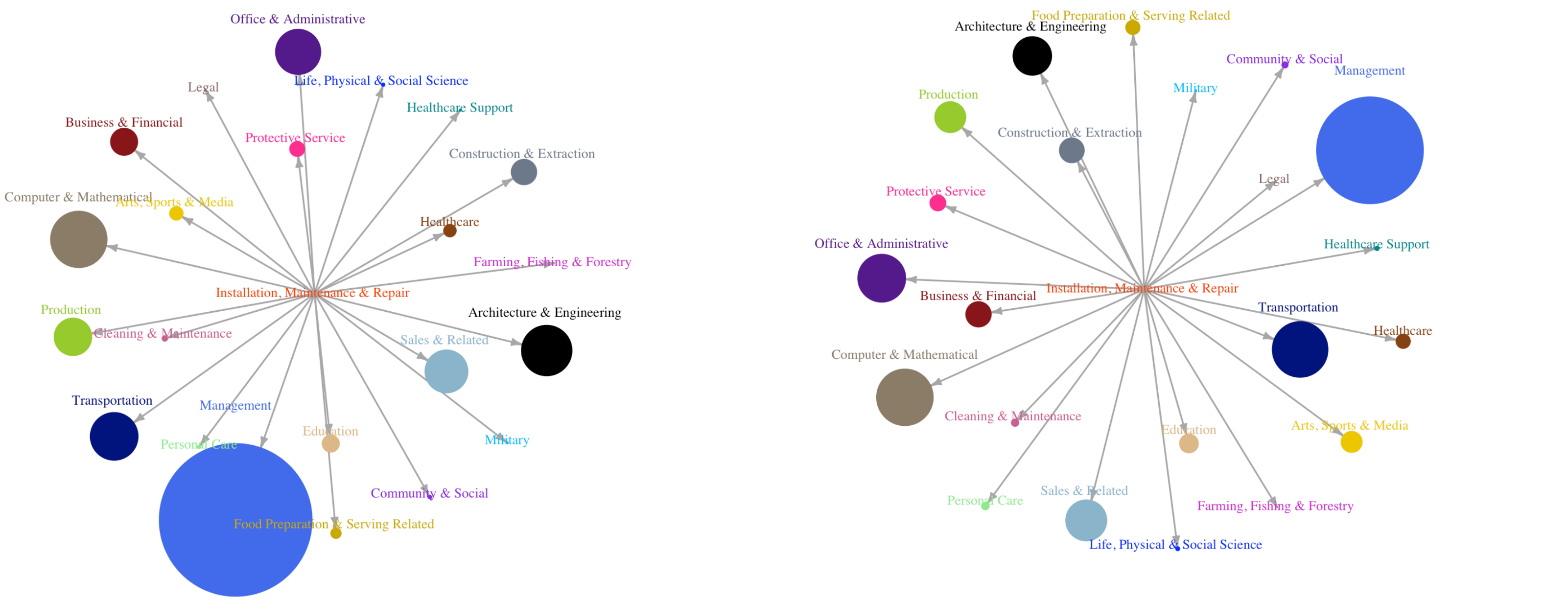
Notes. The figure depicts the share of all workers in our resume sample that transition to better-paid, worse-paid, and (approximately) equal-pay jobs over 5-year time periods between 2000 and 2015—among workers who changed 6-digit SOC 2010 occupations during this time period. We define a move up in wages as a 10% or larger increase in real wages for the occupation-by-state that the employee is in between the first year of the period and the last year. Analogously, a move down is a 10% or larger decrease in real wages over the time period, and "equal wage" indicates a change in real wages that does not exceed either threshold. The shares are computed as a percentage of all workers in the sample in both the beginning and the last year of each period where the end year occupation is different from the beginning year occupations.

Figure A.4: Occupational Transitions From Construction Occupations, 2004 vs 2016



Notes. The figures show the normalized probabilities of transitioning from construction occupations to various other occupation groups. The left figure demonstrates the transitions for 2004 and the right figure demonstrates the transitions for 2016. The size of each bubble indicates the likelihood of transition to the labeled occupation group. Normalized occupational transition probabilities are transition probabilities divided by the probability of occupational transition for the whole sample in that year.

Figure A.5: Occupational Transitions From Installation Occupations, 2004 vs 2016



Notes. The figures show the normalized probabilities of transitioning from installation occupations to various other occupation groups. The left figure demonstrates the transitions for the year 2004 and the right figure demonstrates the transitions for 2016. Size of each bubble indicates the likelihood of transition to the labeled occupation group. Normalized occupational transition probabilities are transition probabilities divided by the probability of occupational transition for the whole sample in that year.

A.3 Comparison Between BGT and Current Population Survey (CPS) Data

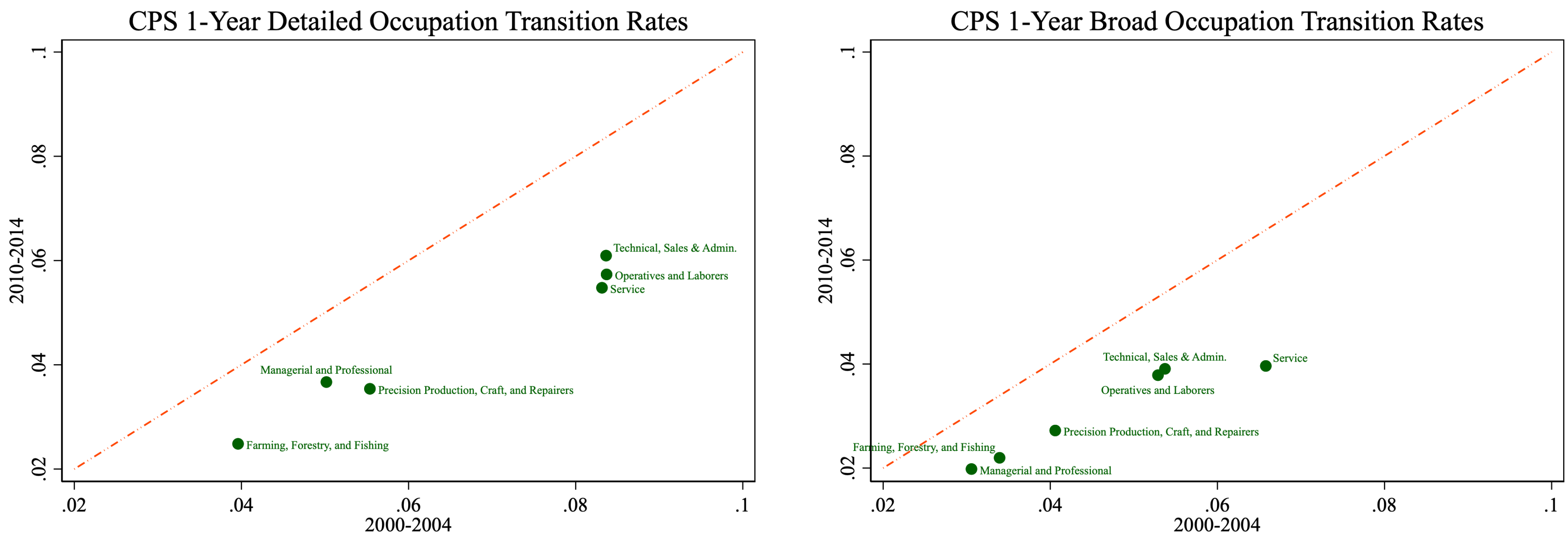
While occupational mobility measurement in the CPS data by the Bureau of Labor Statistics has its own issues related to spurious job changes as a result of measurement error and imputation in the occupational coding (Moscarini and Thomsson, 2007; Kambourov and Manovskii, 2013), we are not interested in matching the level of mobility but rather the overall downward trend over time. We focus on retrospective measures of occupational mobility at a 1-year horizon in the biannual Employee Tenure and Occupational Mobility Supplement, which better captures mobility trends than linking individual responses from the monthly survey over time (Vom Lehn et al., 2022). We limit the sample to male workers, aged 20-64, who are employed at the time of the survey and use harmonized 1990 occupation codes provided by IPUMS-CPS. Figure A.6 compares the changes between the early 2000s and 2010s in the 1-year occupational mobility out of detailed occupations, as well as out of aggregated broad occupation groups, averaged for different broad occupation groups. Moreover, Appendix Figure A.7 shows the trends over time of the national average for these mobility measures. Appendix Figure A.8 shows how the national average mobility rates compare between 5-year periods.

