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AUTOMATION, CAREER VALUES, AND POLITICAL PREFERENCES

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ABSTRACT

Career opportunities and expectations shape people's decisions and can diminish over time. In this paper, we study the career implications of automation and robotization using a novel data set of resumes from approximately 16 million individuals from the United States. We calculate the lifetime "career value" of various occupations, combining (1) the likelihood of future transitions to other occupations, and (2) the earning potential of these occupations. We first document a downward trend in the growth of career values in the U.S. between 2000 and 2016. While wage growth slows down over this time period, the decline in the average career value growth is mainly due to reduced upward occupational mobility. We find that robotization contributes to the decline of average local labor market career values. One additional robot per 1000 workers decreased the average local market career value by $3.9K between 2004 and 2008 and by $2.48K between 2008 and 2016, corresponding to 1.7% and 1.1% of the average career values from the year 2000. In commuting zones that have been more exposed to robots, the average career value has declined further between 2000 and 2016. This decline was more pronounced for low-skilled individuals, with a substantial part of the decline coming from their reduced upward mobility. We document that other sources of mobility mitigate the negative effects of automation on career values. We also show that the changes in career values are predictive of investment in long-term outcomes, such as investment into schooling and housing, and voting for a populist candidate, as proxied by the vote share of Trump in 2016. We also find further evidence that automation affected both the demand side and supply side of politics.

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1 Introduction

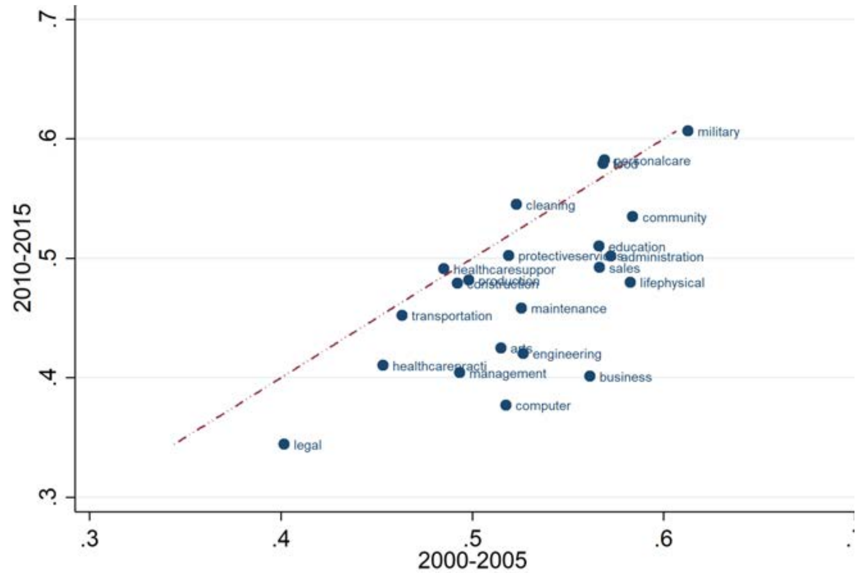
Inequality is on the rise in many countries around the world. The possibility to move up the income ladder, or upward mobility, is a way to mitigate the discrepancies in access to opportunities. One of the defining features of the "American Dream" is that any person who works hard enough can eventually move to the higher income brackets (Samuel, 2012). At the same time, opportunities for promotions and, generally, moving up the income ladder might change over time (Chetty et al., 2017; Putnam, 2015). Economic transformation and, in particular, technological change can affect not only today's outcomes but also future occupations and incomes. In this paper, we study how economic shocks affect career progression and job-related upward mobility as well as the consequences of these changes.

We employ data on job-to-job transitions in the United States from Burning Glass Technologies (BGT). This BGT data set consists of data on individual resumes available on the Internet from more than 3000 online job boards, such as LinkedIn, Monster.com, etc., yielding 178 million sequential worker-year observations. We first document that the number of occupational transitions, including transitions within and between companies, has been declining in 2004-2016 for most occupational groups (see Figure 1).[1] Furthermore, we show that, on average, the transitions to higher-income jobs have declined, while the transitions to lower-income jobs have increased (Figure 2). To figure out what kind of opportunities holding a particular job at a particular moment in time provides, we would like to have a single measure that combines information about both future career mobility and the wage potential of occupations. We propose a measure of expected future income from holding a particular occupation today based on occupation-to-occupation transitional probabilities and wages corresponding to these occupations. We call this measure a *"career value,"* to reflect that it is an expected value of starting a particular career in a given occupation. Consistent with Figure 1 and Figure 2, career value growth has been declining over time, especially after 2008 and the Great Recession. We then study how economic changes affect career values and, thus, expected upward mobility. We analyze how these expected future opportunities affect individual-level long-term decisions. We also look further at how these changes translate to changes in economic and political landscapes. We generally follow Acemoglu and Restrepo (2020) to study the impact of robotization, using industry-level robot adoption in the EU to instrument for potential US robot adoption.

More specifically, we first document several facts about job-to-job transitions. We note that the overall number of these transitions has been declining since 2000, particularly so for upward transitions, i.e., transitions to better-paid jobs or jobs with more responsibilities (management, architecture, and engineering occupation groups). We then use career value 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 this occupation, taking into account the probabilities of transitions from this occupation to future occupations. While doing so, we weight the transition matrix to make the occupation structure representative of the US population. We then estimate the transitional probabilities from the resume data and combine them with the wages,

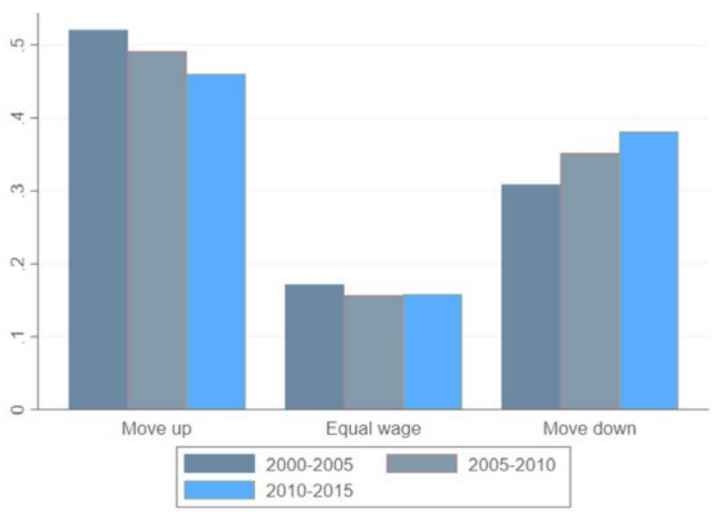
[1] We an analog of this figure based on CPS in the Appendix.