Note that these 1-year CPS mobility rates are not directly comparable to 5-year mobility for a number of reasons: (1) 5-year mobility changes can be affected by changes in the *sequence* of moves which are driven by how worker career changes are correlated over time. (2) CPS occupational mobility measures require a worker to have a job at the survey dates that are compared, as occupation codes are associated with current employment. This means, for example, that career sequences that include intermittent unemployment, e.g. as a result of an automation-related job loss, would be difficult to measure in the CPS, as both the transition into unemployment, and the transition to a different occupation out of unemployment might be missed by the job-to-job occupational mobility measure.

To compute the CPS analogue of Figure 1, we need occupation information and wage data which is not contained in the retrospective survey supplements: instead, we use the basic monthly survey for March of each year and IPUMS provided links between individual respondents over time. With the same demographic sample restrictions as before, we record the differences in harmonized occupation codes between surveys one year apart. Moreover, we assign each worker a predicted wage based on the year's average real wage in each occupation in CPS data, in order to approximate the fact that we are assigning predicted wages in the BGT data based on occupation-by-state wage averages.

Figure A.9 demonstrates the transitions to occupations at higher/similar/lower real wage levels using this CPS data. In order to make this figure more comparable to the 5-year real wage change thresholds applied in the BGT data in Figure 1, we define real wage thresholds for "moving up" and "moving down" in the 1-year mobility data as exceeding a threshold of positive or negative 2% real wage growth. Overall, these results confirm that the mobility trends in the resume data are qualitatively very similar to those in the nationally representative CPS data.

Figure A.6: Probabilities of Transition Out of Occupations in the CPS

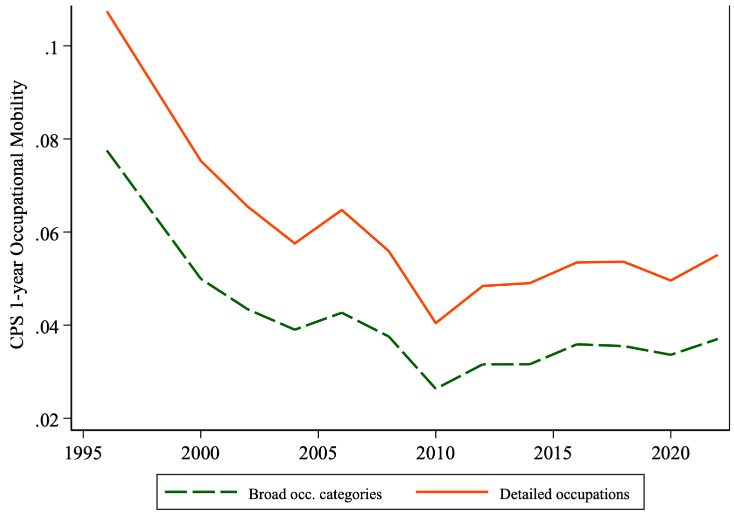


(a) Detailed occ. mobility

(b) Broad occ. group mobility

Notes. Figure shows 1-year occupational mobility measured in CPS Employee Tenure and Occupational Mobility Supplement data among male workers age 20-64 who are employed at the time of the survey for both transitions out of detailed harmonized 1990 Census occupations (left panel), as well as between broad occupation groups (right panel). The mobility rates are averaged by broad occupation groups for better visibility in the graph. The bottom axis averages mobility rates in 2000, 2002, and 2004, and the vertical axis for 2010, 2012, and 2014. The red line in each graph indicates the 45 degree line corresponding to no change in mobility between time periods.

Figure A.7: Occupational 1-year mobility in Current Population Survey data

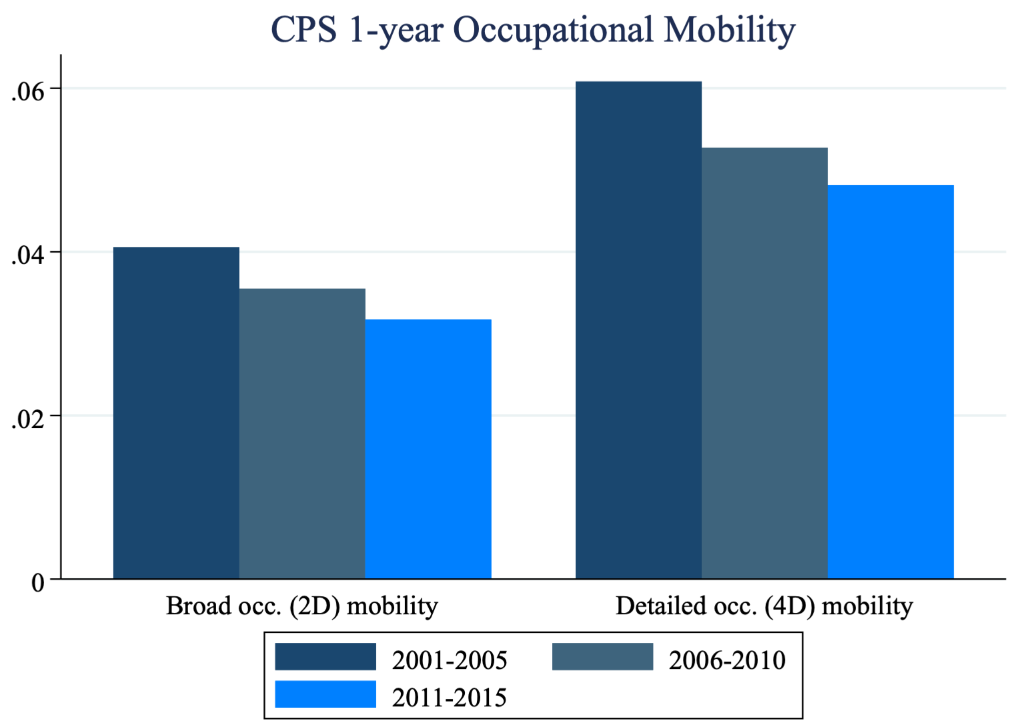


Notes. Figure shows 1-year occupational mobility measured biannually in the CPS Employee Tenure and Occupational Mobility Supplement among male workers age 20-64 who are employed at the time of the survey for both transitions out of detailed harmonized 1990 Census occupations, as well as between broad occupation groups.

A.4 Career Values and Automatability of Occupations

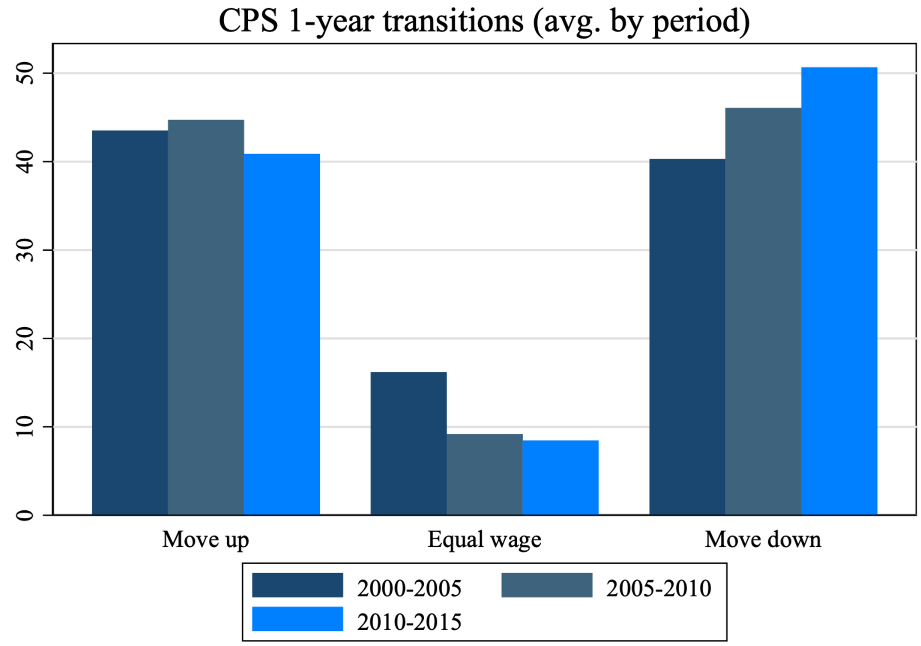
Figure A.10 displays the correlation between the change in career values of occupations between 2000 and 2016 calculated based on the BGT data and the automatability score of the occupation from Frey and Osborne (2017).

Figure A.8: Occupational 1-year mobility in CPS data: 5-year period averages



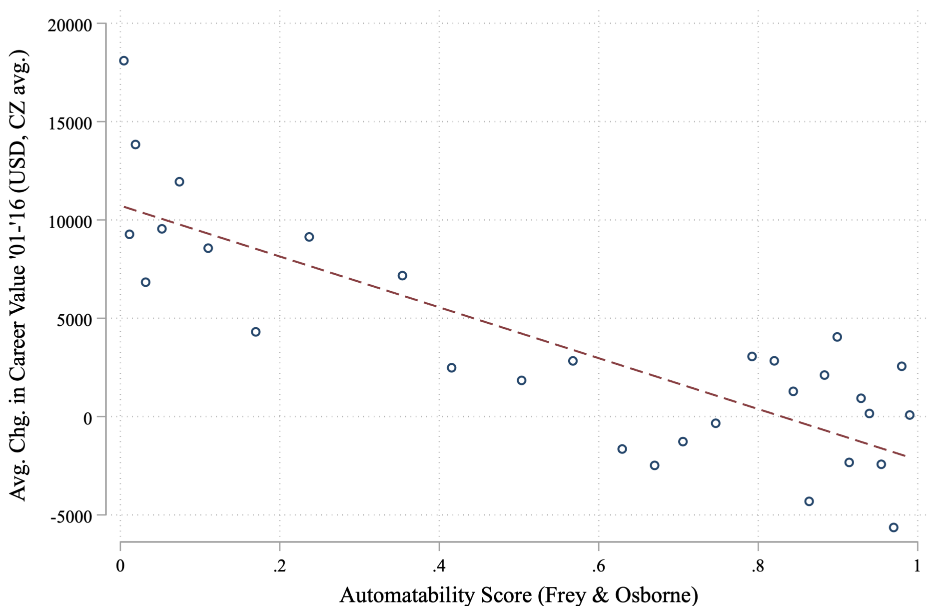
Notes. Figure shows 1-year occupational mobility measured biannually in the CPS Employee Tenure and Occupational Mobility Supplement among male workers age 20-64 who are employed at the time of the survey for both transitions out of detailed harmonized 1990 Census occupations, as well as between broad occupation groups. The bars average the 1-year mobility shown in Figure A.7 over non-overlapping 5-year periods 2001-2005, 2006-2010, 2011-2015.

Figure A.9: 1-year Transitions to Better-/Lower-Paid Jobs in CPS data, Avg. by Time Period



Notes. Figure shows the probability in % that predicted real hourly wages for a worker increase by more than 2% (left), decline by more than 2% (right), or experience a smaller absolute change (middle) at a 1-year horizon in longitudinally linked CPS March Surveys. The sample consists of male workers age 20-64 who are employed at the time of the survey. Predicted real wages are computed as the real wage average for each occupation-by-year cell in the CPS.

Figure A.10: Career Values vs Frey and Osborne Automatability Score, by 2-digit SOC



Notes. The figure depicts the correlation between the change in career values of occupations between 2000 and 2016 and the automatability score of the occupation based on Frey and Osborne (2017), which calculates the susceptibility of occupational groups to automation (computerization) based on machine learning tools. Career values are derived based on the methodology described in Section 3.1.

Additional Tables

A.5 Summary statistics

Table A.1: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max	P25	P75
Δ Local Market Career Values ('000), 04-08	741	-.113	1.088	-4.212	3.857	-.815	.616
Δ Local Market Career Values ('000), 04-16	741	-.202	1.519	-4.990	4.224	-1.237	.747
Δ Local Market Career Values ('000), 08-16	741	-.089	1.254	-3.322	3.487	-.973	.737
Automation Shock US, 04-08	722	.583	.609	.053	5.286	.218	.733
Automation Shock US, 04-16	722	1.419	1.132	.195	9.033	.659	1.837
Automation Shock US, 08-16	722	.836	.542	.136	3.747	.438	1.085
Automation Shock Denmark, 04-16	722	2.228	1.897	-1.291	13.901	.973	3.077
Automation Shock Sweden, 04-16	722	1.475	.736	-1.029	4.967	.972	1.773
Automation Shock Italy, 04-16	722	.569	.781	-6.180	4.981	.290	.871
Automation Shock France, 04-16	722	.311	.315	-3.224	1.038	.230	.437
Automation Shock Finland, 04-16	722	.374	1.722	-5.170	20.617	-.205	.511
Automation Shock Germany, 04-16	722	.846	1.298	-2.243	13.658	.315	6.187
Automation Shock Spain, 04-16	722	.790	.393	.191	2.230	.466	1.018
Automation Shock UK, 04-16	722	.465	.216	.111	1.142	.288	.592
Female Share, 1990	722	.511	.009	.477	.544	.505	.517
Hispanic Share, 1990	722	.057	.118	.001	.939	.006	.046
White Share, 1990	722	.871	.12	.371	.993	.801	.966
Black Share, 1990	722	.076	.116	0	.615	.004	.086
Asian Share, 1990	722	.022	.049	0	.591	.003	.016
High School Degree, 1990	722	.619	.081	.349	.821	.574	.675
College Degree, 1990	722	.101	.031	.039	.233	.078	.118
Master Degree, 1990	722	.032	.012	.014	.106	.024	.038
Above 65 years, 1990	722	.136	.028	.059	.301	.118	.154
Log of population, 1990	722	11.468	1.574	7.155	16.479	10.487	12.478
Manufacturing Share, 1990	722	.224	.104	.043	.554	.139	.292
Female Share in Manufacturing, 1990	722	.077	.047	.014	.245	.041	.102
Light Manufacturing Share, 1990	722	.054	.05	.003	.433	.02	.063
Automation Shock China, 90-07	722	2.947	2.855	-.112	27.958	.91	4.144
Vote share of McCain, 2008	726	56.873	13.048	19.798	90.076	48.007	66.271
Vote share of Romney, 2012	726	60.015	13.986	20.494	91.281	50.307	70.585
Vote share of Trump, 2016	726	65.178	14.922	20.093	95.051	54.936	76.961
18+ school attendance in 2000	722	.067	.025	.033	.249	.05	.075
College rate, 2000	722	.123	.039	.056	.301	.095	.142
Intergenerational mobility, Chetty et al., causal impact of neighborhoods	718	.025	.435	-1.38	1.431	-.29	.28
Wage Change, High School Degree, 2000-2015	722	1.016	1.132	-2.095	5.025	.255	1.577
Wage Change, Some College Degree, 2000-2015	722	1.148	1.305	-2.363	5.928	.301	1.825
Wage Change, College Degree, 2000-2015	722	2.411	1.763	-3.396	7.842	1.264	3.487
Wage Change, Master Degree, 2000-2015	722	2.554	2.550	-6.463	11.294	.860	4.139
Empl. Change, High School Degree, 2000-2015	722	-3.644	2.011	-9.945	2.471	-4.958	-2.258
Empl. Change, Some College Degree, 2000-2015	722	1.381	1.256	-3.002	6.909	.605	2.325
Empl. Change, College Degree, 2000-2015	722	1.411	.844	-1.276	4.216	.829	1.920
Empl. Change, Master Degree, 2000-2015	722	.887	.488	-.417	2.832	.513	1.200
Δ ln(Housing Permits per Capita), 2004-2016	669	-68.623	78.411	-419.580	464.491	-110.124	-33.767
Housing Permits per Capita, 2004	702	.0057	.0059	0	.0447	.0017	.0078
Housing Permits per Capita, 2016	703	.0027	.0026	0	.0211	.0009	.0036
Housing Permits, 2004	719	2875.497	7483.302	0	89,947	74	2085
Housing Permits, 2016	718	1678.862	4636.871	0	44672	42	1120

A.6 Career Value Decomposition and Occupational Changes: Own vs. Other Occupations

Table A.2 decomposes the changes in career value into occupational mobility and wage change expectations for an employee's current (own) occupation and other occupations. Higher automation exposure lowers lifetime earnings from both one's own career (column 1) and career in other occupations (column 5). Moreover, the decline in career mobility is coming mostly from other future occupations (column 7).