Figure 1: Probabilities of Transition out of 2-digit Occupation Groups, 2000-2015



Notes. For any sector and time period, the probability of transition out of the sector 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.

Figure 2: Transitions to Different Types of Occupations, by Time Period



Notes. The figure depicts the normalized transitions to better-paid, worse-paid, and (approximately) equal-pay jobs over 5-year time periods between 2000 and 2015. 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 time 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.

corresponding to these occupations, at the state level. We thus use realized occupational transitions to measure expected occupational transitions and realized wages at the local (commuting zone) and occupational levels as the best available proxies for the expected wages.

Second, we show that automation and robotization affected both transitions and career values. Higher robot adoption led to more transitions to similar-wage jobs and fewer transitions to higher-wage jobs, more so in high-manufacturing commuting zones (i.e., commuting zones with above-median manufacturing employment). We further note that exposure to robots reduced career value components coming from both wages and upward transition probabilities. Moreover, although both low- and high-skilled workers face wage declines at similar rates in response to automation, expected upward job mobility declined substantially more for low-skilled workers compared to high-skilled workers. These results together point out towards the decline in middle-level jobs as being a mechanism for the career effects of robotization.

Third, we document several related economic effects that help explain other mechanisms behind the automation-induced decline in upward mobility. In particular, we find that automation affected not only jobs in manufacturing but also jobs in other, mostly non-tradable industries, such as services and retail. We see a related decline in consumer expenditures. In addition, we report a decline in economic expectations, as measured by Gallup survey data. These findings together suggest the existence of important spillovers that are responsible for the changes that we document.

Fourth, we find that the negative effects of automation are mitigated in places with higher opportunities for upward mobility. Getting education is the main source of upward mobility, and we observe this mitigation effect for school enrollment of individuals 18 and over. We also report a similar, albeit weaker, effect for the intergenerational mobility effect of neighborhood characteristics (Chetty and Hendren, 2018).

Fifth, 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 and political behavior. We instrument career values using wages and occupational transitions in commuting zones further than 100 miles away from the focal commuting zone and find positive effects on new home construction, the share of individuals in higher education, and vote shares in 2016 presidential elections.

Finally, we zoom in on the impact of automation on political outcomes. We document the reduced-form relationship between local automation, as predicted by labor market shares in the 1990s, and industry-level automation in EU countries, and voting for Trump in the 2016 presidential elections. We find supportive evidence that the effect of automation on voting comes from both the supply side of politics, as captured by voting patterns of congressional representatives and patterns of campaign visits, and the demand side of politics, as captured by parallels in automation effects on individual economic outcomes and voting intentions. We observe a stronger relationship between Donald Trump's vote share and the family economic situation of younger respondents, which further supports a career value-based interpretation.

There are several caveats about our findings. Migration could contribute to our estimates of career values by changing the occupational composition of workers. However, most US workers don't move across commuting zones for job related reasons (e.g., Marinescu and Rathelot (2018)). Moreover, our results suggest that robotization had no effect on the occupational composition. Though in-migration indeed responds to robotization (Faber et al., 2019), it does not major enough to shift aggregate career values.

Globalization could be another factor contributing to the decline in career values. Following Acemoglu and Restrepo (2020), we check that our results are robust to controlling for China shock (Autor et al., 2013). We do not study China shock as a separate source of variation for the following reason: for China shock, most variation is cross-sectional for our time period (2000-2016), while our aim is to study economic shocks over time and the corresponding change in career values. For robotization, time-series component of variation is at least as important as cross-sectional one.

Heterogeneity of the results could be important to keep in mind while thinking about career implications of robotization. We study heterogeneity for high- vs low-skilled career values. We did not find any gender-specific differences, either because spillover effects of robotization are large, or BGT gender identification algorithms are imperfect. We also looked at the heterogeneity for other sources of mobility (education, intergenerational mobility), and we document that our sources of mobility mitigate the effects of robotization on career values.

Overall, our results imply that in 2000-2016, there has been a decline in economic opportunities, i.e., job-related upward mobility, and robot adoption contributed to this decline. Moreover, low-skilled workers' career prospects were affected the most. This decline in opportunities made people change their long-term decisions, such as housing and education. They also change their voting behavior, e.g., vote more prominently for Trump in the 2016 general elections, while politicians, in turn, change their behavior to address these new demands.

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 decline in intergenerational mobility among community zones over time in the U.S. Putnam (2015) highlights declining opportunities for children. We add to this literature by documenting the declining rates of job-related upward mobility, as measured by the transitions to better-paid jobs or career values, in the U.S. in 2000-2016. We, furthermore, document that technological change, in particular robotization, contributed to this decline. We also find that other sources of upward mobility, such as more opportunities to get higher education or higher intergenerational mobility, mitigate the negative effects of robotization.

Second, there is literature on growing income inequality and economic changes that contribute to it, e.g., trade and globalization (Helpman et al., 2016; 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), or housing expenditures (Dustmann et al., 2021). Our findings suggest that technological change and, in particular, robotization contributed to the growing inequality and the rising gap between the high- and the low-skilled by diminishing opportunities for job-based upward mobility.