Table A.3 summarizes the effect of robotization on the change in the probability of moving away from particular types of occupations conditional on moving away from any occupation. We map occupations to classifications as in Autor et al. (2003), based on manual (column 1) vs. cognitive (column 2) and non-routine (column 3) vs. routine (column 4) and the combinations of these two dimensions (columns 5-8). The change in the conditional probability of transitioning away from manufacturing occupations is also provided as a reference (column 9).

The table indicates a positive change in the likelihood of moving away from manual job categories (column 1), for both non-routine (column 5) and routine (column 6) occupations in regions that were more exposed to robotization. We observe a positive and partially significant effect of similar magnitude for the manufacturing occupations (column 9). We do not observe a significant effect of robotization on movement from cognitive occupations.

Table A.2: Exposure to Robots and Career Value (CV) Changes: Own vs. Other Occupations (IV Lasso)

	Δ CV (Own Occupation)				Δ CV (Other Occupation)			
	Total	Δ w	$\Delta\psi$	$\Delta\psi \times \Delta$ w	Total	Δ w	$\Delta\psi$	$\Delta\psi \times \Delta$ w
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
U.S. Robot Exposure '04-'16	-0.044***	-0.063***	0.021**	-0.003*	-0.289***	-0.140***	-0.139***	-0.010
	(0.010)	(0.014)	(0.010)	(0.002)	(0.036)	(0.032)	(0.022)	(0.007)
Mean of D.V.	-0.446	0.252	-0.670	-0.027	0.090	0.815	-0.569	-0.156
F-stat.	23.379	92.343	11.479	10.314	66.920	43.240	26.149	5.501
Census Division FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
A&R Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	722	722	722	722	722	722	722	722

Note. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Robust standard errors are in parentheses and clustered by state. All columns include census division dummies as well as controls for demographic characteristics of commuting zones in 1990 identical to those in Acemoglu and Restrepo (2020) (log population; the share of females; the share of population above 65 years; the shares of population with no college, some college, college and professional degrees, and masters and doctoral degrees; the shares of Whites, Blacks, Hispanics, and Asians; the share of employment in manufacturing; the share of female employment in manufacturing; and the share of employment in light manufacturing, namely, textile industry and the paper, publishing, and printing industry). U.S. Robot Exposure is instrumented using robot exposure in Denmark, Italy, Sweden, Finland, France, Germany, Spain and the UK in the same time periods. Observations are weighted by commuting zone population.

Table A.3: Exposure to Robots and Probability of Transitions From Occupations (IV Lasso)

	Conditional Probability Occupational Transition From								
	Manual	Cognitive	Non-Routine	Routine	Manual Non-Routine	Manual Routine	Cognitive Non-Routine	Cognitive Routine	Manufacturing
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
U.S. Robot Exposure '04-'16	0.01825**	0.00177	0.01500	0.01111	0.01627*	0.02141***	0.00729	0.00724	0.01534*
	(0.00809)	(0.01129)	(0.01223)	(0.00904)	(0.00947)	(0.00689)	(0.01194)	(0.01085)	(0.00840)
Mean of D.V.	-0.000	0.000	0.000	0.000	0.000	-0.000	-0.000	0.000	-0.000
F-stat.	2.389	0.040	1.202	0.660	1.986	2.464	0.186	0.361	0.760
Census Division FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
A&R Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	722	722	722	722	722	722	722	722	722

Notes. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Table reports the likelihood of transitions among the individuals who are changing occupations. Probabilities are computed by dividing the number of transitions to/from a particular occupation in a commuting zone in a given period by the total number of occupational transitions. All probabilities standardized by subtracting the mean and dividing by the standard deviation for each category of occupations. The outcome is the difference in probability of transitions between 2016 and 2004. We look at three-year periods to judge transitions, so an occupational transition is said to take place in 2004 if a person's 2003 occupation is different from their 2006 occupation, and in 2016 if a person's 2013 occupation is different from their 2018 occupations. Occupational classifications are based on 2-digit SOC codes. Non-routine cognitive occupations consist of managers, professionals and technicians, routine cognitive occupations of sales and office and administrative positions, routine manual occupations of production occupations and operators and laborers, and lastly, non-routine manual occupations consist of protective services, food and cleaning services and personal care services. Robust standard errors are in parentheses and clustered by state. All columns include census division dummies as well as controls for demographic characteristics of commuting zones in 1990 identical to those in Acemoglu and Restrepo (2020) (log population; the share of females; the share of population above 65 years; the shares of population with no college, some college, college and professional degrees, and masters and doctoral degrees; and the shares of Whites, Blacks, Hispanics, and Asians). U.S. Robot Exposure is instrumented using robot exposure in Denmark, Italy, Sweden, Finland, France, Germany, Spain and the UK in the same time periods. Observations are weighted by commuting zone population.

A.7 Heterogeneity of Automation Effects with Respect to Upward Mobility

In this section, we estimate how opportunities for upward mobility mitigate the effects of robotization on career values, focusing on the effects of average level of education (Table A.4) and local intergenerational mobility (Table A.5). The latter is measured using neighborhood intergenerational mobility effects from Chetty et al. (2016). Table A.4 shows being in a region with high educational attainment is high mitigates the negative effects of robotization on career values for those with lower educational attainment (below college) (column (2)). We do not see effects for the overall population. In Table A.5, we see that being in a region with greater intergenerational mobility does not sufficiently mitigate the negative effects of robotization on career values.

Table A.4: Automation, Career Values, and Education

	ΔCareer Values '00-'16			ΔWage '00-'15	ΔEmployment '00-'15
	All	Below College	College or Higher		
	(1)	(2)	(3)	(4)	(5)
EU Instrument '04-'16	-0.563*	-1.190**	-0.544*	-0.016	-0.306
	(0.300)	(0.457)	(0.310)	(0.010)	(0.377)
College Rate '00	7.049	-8.987	7.051	0.816**	-4.603
	(6.588)	(7.010)	(6.928)	(0.349)	(7.368)
EU Instrument × College rate	0.900	4.519*	0.743	0.022	-0.422
	(1.603)	(2.472)	(1.661)	(0.063)	(2.237)
Mean of D.V.	-0.238	-0.136	-0.161	0.135	0.036
R-squared	0.484	0.325	0.471	0.536	0.744
Census Division FE	Yes	Yes	Yes	Yes	Yes
A&R Controls	Yes	Yes	Yes	Yes	Yes
Observations	722	722	722	722	722

Notes. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Robust standard errors are in brackets and clustered by state. All columns include census division dummies as well as controls for demographic characteristics of commuting zones in 1990 identical to those in Acemoglu and Restrepo (2020) (log population; the share of females; the share of population above 65 years; the shares of population with no college, some college, college and professional degrees, and masters and doctoral degrees; the shares of Whites, Blacks, Hispanics, and Asians; the share of employment in manufacturing; the share of female employment in manufacturing; and the share of employment in light manufacturing, namely, textile industry and the paper, publishing, and printing industry). The EU instrument is the average robot exposure in Denmark, Italy, Sweden, Finland and France during 2004-2016. Observations are weighted by commuting zone population.

A.8 Investment in Schooling by Manufacturing Regions

We investigate the differential effects of career values on educational attainment by the concentration of manufacturing in the CZs. Table A.6 reports the coefficients of the regression of the share of individuals in college or with some college between 2000 and 2015 on the average career values in a CZ for the years 2004-08, 2008-16, and 2004-16. In columns (1) and (2), we only find significant effects for both high concentration areas of manufacturing. In columns (3)-(6), the effects are comparable across the two regions, but a unit increase in career values is associated with greater levels of change schooling in low-manufacturing areas. High manufacturing areas thus may need greater boost in their LMCV to attain the same level of improvement in schooling.