Third, we contribute to the literature on the economic and political consequences of automation, robotics, and artificial intelligence (AI) on jobs, wages, and society in general (Frank et al., 2019). Acemoglu and Restrepo (2019) and Furman and Seamans (2019) argue that automation growth could result in the creation of new jobs and occupations due to increased productivity effects while displacing some labor at the same time, so a decline in employment may not ex ante be the prediction. Alekseeva et al. (2021) also find that the demand for AI skills in the labor market has increased dramatically during the 2010-2019 period, suggesting that some job creation is taking place in response to new technologies. Battisti et al. (2023) find that automation reduces firm demand for routine jobs relative to the demand for abstract, task-based jobs. Despite some evidence of creative destruction, Acemoglu and Restrepo (2020) document that between 1990 and 2007, the adoption of robots resulted in loss of jobs in the U.S. Arntz et al. (2017) argues that these are overestimates. Graetz and Michaels (2018) running a study of 17 countries, find evidence for increased productivity growth from higher rates of adoption of robots. Faber et al. (2019) find that robotization affects migration, and they also, independently of us, document spillover effects of automation and robotization. Cockriel (2023) finds that historically, artisan shoemakers lost their life-time earnings as a result of technological change towards factory-based shoe production. Paolillo et al. (2022) compute job robotization risks and discuss workers' alternatives. We contribute to this literature by studying the impact of robot adoption on future career opportunities and the implications of our forward-looking measure of lifetime income on long-term individual decisions and other outcomes.

Fourth, we build on a literature in urban and labor economics that shows the importance of considering wage growth through job mobility when thinking about labor markets (e.g., Topel and Ward, 1992). The importance of variation in these career dynamics across cities is shown by Glaeser and Mare (2001), who find that the urban wage premium is driven in part by higher wage growth over time in urban areas, so the trajectory of wages is important for understanding the attractiveness of different labor markets.

More recently, Bilal and Rossi-Hansberg (2021) develop and test a model where location choices are an investment in a forward-looking "location asset" that, in part, reflects expected payoffs coming from future local job opportunities. Consistent with our analysis of the effect of "career values," they find that these forward-looking location characteristics can affect current household choices. We contribute to this literature by documenting local changes in expected career dynamics over time and how they are affected by automation shocks, all focusing on a forward-looking measure of individuals' lifetime income.

Fifth, we also contribute to the literature on populism. Populist movements around the world have vastly different agendas (Rodrik, 2018), but common identifiers (Guriev and Papaioannou, 2022). Populist rhetoric relies on policies tailored to demote redistributive measures (Drake, 1982; Dornbusch and Edwards, 1991), exploiting people's fear of the rich capturing the political process (Dornbusch and Edwards, 1991; Acemoglu et al., 2013; Di Tella and Rotemberg, 2018), economic insecurity (Autor et al., 2016; Guiso et al., 2017; Panunzi et al., 2020; Dippel et al., 2015), and low trust (Algan et al., 2017). In line with this literature, the Brexit campaign in the U.K., the anti-immigrant movements in Germany and France, Erdogan in Turkey, Putin in Russia, and Trump's anti-trade and anti-immigrant narratives ring an anti-establishment and anti-elite tone. A growing group of papers estimates the impact of economic shocks related to technology and globalization on the political fortunes of politicians in the US (Autor et al., 2020a, 2016; Che et al., 2022; Heins, 2023; Frey et al., 2018), Europe (Colantone and Stanig, 2018b; Anelli et al., 2021), UK (Gallego et al., 2022), Germany (Dippel et al., 2015), and France (Malgouyres, 2017). Enke (2020) argues that increased polarization in moral values contribute to the recent changes in vote patterns in the United States. We contribute to this literature by studying the impact of forward-looking economic expectations on electoral preferences for extreme candidates in the US and associated demand- and supply-side political changes.

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 automation at the local level, and provides descriptive evidence. Here, we also summarize the basic relationship between local labor market career values and automation. Section 5 studies the mechanisms, and section 6 studies the implications of changes in career values for long-term decisions. Section 7 discusses the political effects of automation and the associated changes in career values. Section 8 concludes.

2 Job Transitions Data

Employment History Data We use data from Burning Glass Technologies, one of the largest repositories of resumes available online in the United States. The data set combines resumes of over 16 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 contain 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 list the companies that candidates worked at, the job start and end dates, their education and certification, and their location at a zip-code level, and are parsed to create a personal career history, starting from the first reported job to the most recent occupation that they hold. 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.

Working with a large and detailed resume data set provides us with a number of advantages, most importantly, 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, 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 shows that these occupations are substantially overweighted in the BGT data. Data underrepresent construction/transportation and hospitality/tourism sectors, where most occupations can be seasonal. Occupations in other industries seem to have shares comparable

Table 1: Summary of the Job Characteristics

	Mean	SD	Min	Max	N
Female	0.50	0.50	0.00	1.00	14,442,178
Age	28.42	7.00	16.00	94.00	16,737,721
College Degree	0.17	0.37	0.00	1.00	16,737,721
First Year Data	2001.62	7.75	1990.00	2017.00	16,737,721
Last Year Data	2013.46	5.06	1990.00	2017.00	16,737,721
Years of Work	12.84	7.93	1.00	28.00	16,737,721
Average Number of Occupation Changes	2.31	2.63	0.00	92.24	16,737,721
Average Number of Occupation Changes per Year	0.22	0.22	0.00	8.39	16,737,721
Average Number of Moves Up (wage-wise)	0.96	1.21	0.00	40.13	16,737,721
Average Number of Moves Down (wage-wise)	0.74	1.06	0.00	55.61	16,737,721
Average Number of Same Pay Moves	8.04	6.60	0.00	122.00	16,737,721
Number of Unique Occupations (per worker)	2.89	1.57	1.00	17.00	16,737,721
Number of Unique Firms (per worker)	2.91	1.92	0.00	22.00	16,737,721
	Total				
Number of Unique Workers	16,737,721				
Number of Unique Occupations	1,070				
Number of Unique Firms	18,100,000				

Notes: Statistics are calculated using the resume data from BGT, calculated over the years 2000–2016.

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. are represented in the data.

A third concern with the data 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.[2] 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

[2]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).

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, 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.

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 the 15 years.[3] As Figure 1 suggests, occupational transitions seem to have slowed during 2010-2015 relative to the 2000-2005 period.[4] Such 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 right figures, the probability of transitions from production to "management" and "architecture and engineering" occupation groups—which likely represent upward transitions—seem to have declined between 2004 and 2016. Appendix figures A.3 and A.4 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.

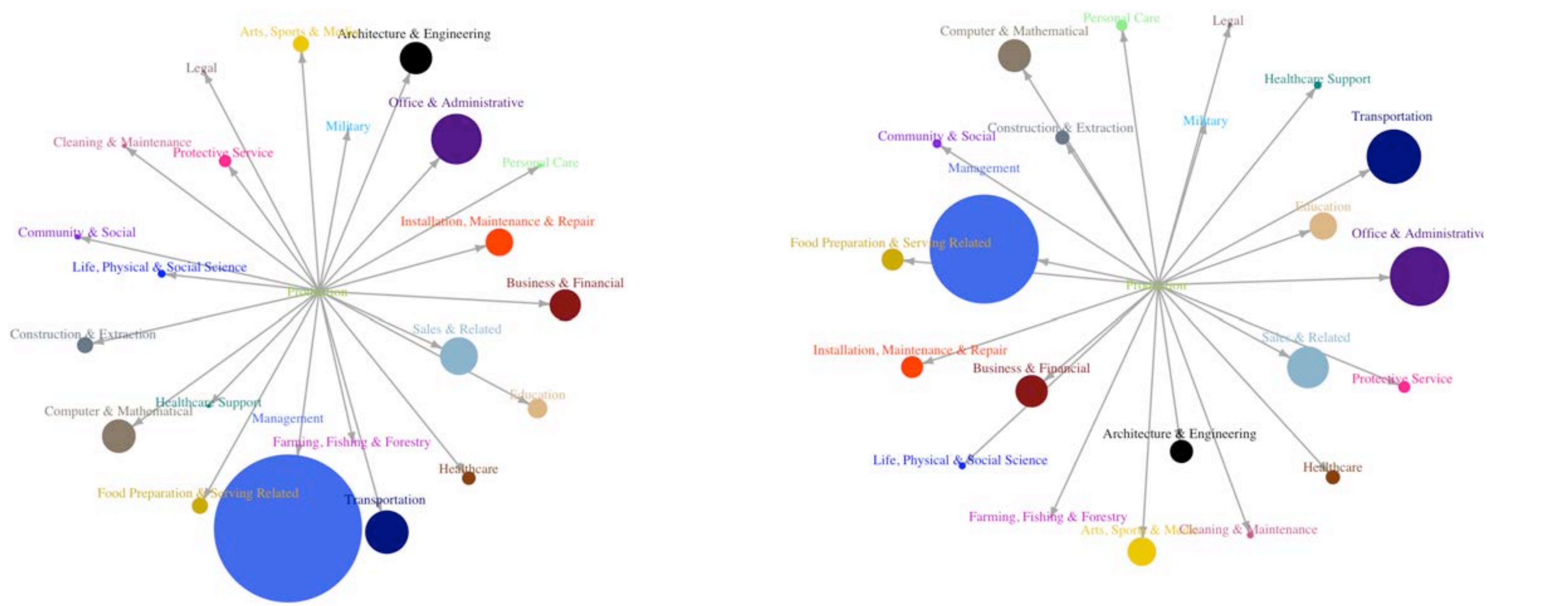
Figure 4 complements the earlier figures by depicting the trends for transitioning out of production occupations and transitions to management occupations. This figure shows the numbers normalized by the total number of transitions, to correct for natural variation coming from the business cycles. As one can see, the first type of transitions seems to be going up over time, while the second type of transitions seems to be going down. The normalized transition probabilities for moving to occupations in management, engineering, construction, maintenance, and production for each 5-year period between 2000 and 2015 are summarized in Figure 5. This figure is, again, consistent with the decline of upward mobility over time: the transitions to "management" and "architecture and engineering" occupations seem to be declining over time, while other occupation groups do not demonstrate a clear trend.

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 2, we summarize changes as transitions to better-paid jobs, worse-paid jobs, and to (approximately) equal-payment jobs

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

[4]The latter period may also include the long-term consequences of the 2008 economic recession. However, since the recession resulted in job losses, transitions may be expected to intensify in this period.

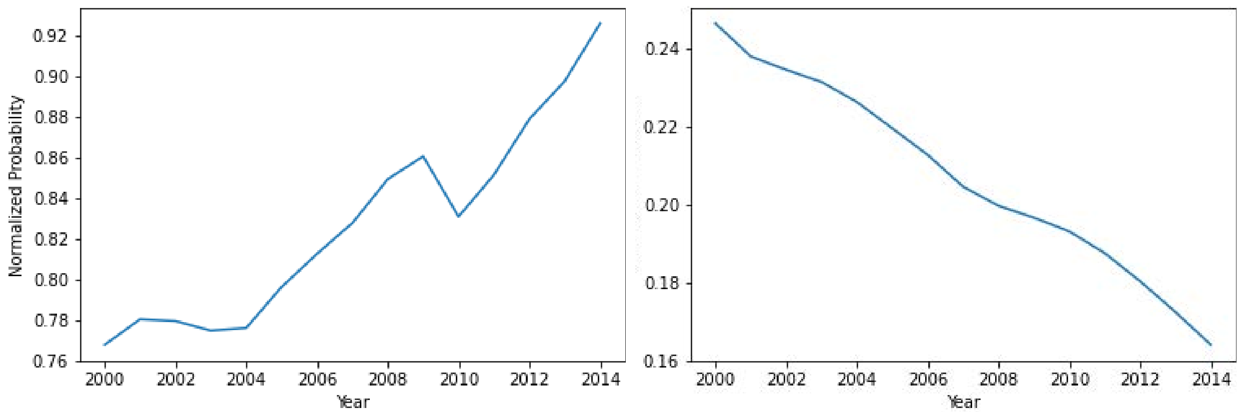
Figure 3: Probabilities of Transitioning out of Production Occupations, 2004 vs 2016



(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

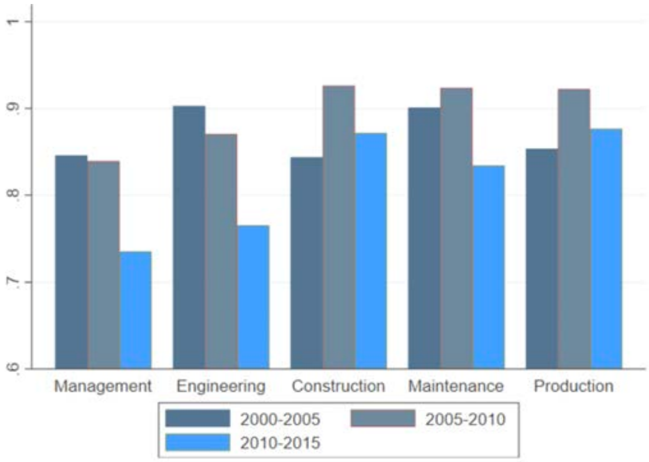
Notes. Panel (a) shows the probability of transitioning from the "production" two-digit occupation group to any other occupation, and panel (b) shows the probability of moving from any occupation to the management occupations. Annual job transition probability out of occupation o is calculated as the 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 $t+1$. Normalization is carried out by dividing the transition probabilities between specific occupations by the overall probability of transitioning between any two occupations 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.