Table A.5: Automation, Career Values, and Intergenerational Mobility

	ΔCareer Values '00-'16			ΔWage '00-'15	ΔEmployment '00-'15
	All	Below College	College or Higher		
	(1)	(2)	(3)	(4)	(5)
EU Instrument '04-'16	-0.429***	-0.671***	-0.430***	-0.019***	-0.292*
	(0.083)	(0.128)	(0.088)	(0.005)	(0.149)
Intergenerational Mobility	0.525	0.172	0.555	0.057***	2.084***
	(0.487)	(0.511)	(0.492)	(0.021)	(0.633)
EU Instrument × Int mobility	0.416	0.097	0.435	-0.013	0.166
	(0.263)	(0.344)	(0.270)	(0.012)	(0.352)
Mean of D.V.	-0.267	-0.165	-0.190	0.132	-0.039
R-squared	0.394	0.229	0.387	0.518	0.720
Census Division FE	Yes	Yes	Yes	Yes	Yes
A&R Controls	Yes	Yes	Yes	Yes	Yes
Observations	702	702	702	702	702

Notes. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Robust standard errors are in brackets and clustered by state. All columns include census division dummies as well as controls for demographic characteristics of commuting zones in 1990 identical to those in Acemoglu and Restrepo (2020) (log population; the share of females; the share of population above 65 years; the shares of population with no college, some college, college and professional degrees, and masters and doctoral degrees; the shares of Whites, Blacks, Hispanics, and Asians; the share of employment in manufacturing; the share of female employment in manufacturing; and the share of employment in light manufacturing, namely, textile industry and the paper, publishing, and printing industry). The EU instrument is the average robot exposure in Denmark, Italy, Sweden, Finland and France during 2004-2016. Intergenerational mobility measures are the neighborhood mobility measures from (Chetty et al., 2016). Observations are weighted by commuting zone population.

Table A.6: Career Values, Schooling, and Manufacturing

	Δ College Share 2000-15	Δ Some College Share 2000-15	Δ College Share 2000-15	Δ Some College Share 2000-15	Δ College Share 2000-15	Δ Some College Share 2000-15
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: High-Manufacturing Commuting Zones						
Δ LMCV '04-'08	1.686***	1.093**				
	(0.624)	(0.537)				
Δ LMCV '08-'16			0.642***	0.416**		
			(0.126)	(0.170)		
Δ LMCV '04-'16					0.465***	0.301**
					(0.095)	(0.122)
Mean of D.V.	2.951	7.720	2.951	7.720	2.951	7.720
KP F-stat.	10.800	10.800	61.516	61.516	87.282	87.282
Observations	362	362	362	362	362	362
Panel B: Low-Manufacturing Commuting Zones						
Δ LMCV '04-'08	6.260	6.304				
	(10.471)	(10.751)				
Δ LMCV '08-'16			0.697***	0.702***		
			(0.221)	(0.239)		
Δ LMCV '04-'16					0.627***	0.631***
					(0.167)	(0.195)
Mean of D.V.	2.924	6.600	2.924	6.600	2.924	6.600
KP F-stat.	0.326	0.326	21.398	21.398	48.024	48.024
Observations	360	360	360	360	360	360
Census Division FE	Yes	Yes	Yes	Yes	Yes	Yes
A&R Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes. Robust standard errors in brackets. ***p<0.01, **p<0.05, *p<0.1. All columns include census division dummies, demographic characteristics of CZs in 1990 identical to those in Acemoglu and Restrepo (2020) (log population; the share of females; the share of population above 65 years; the shares of population with no college, some college, college and professional degrees, and masters and doctoral degrees; and the shares of Whites, Blacks, Hispanics and Asians).

Table A.7: Vote Shares and Automation Shocks, 1988-2004, IV Lasso

	Voter Share of the Republican Presidential Candidate				
	2004	2000	1996	1992	1988
	(1)	(2)	(3)	(4)	(5)
U.S. Robot Exposure '04-'16	-0.038	0.028	-0.180	-0.283	-0.011
	(0.111)	(0.071)	(0.135)	(0.196)	(0.126)
Mean of D.V.	60.772	59.340	51.091	50.805	56.432
F-stat.	0.036	0.195	2.179	5.973	0.007
Census Division FE	Yes	Yes	Yes	Yes	Yes
A&R Controls	Yes	Yes	Yes	Yes	Yes
Observations	722	722	722	722	722

Notes. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Robust standard errors are in brackets and clustered by commuting zone. All columns include census division dummies, demographic characteristics of commuting zones in 1990 identical to those in Acemoglu and Restrepo (2020) (log population; the share of females; the share of population above 65 years; the shares of population with no college, some college, college and professional degrees, and masters and doctoral degrees; the shares of Whites, Blacks, Hispanics, and Asians; the share of employment in manufacturing; the share of female employment in manufacturing; and the share of employment in light manufacturing, namely, textile industry and the paper, publishing, and printing industry). We also control for the Republican vote shares in the previous presidential election from 4 years before. U.S. Robot Exposure is instrumented using robot exposure in Denmark, Italy, Sweden, Finland, France, Germany, Spain and the UK in the same time periods. Observations are weighted by the commuting zone population.

A.9 Robustness Checks with Additional Controls

Table A.8: Exposure to Robots and Labor Market Career Value Change (OLS and IV Lasso)

	Local Market Career Value (OLS)			Local Market Career Value (IV)		
	Δ LMCV (1)	Δ LMCV (2)	Δ LMCV (3)	Δ LMCV (4)	Δ LMCV (5)	Δ LMCV (6)
U.S. Robot Exposure ’04-’08	-0.361***			-0.381***		
	(0.076)			(0.085)		
U.S. Robot Exposure ’08-’16		-0.160			-0.262***	
		(0.121)			(0.094)	
U.S. Robot Exposure ’04-’16			-0.310***			-0.337***
			(0.044)			(0.039)
Mean of D.V.	-0.150	-0.088	-0.238	-0.150	-0.088	-0.238
F-stat.				44.396	5.527	63.378
Census Division FE	Yes	Yes	Yes	Yes	Yes	Yes
A&R Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	722	722	722	722	722	722

Notes. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Robust standard errors are in parentheses and clustered by state. All columns include census division dummies as well as controls for demographic characteristics of commuting zones in 1990 identical to those in Acemoglu and Restrepo (2020) (log population; the share of females; the share of population above 65 years; the shares of population with no college, some college, college and professional degrees, and masters and doctoral degrees; the shares of Whites, Blacks, Hispanics, and Asians; the share of employment in manufacturing; the share of female employment in manufacturing; and the share of employment in light manufacturing, namely, textile industry and the paper, publishing, and printing industry). In addition, we include share of employment in routine occupations and change exposure to imports from China from 1990 to 2007 as controls. U.S. Robot Exposure is instrumented using robot exposure in Denmark, Italy, Sweden, Finland, France, Germany, Spain and the UK in the same time periods. Observations are weighted by commuting zone population.

Table A.9: Exposure to Robots and Job Transitions. IV Lasso

	Probability of transitions to: equal wage occupations	Probability of transitions to: higher wage occupations	Probability of transitions to: lower wage occupations	Probability of transitions to: equal wage occupations: high-manuf.	Probability of transitions to: equal wage occupations: low-manuf.	Probability of transitions to: higher wage occupations: high-manuf.	Probability of transitions to: higher wage occupations: low-manuf.	Probability of transitions to: lower wage occupations: high-manuf.	Probability of transitions to: lower wage occupations: low-manuf.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
U.S. Robot Exposure '04-'16	0.078***	-0.065***	0.054**	0.171***	1.670*	-0.065***	-0.158	0.104***	0.412
	(0.028)	(0.010)	(0.023)	(0.020)	(0.971)	(0.024)	(0.220)	(0.017)	(0.341)
Mean of D.V.	0.007	0.008	0.008	0.256	0.073	0.259	0.073	0.258	0.074
F-stat.	35.322	99.685	13.524	169.418	32.102	37.137	1.031	45.051	5.079
Census Division FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
A&R Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	722	722	722	362	360	362	360	362	360

Notes. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Robust standard errors are in brackets and clustered by state. All columns include census division dummies as well as controls for demographic characteristics of commuting zones in 1990 identical to those in Acemoglu and Restrepo (2020) (log population; the share of females; the share of population above 65 years; the shares of population with no college, some college, college and professional degrees, and masters and doctoral degrees; the shares of Whites, Blacks, Hispanics, and Asians; the share of employment in manufacturing; the share of female employment in manufacturing; and the share of employment in light manufacturing, namely, textile industry and the paper, publishing, and printing industry). In addition, we include share of employment in routine occupations and change exposure to imports from China from 1990 to 2007 as controls. All columns include controls for the total number of career values with potential transition to equal, high or lower wage occupations for the years 2004 and 2016 depending on the outcome variable. In columns (4)-(9), these controls are for the high and low manufacturing zones exclusively. Columns (4)-(9) also control for the overall probability of transition to equal, high or lower wage occupations in 2004. U.S. Robot Exposure is instrumented using robot exposure in Denmark, Italy, Sweden, Finland, France, Germany, Spain and the UK in the same time periods. Observations are weighted by commuting zone population.