over 5-year time periods. As one can see, transitions to worse-paid jobs increased, while transitions to better-paid jobs decreased between 2000-2005 and 2010-2015.[5] Overall, the basic descriptive analysis of occupational transitions presented in this subsection suggests a decline in upward transitions 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 data source. To confirm that this pattern is robust, we 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). While occupational mobility measurement in the CPS 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 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

[5] A period of unemployment may result in transitions to temporary, low-wage occupations to 'make ends meet.' To avoid temporary positions, we consider occupations held for a period of 6 months at a minimum. However, such temporary jobs are less likely to be reported on resumes, as applicants see them as irrelevant or even damaging to their careers.

Figure 5: Transitions to Various Occupation Groups, by Time Period



Notes. The figure presents the normalized transition probabilities for moving into occupations in management, engineering, construction, maintenance, and production for 5-yearly periods between 2000 and 2015. 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 time 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 $t+1$ (see p. 14 for details). Occupations held for less than 180 days are excluded. Plotted probabilities are moving averages over 3 years around the year of interest.

the time of the survey and use harmonized 1990 occupation codes provided by IPUMS-CPS. The trends over time in 1-year occupational mobility out of detailed occupations, as well as out of aggregated broad occupation groups, in the CPS are shown in Appendix Figure A.6. We find that, similar to the mobility in the resume data, there is a clear downward trend since the mid-1990s that only partially reverts in the 2010s. Appendix Figure A.5 shows the change between the early 2000s and early 2010s in mobility averaged by broad occupation groups, which shows a similar pattern to that seen in Figure 1 and shows that the finding of declining mobility is not driven only by particular occupations, or by idiosyncrasies of the resume data. This aligns with other recent papers that find declining occupational mobility since the 1990s in CPS data (Moscarini and Thomsson, 2007; Xu, 2018; Vom Lehn et al., 2022).[6]

To compute the CPS analogue of Figure 2, 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 hourly wages between surveys one year apart, conditional on the recorded harmonized occupation code being different. While the occupational moves are more likely to contain measurement error in this data, it has the advantage that we can construct our mobility estimates for a longer time period. Appendix Figure A.7 shows the likelihood of transitioning into a job with higher, lower, or similar wage to the previous job, conditional on moving between detailed occupations, for 1981-2020. We find that there has been a marked increase in the likelihood of experiencing declining wages when switching occupations in the 2000s and 2010s relative

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

to previous decades in the CPS, and also a decline in the chance of higher wages throughout the 2000s, which only partially reversed during the 2010s. Overall, these results confirm that the mobility trends in the resume data are qualitatively very similar to those in the nationally representative CPS data.

However, looking at the probability of one-time transitions does not take into account the lifetime gains from this transition. For instance, individuals may choose to move to a worse-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 the individual job histories, in the following section, we will formally define the concept of career values. Following that, we will describe the trends in career values in the US and demonstrate a recent decline, partly stemming from reduced occupational mobility. We will then discuss automation and robotization as one factor that contributed 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 the 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 her career by considering the probabilistic path of occupations she is likely to hold in periods $t+1, t+2, ...$ 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 $\{o, p, q, r, \dots N_{Occ}\}$:

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

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. 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:

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

where the diagonal of the 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 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 can be justified if workers calculate career expectations based on their recent observations, rather than using a sophisticated model to project the evolution of the US 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 construct their beliefs about future earnings.[7] [8] We further assume that workers can anticipate the transitions that follow an immediate transition. This is a realistic assumption since Table 1 indicates the average occupational transitions per worker is 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.[9] This

[7]Experts with advanced degrees often do not agree about the growth trends in the labor markets (e.g., Graetz, 2020), and we presume that the workers also lack perfect foresight about it.

[8]We also assume that workers use the wages in their local market to calculate future career expectations rather than the wages in other local markets. This implicitly assumes that workers consider geographic moves too unlikely to be relevant in this calculation.

[9]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.

unconditional occupational transition probability is our proxy for $\pi_{o\to p}$:

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

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 2003–2005 period.[10]

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 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) and we set the discount factor to $\beta = 0.85$.[11]

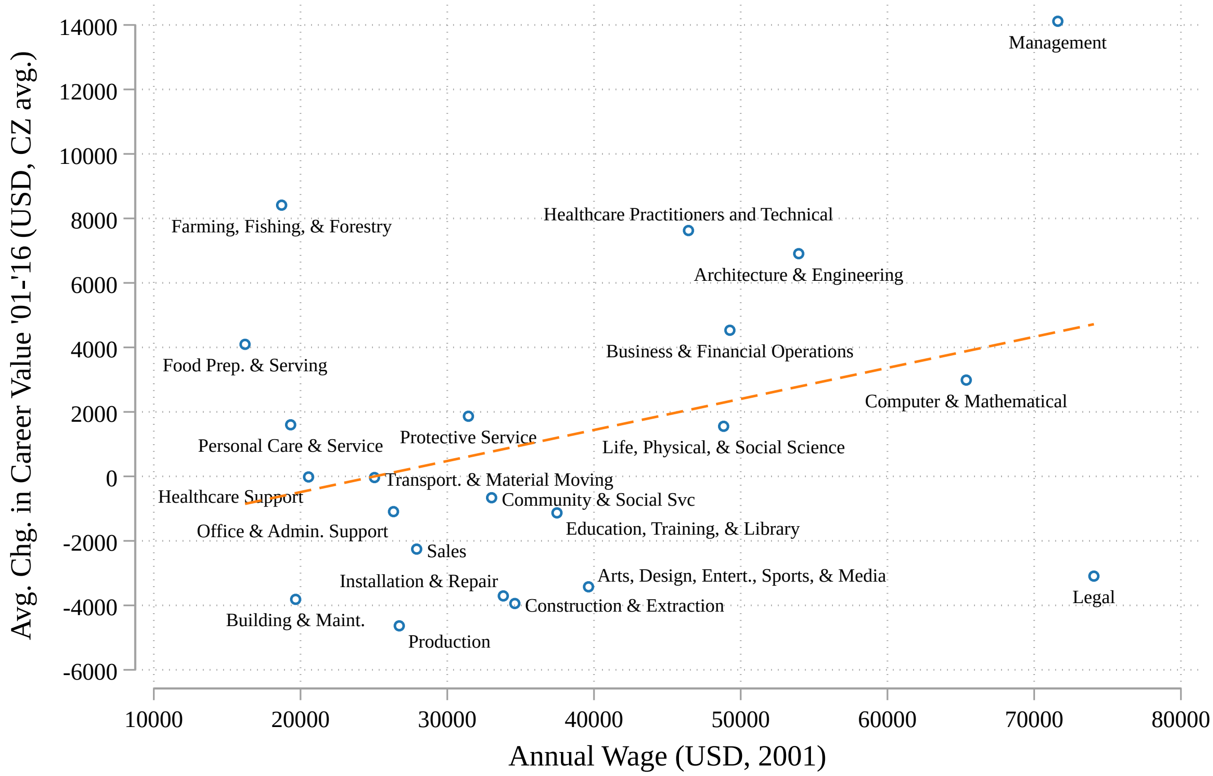
[10] Our methodology for estimating the job transitions from BGT data is similar to Schubert et al. (2021), Section 2.

[11] 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.

3.2 Career Values, Wages, and Automatability

Figure 6 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 7). The comparison of Figures 6 and 7 suggests that occupations are different not only in the wage gains, but also in the career mobility opportunities they offer, and the career values of occupations in Figure 6 are more dispersed.

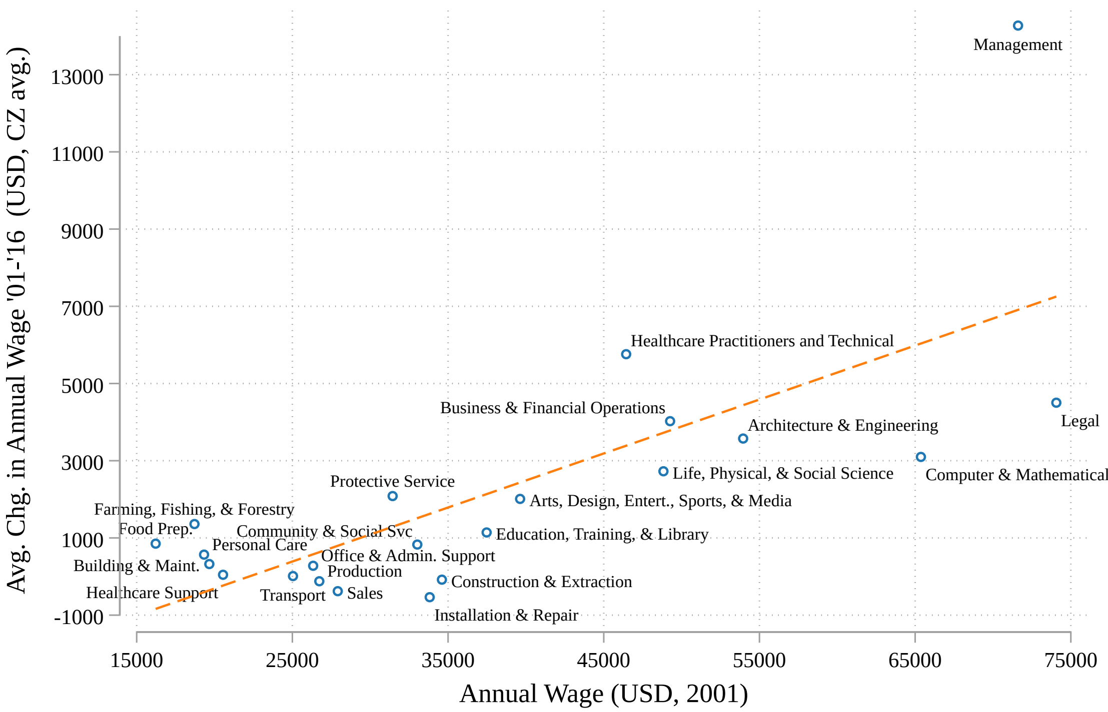
Figure 6: Average Career Value Change Between 2000 and 2016 vs. Starting Wage, by 2-digit SOC



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 $\beta = 0.85$.

In appendix Figure A.8, 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 to the figure, an approximate 0.2 unit increase in the automatability score is associated with $2,500 less

Figure 7: Average Wage Change Between 2000 and 2016 vs Starting Wage, by 2-digit SOC



Notes. 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).

in upward career value change between 2000 and 2016.

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:

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

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 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:

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

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:

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

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 were growing in the 2000-2008 period, while there is 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, at a discount factor of 0.85, and assuming rational expectations of career values.

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 an earlier period industry shares for each industry potentially affected by robotization. CZs differ in their exposure to automation 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:

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

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 for period t_1 and includes 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). 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 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 US For more details on this dataset, please see appendix B.[12]

Exposure to robots in CZ c in period (t_0, t_1), $Exposure\_to\_robots_{c,(t_0,t_1)}$, is constructed by weighting over local industry employment shares 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 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, $Cov(\varepsilon^{\ell}_{c,(t_0,t_1)}, Exposure\ \_to\_robots_{c,(t_0,t_1)}) \neq 0$—, 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 US[13] 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 US 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 US 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 US. That is, intuitively, we can think of the IV Lasso procedure as constructing a first-stage predicted variation in local robot exposure given by

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

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

[12]We handle the limitations with the IFR data similarly to 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 US 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."

[13]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 US 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 US should see an increase in robot adoption.

requires $Cov(\varepsilon^{\ell}_{c,(t_0,t_1)}, \overline{Exposure\_to\_robots}_{c,(t_0,t_1)}) = 0$, 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 US 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.

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 B.