Table A.10: Promotion and Demotion Category Results: Interaction Terms

Panel A: Promotion			
	(1)	(2)	(3)
Years of Experience			
11–20 × EU Instrument ’04–’16	0.0051***		
	(0.0016)		
>20 × EU Instrument ’04–’16	0.0038		
	(0.0024)		
Age			
18–25 × EU Instrument ’04–’16		0.0000	
		(.)	
26–40 × EU Instrument ’04–’16		0.0055***	
		(0.0017)	
>40 × EU Instrument ’04–’16		0.0077***	
		(0.0025)	
Job Zone			
Some Preparation Needed × EU Instrument ’04–’16			0.0077***
			(0.0023)
Medium Preparation Needed × EU Instrument ’04–’16			0.0105***
			(0.0023)
Considerable Preparation Needed × EU Instrument ’04–’16			0.0112***
			(0.0026)
Extensive Preparation Needed × EU Instrument ’04–’16			0.0117***
			(0.0025)
Observations	2,640,823	1,782,900	2,625,442
R-squared	0.0074	0.0051	0.0057
Panel B: Demotion			
Years of Experience			
11–20 Years of Experience × EU Instrument ’04–’16	-0.0010		
	(0.0010)		
>20 Years of Experience × EU Instrument ’04–’16	-0.0004		
	(0.0018)		
Age			
26–40 × EU Instrument ’04–’16		0.0008	
		(0.0012)	
>40 × EU Instrument ’04–’16		-0.0001	
		(0.0028)	
Job Zone			
Medium Preparation Needed × EU Instrument ’04–’16			-0.0068*
			(0.0036)
Considerable Preparation Needed × EU Instrument ’04–’16			-0.0061*
			(0.0031)
Extensive Preparation Needed × EU Instrument ’04–’16			-0.0079**
			(0.0036)
Observations	2,132,878	1,523,774	2,132,673
R-squared	0.0084	0.0077	0.0089
Commuting Zone FE	Yes	Yes	Yes
Main Effect Included	Yes	Yes	Yes

Notes. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors, clustered by state, are shown in brackets. All columns include commuting-zone fixed effects, controls for gender, and an indicator for having an advanced degree before 2006. The EU instrument is the average robot exposure in Denmark, Italy, Sweden, Finland and France during 2004-2016. All columns include the main effect of the interacted variable. Years of Experience represents the number of years of job experience in 2004, Age represents the age in 2004 and Job Zone represents how much experience/training a job requires, so they measure the skill level required. It comes from the ONET Classification. Baseline of Years of Experience is less than 10 years in 2004, of Age is between 18 and 25 years in 2004 and Job Zone is "Little or No Preparation Needed".

B Automation, Career Values, and Political Outcomes

The results in Table 12 (columns 6 and 7) suggest that career prospects may also have effects on political outcomes. In this section, we investigate *how* both economic transformation and job opportunities may be affecting the political landscape. The theoretical literature starting with Meltzer and Richard (1981) suggests that individual income should affect preferences for redistribution. Then, if the income of a median voter goes down, which happens when inequality goes up, that should increase the support of left-wing candidates and parties. At the same time, economic transformations of recent years also changed the political structure, with new candidates/parties and candidates with a new, populist agenda becoming increasingly popular, with a more traditional left-to-right cleavage becoming less salient. Autor et al. (2020), Autor et al. (2016), and Colantone and Stanig (2018) suggest that globalization plays an important role in the rise of populism support, while refugee migration also is becoming an increasingly important issue (Dustmann et al. (2018), Halla et al. (2017), (Noury and Roland, 2020)). Anelli et al. (2021), Gallego et al. (2022), and Frey et al. (2018) go one step further and study the impact of robotization on political preferences, while Upward and Wright (2023) study the impact of individual job loss.

Our focus on career values allows us to enrich this analysis. We contribute to the literature in several ways. First, we focus on the impact of career prospects in parallel with the study of automation, thus being able to understand how many of the results are driven by forward-looking expectations. Second, we study if heterogeneity analysis is consistent with economic transformation driving political outcomes and if economic shocks parallel changes in political preferences. Third, we also focus on the supply-side factors, by looking at campaign visits and policy positions.

Theoretically, there are reasons why economic changes can lead to more populist votes. In theory, negative economic shocks can lead to the support of extreme left or extreme right politicians (Margalit, 2019). Guiso et al. (2017) and Di Tella and Rotemberg (2018) argue that income loss and the feeling of betrayal can generate anti-elite preferences, thus leading to more populist voting. Panunzi et al. (2020) argue that it can make people unhappy about their income and make them more risk-loving, thus also increasing the support for populism. Our preliminary results from Table 12 suggested that changes in career values affected voting for Trump, arguably the most populist out of all general election presidential candidates in the United States.

More generally, this part of the analysis contributes to the literature on the drivers of populism, recently reviewed by Guriev and Papaioannou (2022). Recent literature suggests that the economic crises (e.g., the Great Recession), and more generally the negative economic shocks, have contributed to the popularity of populism (e.g., Eichengreen, 2018; Rodrik, 2018; Autor et al., 2020; Guiso et al., 2019, 2020; Dippel et al., 2017; Fetzer, 2019; Anelli et al., 2019). Moreover, low levels of trust, identity politics, and growing hostility towards immigrants also contributed to the growth of populism (Algan and Cahuc, 2014; Dustmann et al., 2017; Gennaioli and Tabellini, 2023), as did the internet and social media (Guriev et al., 2021; Manacorda et al., 2022). We contribute to this literature by focusing on forward-looking measures of people's welfare and by exploring the mechanisms behind the results.

B.1 Automation and Political Preferences

In this subsection, we look at the impact of automation on the vote shares of Republican candidates for various years, obtained from the Election Atlas. We use the IV Lasso specification, as outlined above (equation (5)). In Table B.1, we find that robotization positively affected the vote share of Trump in 2016 (column 1, the coefficient is positive and significant at 1% level), but not the vote shares of the 2008 Republican presidential candidate John McCain or the 2012 Republican presidential candidate Mitt Romney. The point estimate implies that one extra robot per 1000 workers led to a 0.38 p.p. increase in the vote share of Trump.[24]

In columns (4)-(6) of the table, we report what happens if vote shares were predicted by local labor market career values, again using commuting zones beyond 100 miles radius to instrument for local career values. Column (4) (career values and voting for Trump) reproduces the results from column (7) of Table 12, while the effect of career values on voting for McCain and Romney in 2008 and 2012, respectively, is numerically smaller and statistically insignificant. Numerically, one standard deviation decrease in career value led to a 0.68 p.p. increase in Trump vote share in a given commuting zone; for earlier years, we can rule out the effects larger than 0.41 p.p. for 2012 and larger than 0.30 p.p. for 2008. These findings are consistent with the idea that economic shocks strengthen voting for extreme candidates (Margalit, 2019). Further analysis in this section is aimed at understanding a more nuanced picture of what's going on.

Table B.1: Vote Shares and Automation Shocks, 2008-2016, IV Lasso

	Voter Share of Republican Presidential Candidate					
	2016	2012	2008	2016	2012	2008
	(1)	(2)	(3)	(4)	(5)	(6)
U.S. Robot Exposure '04-'16	0.380***	0.039	-0.022			
	(0.104)	(0.130)	(0.139)			
Δ LMCV '04-'16				-0.445**	-0.105	0.080
				(0.227)	(0.156)	(0.193)
Mean of D.V.	65.368	60.204	57.053	65.368	60.204	57.053
F-stat.	16.794	0.069	0.617	7.398	0.613	0.171
Census Division FE	Yes	Yes	Yes	Yes	Yes	Yes
A&R Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	722	722	722	722	722	722

Notes. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Robust standard errors are in brackets and clustered by commuting zone. All columns include census division dummies, demographic characteristics of commuting zones in 1990 identical to those in Acemoglu and Restrepo (2020) (log population; the share of females; the share of population above 65 years; the shares of population with no college, some college, college and professional degrees, and masters and doctoral degrees; the shares of Whites, Blacks, Hispanics, and Asians; the share of employment in manufacturing; the share of female employment in manufacturing; and the share of employment in light manufacturing, namely, textile industry and the paper, publishing, and printing industry). U.S. Robot Exposure is instrumented using robot exposure in Denmark, Italy, Sweden, Finland, France, Germany, Spain and the UK in the same time periods. The change in local market career values is instrumented using the mean change in local market career values in commuting zones farther than 100 miles. Observations are weighted by the commuting zone population.