Local business dynamics and demographics. We use the County Business Patterns (CBP) data from the Census to measure county-level employment, wages, and number of establishments by NAICS industry. The data are at the county-level, and we aggregate values to the 1990 commuting zone level. We measure local employment shares for 2000 and 2010 by demographic group using American Community Survey microdata accessed through IPUMS. These data can be accessed via IPUMS.

Spending and investment activity data from NielsenIQ LLC and US Census. We construct data on consumer behavior in various dimensions: we use NielsenIQ Consumer Panel data to measure changes in household spending 2004-2016. These data are accessed through the Kilts Center at the University of Chicago Booth School of Business.

New housing construction permits by commuting zones are constructed from county-level counts of permits available from the Census Building Permits Survey for 1990-2018, aggregated at the level of 1990 commuting zone. The data are available through the US Census Bureau. Some counties do not report permit numbers. Thus, in cases where not all component counties of a CZ are reporting, we scale the reported numbers in proportion to the reporting counties' share of the CZ population to make up for the missing share, using county populations in 2000 as weights.

Gallup Poll Social Series (GPSS) We use data from the Gallup Poll Social Series (GPSS) to study effects on people's perception of the economy. The data are from 2016 and respondents are asked about whether they think the economy has improved or worsened. Access to the GPSS is through the Penn Libraries of the University of Pennsylvania.

Political Outcomes We study political outcomes such as voter shares, voting intentions, political ideologies and campaign visits. Data on electoral outcomes are from Dave Leip's Atlas of the US Presidential Elections, referred to as the Election Atlas. We use data from the Cooperative Election Study, which was previously called the Cooperative Congressional Election Study (CCES), to measure people's voting intentions in US presidential elections. Data on campaign visits are from Devine (2018). We measure political ideologies by using NOMINATE and Nokken and Poole scores for the US House of Representatives for the year 2016 available via VoteView.

4 Empirical Results

The previous section showed 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 the recent decades: exposure to automation and robotization.

The analysis estimates the effect of robot exposure on labor market outcomes—consisting both of changes in contemporaneous outcomes such as unemployment and wages, as well as 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 an important contemporary technological process, 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 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 (columns 1-3) and IV Lasso (columns 4-6). OLS coefficients are slightly smaller than the IV coefficients, which may point to measurement error, but we do not observe a large bias for OLS estimates in either direction. Coefficients in columns (4)-(6) suggest that higher exposure to robots resulted in a decline in the expected LMCVs. The shrinkage in career value is significant for all three periods (2004 to 2008, 2008 to 2016, and 2004 to 2016), 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 \$3.9K between 2004 and 2008 and by \$2.48K between 2008 and 2016. These values correspond to about 1.7% and 1.1% of the average career value in 2000 (\$230,957). Table A.18 in the appendix replicates these results but includes the share of employment in routine occupations and change 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)

	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	-0.370*** (0.074)			-0.390*** (0.082)		
U.S. Robot Exposure '08-'16		-0.191* (0.108)			-0.248*** (0.095)	
U.S. Robot Exposure '04-'16			-0.318*** (0.041)			-0.338*** (0.037)
Mean of D.V.	-0.124	-0.015	-0.139	-0.124	-0.015	-0.139
F-stat.				47.369	4.510	63.210
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). 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.

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 indicate that the LMCV does not change substantially due to the market composition, with our confidence intervals allowing us to rule out the effect of up to $66.8 for a mean dependent variable of $2,147. This suggests that migration, 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 ($2,040 decline) being due to the decline in wages, and one-third of the effect ($1,170 decline) being due to the decline in career path, i.e., a decline in upward transitions if we hold wages fixed (both numbers are for 1 additional robot per 1000 workers).

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 the implied first stage for the IV Lasso procedure is much weaker for low-manufacturing commuting zones, which is in line with intuition.

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 (-0.292) from one additional robot per 1000 workers is about 6 times that for the current occupation (-0.043). 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). Put differently, regions with higher robot exposure experienced a decline in mobility between occupations: the likelihood of staying in the same occupation is higher, and transferring to another occupation is less likely.

Automation Exposure and Job Transitions

To better understand the results in Table 3 and Table 4, we look into the impact of exposure of 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 2. 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 lower-wage occupations increased 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

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	-0.334***	-0.204***	-0.117***	-0.013*	-0.008**
	(0.004)	(0.038)	(0.045)	(0.022)	(0.007)	(0.003)
Mean of D.V.	0.215	-0.244	1.072	-1.140	-0.176	-0.110
F-stat.	0.937	76.622	58.281	19.728	7.107	6.796
Observations	722	722	722	722	722	722
Panel B: High-Manufacturing Commuting Zones						
U.S. Robot Exposure '04-'16	0.002	-0.355***	-0.218***	-0.120***	-0.016	-0.006**
	(0.007)	(0.031)	(0.034)	(0.024)	(0.010)	(0.003)
Mean of D.V.	0.228	-0.630	0.666	-1.152	-0.144	-0.084
F-stat.	0.136	67.760	49.422	15.719	4.309	4.060
Observations	359	359	359	359	359	359
Panel C: Low-Manufacturing Commuting Zones						
U.S. Robot Exposure '04-'16	0.244	0.405	0.414	0.074	-0.084	0.346*
	(0.288)	(1.808)	(1.117)	(1.197)	(0.349)	(0.181)
Mean of D.V.	0.199	0.123	1.466	-1.138	-0.206	-0.135
F-stat.	1.524	0.146	0.365	0.010	0.131	13.275
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.

average a 7.2% increase in the number of transitions to similar pay jobs (column 1), a 6.2% decrease in the number of transitions to better-paid jobs (column 2), and a 5.9% increase in the number of transitions to lower-paying jobs (column 3). For high-manufacturing commuting zones, the corresponding estimates are a 16.9% 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.19 in the appendix replicates these results but includes the share of employment in routine occupations and change exposure to imports from China from 1990 to 2007 as controls.