[24]Note that we can extend the robot exposure part of the table back to 1988 in online appendix Table A.7, where the effect of exposure on Republican Presidential candidate vote share is insignificant in each year.

B.2 Distributional Effects of Automation and Voting Preferences

The hypothesis that economic changes affect voting is almost as old as the modern political economy literature. However, this hypothesis implies important heterogeneity: people who are the most affected by the shock should be people who change their voting behavior in response. This is a sanity check that the literature rarely tests for. Our data allow us to carry out this heterogeneity analysis, looking in parallel at the distributional effects of robotization and voting intentions. Put differently, we study the distributional effects of robot exposure on economic outcomes and then compare them against the distributional effects of robot exposure on electoral outcomes.

For example, Table 6 suggests that low-skilled people are more likely to be affected by robot exposure, more so in high manufacturing commuting zones. In Table B.2, we look at the distributional effects of robotization employment. We confirm that for contemporary effects on employment, the low-skilled—those with some college education or below—are more likely to be affected compared to those with college (as in columns (1) and (2) in Panel A). For wages, this similarly holds for manufacturing occupations (columns (4) and (5) in Panel B).

Table B.2: Distributional Effects of Automation by Education. IV Lasso

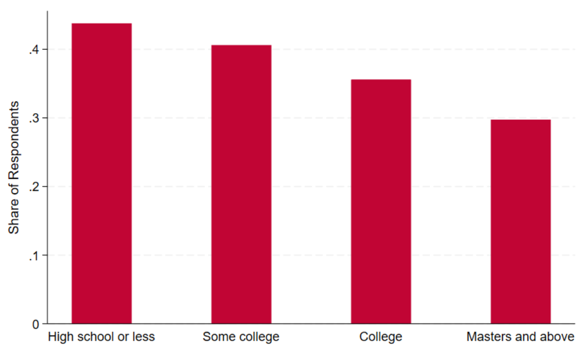
Panel A. Employment	**ACS Change in Employment, 2000-2015**					
	All Private Sector			Manufacturing Only		
	High School or below	Some College	College	High School or below	Some College	College
	(1)	(2)	(3)	(4)	(5)	(6)
U.S. Robot Exposure '04-'16	-0.476**	-0.401***	-0.249*	-0.158*	-0.328***	-0.163**
	(0.195)	(0.109)	(0.136)	(0.090)	(0.126)	(0.069)
Mean of D.V.	0.530	-0.060	2.542	-1.472	-1.617	-0.664
Mean of Employment 2000	29.903	37.745	32.853	7.061	6.836	5.176
F-stat	42.753	42.617	14.364	12.979	63.542	16.096
Observations	722	722	722	722	722	722
Panel B. Wages	**ACS Change in Wages, 2000-2015**					
	All Private Sector			Manufacturing Only		
	High School or below	Some College	College	High School or below	Some College	College
U.S. Robot Exposure '04-'16	-0.213***	-0.279***	-0.278***	-0.480***	-0.480***	-0.186**
	(0.044)	(0.081)	(0.055)	(0.045)	(0.037)	(0.073)
Mean of D.V.	1.058	1.106	2.832	1.283	1.430	4.663
Mean of Wage 2000	12.928	14.964	22.148	14.514	17.388	23.787
F-stat	76.548	75.431	28.634	176.685	99.329	3.317
Observations	722	722	722	722	722	722
Census Division FE	Yes	Yes	Yes	Yes	Yes	Yes
A&R Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Robust standard errors are in brackets and clustered by state. All columns include census division dummies as well as controls for demographic characteristics of commuting zones in 1990 identical to those in Acemoglu and Restrepo (2020) (log population; the share of females; the share of population above 65 years; the shares of population with no college, some college, college and professional degrees, and masters and doctoral degrees; the shares of Whites, Blacks, Hispanics, and Asians; the share of employment in manufacturing; the share of female employment in manufacturing; and the share of employment in light manufacturing, namely, textile industry and the paper, publishing, and printing industry). U.S. Robot Exposure is instrumented using robot exposure in Denmark, Italy, Sweden, Finland, France, Germany, Spain and the UK in the same time periods. Observations are weighted by commuting zone population.

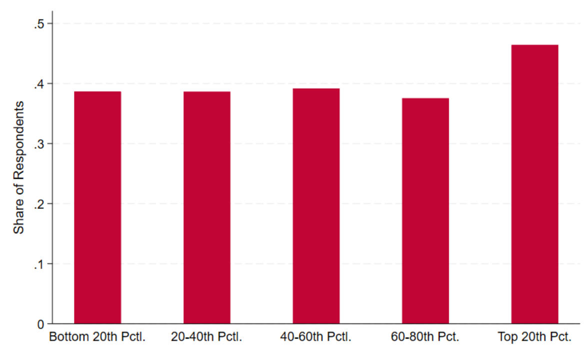
We study whether those who are most likely to be affected are also more likely to vote for Trump. Figure B.1 shows the shares of self-reported Trump voters by their levels of education. We find that, parallel to the results in Table 6 and Table B.2, lesser-educated people had the highest share of Trump voters. Furthermore, as Figure B.1 suggests, people from the highest quintile of manufacturing employment were also the most likely Trump voters. Thus, heterogeneity analysis with respect to education is consistent with the idea that the least educated voters supported Trump and likely suffered from the negative economic consequences of robotization.

Figure B.1: Voting Intentions by Education and Share of Manufacturing, 2016 Presidential Elections

(a) By Educational Attainment



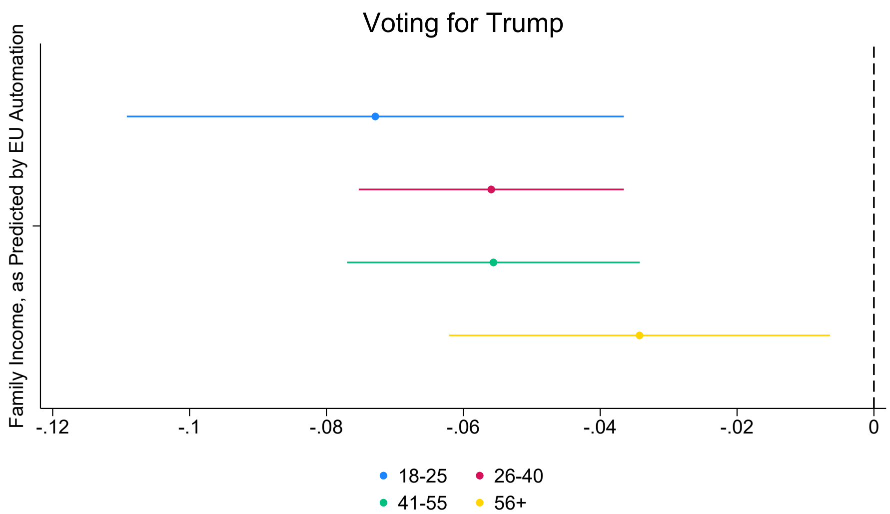
(b) By Share of Employment in Manufacturing



Notes. The source of data is the Congressional Cooperative Election Survey (2016). Commuting zones are classified by the percentile into which the share of employment in manufacturing in 1990 falls.

Next, we ask whether the link between automation and income shocks is stronger for younger voters. More specifically, we estimate vote choice as a function of household income and demographic characteristics, with household income instrumented by CZ's predicted exposure to automation, using EU industry-level automation to construct the instrument. Dependent variable data comes from the Congressional Cooperative Election Survey. These results are reported in Figure B.2. The figure suggests that the association is numerically strongest for the youngest people, while, at the same time, it becomes numerically smaller and statistically insignificant for 56 and over. Although suggestive, this evidence strengthens our interpretation of voting for Trump as partly an economic phenomenon. Age heterogeneity is consistent with a career-value-based explanation: income is a less important predictor of voting for the oldest workers, for whom most of their career transitions already occurred in the past, and a more important predictor of voting for the youngest voters, who care most about their career values and associated opportunities for upward mobility.

Figure B.2: Trump Voting Intentions, Predicted Family Income, and Age



Notes. Robust standard errors are clustered at the commuting zone level. Census division dummies are included. The source of data is the Congressional Cooperative Election Survey (2016). Household income is predicted by robot exposure in Denmark, Italy, Sweden, Finland, France, Germany, Spain and the UK.

C Data Appendix

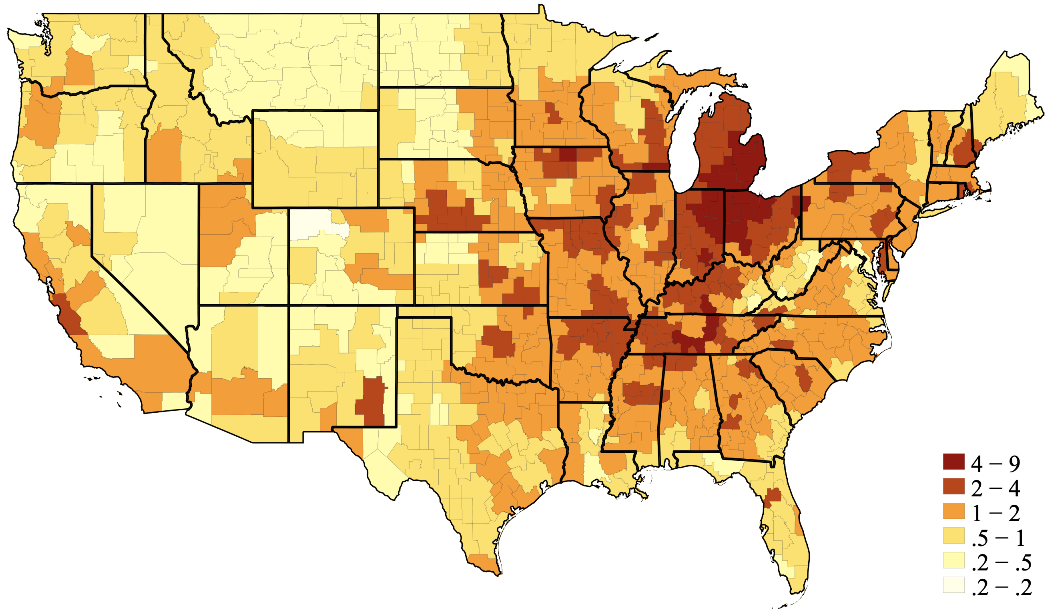
C.1 Industrial Robots Data

The IFR compiles data from annual industry surveys and covers robots carrying tasks related to manufacturing, agriculture, forestry and fishing; mining; utilities; construction; education, research and development; and services. As detailed in Acemoglu and Restrepo (2019), stock of robots going back to the 1990s is only available for Denmark, Finland, France, Germany, Italy, Norway, Spain, Sweden, and the United Kingdom, which together account for 41 percent of the world industrial robot market. The robots cover a range of disaggregated industries, including food and beverages; textiles; wood and furniture; paper and printing; plastics and chemicals; minerals; basic metals; metal products; industrial machinery; electronics; automotive; shipbuilding and aerospace; and miscellaneous manufacturing (e.g., production of jewelry and toys).

For industrial robots in stock, we use data provided by the International Federation of Robotics (IFR). The dataset covers 38 industry codes with the International Standard Industrial Classification (ISIC) code. While the data contain information about the operational stock of industrial robots in about 50 countries between 1993 and 2016 (corresponding to about 90% of the industrial robots market), the industry breakdown of the robot stocks starts in 2004. Therefore, we focus on the data after 2004 to calculate automation exposure in the US. We address the limitations of the IFR data in the same way as Acemoglu and Restrepo (2019) and collapse industries into the following categories: 1) agriculture, forestry, fishing; 2) mining and quarrying; 3) food and beverages; 4) textiles; 5) wood and furniture; 6) paper; 7) plastic and chemical products; 8) glass, ceramics, stone, mineral products (non-auto); 9) basic metals; 10) metal products; 11) industrial machinery; 12) electrical/electronics; 13) automotive; 14) other vehicles; 15) all other manufacturing branches; 16) electricity, gas, water supply; 17) construction; 18) education/research/development; 19) all other non-manufacturing branches. Acemoglu and Restrepo (2019) note that about 30% of robots are not assigned to an industry. Similar to Acemoglu and Restrepo (2020), we assign unclassified robots to industries in the same proportion as the classified data. Also, similar to the authors, we use the overall stock of robots for North America to measure the U.S. exposure to robots. The authors state that this is not a concern “since the United States accounts for more than 90% of the North American market.”

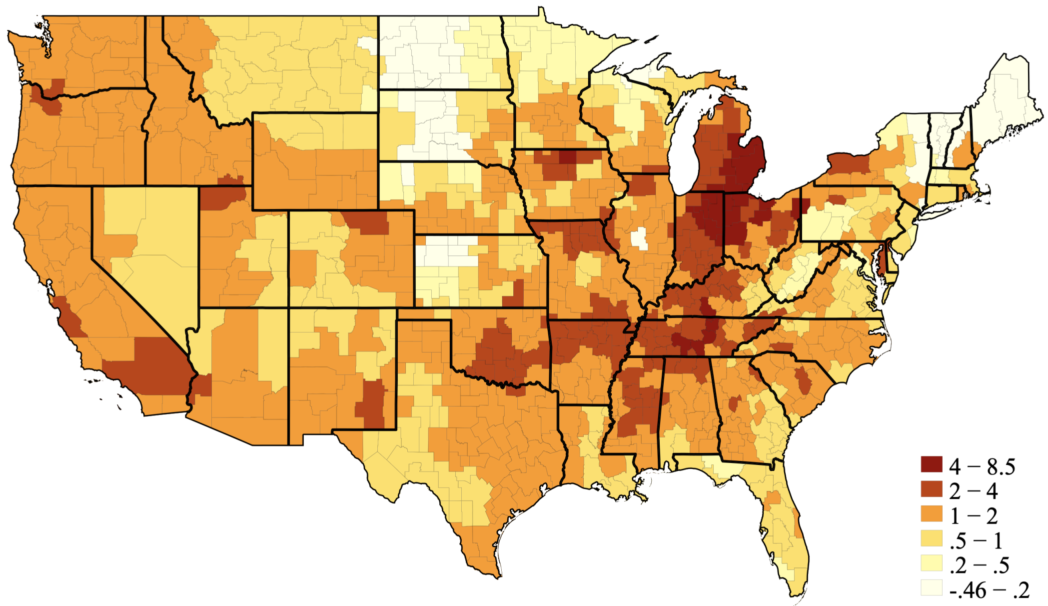
Figures C.1 shows the number of robots added per 1,000 workers in the U.S. between 2004 and 2016. Figure C.2 shows exposure after accounting for census-division fixed effects.

Figure C.1: US Automation/Robot Exposure, 2004 to 2016



Notes. Source of Data: International Federation of Robotics.

Figure C.2: US Automation/Robot Exposure, 2004 to 2016 (Division Fixed Effects Residualized)



Notes. Source of Data: International Federation of Robotics.

C.2 BGT Baseline, Software and Specialized Skills Examples

Table C.1: Most Common Examples of Skills by Category

Baseline Skills	**Software Skills**	**Specialized Skills**
Microsoft Excel	Microsoft Excel	Customer Service
Microsoft Office	Microsoft Office	Sales
Microsoft PowerPoint	Microsoft PowerPoint	Budgeting
Microsoft Word	Microsoft Word	Scheduling
Organizational Skills	Microsoft Windows	Project Management
Communication Skills	Microsoft Access	Insurance Knowledge
Research	Adobe Photoshop	Staff Management
Planning	SQL	Business Administration
Computer Literacy	Oracle	Administrative Support
Problem Solving	Lotus Applications	Customer Billing
Microsoft Windows	Microsoft Outlook	Hardware Experience
Teamwork / Collaboration	QuickBooks	Accounting
Troubleshooting	UNIX	Repair
Writing	SAP	Data Entry
Leadership	Microsoft Visio	Quality Assurance and Control
Microsoft Access	Lotus Notes	Technical Support
Creativity	Microsoft Project	Teaching
Typing	Linux	Customer Contact
Building Effective Relationships	Java	Purchasing
English	C++	Spreadsheets

Note: This table displays the 20 most common specific skills for each category. Skills are grouped into clusters. The Baseline category includes basic IT, administrative, and soft skills. The Software category encompasses skills related to administration, design, finance, analysis, engineering, media, writing, security, and research software. The Specialized category covers industry-specific knowledge, supply chain and logistics, administration, engineering, manufacturing, healthcare, human resources, legal, and research training.