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

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.	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	0.072**	-0.062***	0.059**	0.169***	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	0.260	0.073	0.263	0.073	0.263	0.074
F-stat.	25.333	86.895	16.673	161.287	32.425	35.045	1.026	42.940	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	359	360	359	360	359	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). 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 and France 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.

occupations (columns 2, 7, and 8). Table A.4 estimates the effect of exposure to robots separately for on occupational change (column 1) and employer change (column 2), as well as the changes of employer within an occupation (column 3) and changes to occupations within one's current employer (column 4). We find that higher robotic exposure is associated with a higher likelihood of changing employers and lower likelihood of changing occupations overall. These results are consistent with our interpretation that upward job transitions declined as a result of automation and robotization, and this is a reason contributing to overall decline in upward mobility observed in recent years.

College Premium, Heterogeneity, and Inequality

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, and more generally other sources of upward mobility, can mitigate the negative effect of robot exposure.

Career Values by Education and Automation. One of the principal sources of upward mobility is education. Getting 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.[14]

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, column (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 the wages constant (column 4). Columns (5) and (6) show the results for the interactions.

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

	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	-0.005	-0.388***	-0.237***	-0.152*	0.001	-0.014***
	(0.007)	(0.095)	(0.046)	(0.078)	(0.013)	(0.004)
Mean of D.V.	0.345	-0.162	1.162	-1.120	-0.205	-0.415
F-stat.	0.388	27.243	72.338	4.908	0.550	5.570
Observations	722	722	722	722	722	722
Panel B: College and Higher						
U.S. Robot Exposure '04-'16	-0.008	-0.341***	-0.241***	-0.104***	0.004	-0.010***
	(0.007)	(0.032)	(0.041)	(0.030)	(0.006)	(0.004)
Mean of D.V.	-0.033	-0.189	1.163	-1.188	-0.164	-0.039
F-stat.	0.543	66.896	72.950	13.638	0.134	6.503
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 to avoid taking education split and its correlates to take into account twice. U.S. Robot Exposure is instrumented using robot exposure in Denmark, Italy, Sweden, Finland and France in the same time periods. Observations are weighted by commuting zone population.

On average, exposure to robots affects both types of workers negatively. However, the magnitudes of these effects are different for some outcomes and similar for others. In particular, the wage component of career values is affected similarly for high- and low-skilled workers, with one additional robot per 1000 workers leading to approximately \$2.4k reduction in their lifetime income if their career opportunities were fixed over time. The magnitudes in column (3) for Panel A and Panel B (0.237 vs 0.241) indicate comparable estimates for those below-college and college-level education, with the same 1% level of statistical significance. 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, looks similarly more negative for the low-skilled workers. For low-skilled workers, the effect is -0.152, while for high-skilled workers it is equal to -0.104. This implies that for high-skilled, education mitigates the negative effect of robotization,

[14]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.

and high-skilled workers' lifetime career prospects are less affected. Numerically, these changes imply that 1 extra robot per 1000 workers leads to approximately $1,520 reduction in lifetime earnings from upward mobility for low-skilled workers and $1040 reduction in lifetime earnings from upward mobility for high-skilled workers, and this contrast is even more striking taking into account that average career values are lower for low-skilled workers.

Overall, the results in Table 6 suggest that robotization mostly affects the career prospects of low-skilled workers, thus widening the gap between high- and low- skilled workers and exacerbating inequality.

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 Lorentz curve. After that, we can compute different percentile measures of inequality in carer values. We present these results in Table 7. As one can see, 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. Table A.20 in the appendix replicates these results but includes the share of employment in routine occupations and change exposure to imports from China from 1990 to 2007 as controls.

Table 7: 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, and France 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.

Heterogeneity with Respect to Sources of Upward Mobility. Another way of studying whether education indeed helps to mitigate the negative effects of robotization is carrying out a heterogeneity analysis. In particular, we would like to know whether education and other sources of upward mobility help to significantly mitigate the negative effect of robotization on the labor markets. To do so, we estimate the following reduced-form regression equation:

$$\Delta y_{c,(t_0,t_1)} = \beta_1 + \beta_2 RbtEU_{c,(t_0,t_1)} \times Mblty_{c,t_0} + \beta_3 RbtEU_{c,(t_0,t_1)} + \beta_4 Mblty_{c,t_0} + \beta \mathbf{X}_c + \varepsilon^{\ell}_{c,(t_0,t_1)}, \qquad (8)$$

Here $\Delta y_{c,(t_0,t_1)}$ is the outcome of interest, $RbtEU_{c,(t_0,t_1)}$ is an average robot exposure in EU countries weighted by commuting zone pre-existing employment in manufacturing, while $Mblty_{c,t_0}$ is a measure of education or upward mobility, to be specified subsequently. Note that we had to change our empirical strategy here by switching to a reduced form estimation. It is conceptually similar to the IV specification but precise, which is important for the case of the interaction term. As an instrument, we use the average robot exposure in 5 European countries.[15] Our results are robust to using different sets of countries.

We estimate equation (8) and present the results in Table 8. We first use school enrollment among those aged 18 and above as a proxy for the opportunities for upward mobility among the younger population, who are more vulnerable to the effects of limited mobility from a career perspective. 18+ school enrollment combines college education, delayed high school completion, and vocational training. Column (1) suggests that career values decline less in places with higher 18+ school enrollment rates, and this interaction effect is especially pronounced for low-skilled workers (column 2), while it's markedly smaller and insignificant for high-skilled workers (column 3). We believe that the result in column (2) is mostly explained by the presence of community colleges and vocational training programs, which allow affected workers to adjust their skills to the demands of the market. In columns (4) and (5) we re-estimate equation (8) using contemporaneous average wages (column 4) or employment (column 5) as dependent variables. For these outcomes, we no longer see the effect of robotization mitigated. The coefficient of the interaction term for wages (column 4) is negative and significant, rather than being positive. The same coefficient for employment (column 5) is positive, though insignificant. These results suggest that the opportunities to obtain education may increase people's career prospects, rather than their contemporaneous labor market outcomes. Overall, the results from Table 8 highlight the importance of looking at career prospect measures like career values when studying the impact of economic changes on labor market outcomes.

In the appendix, we also repeat the estimation of equation (8) using alternative proxies for opportunities for upward mobility, specifically average level of education (Table A.5) and local intergenerational mobility (Table A.6).[16] The results are qualitatively similar to the results in Table 8.

[15] By doing so, we follow Acemoglu and Restrepo (2020).

[16] More specifically, we used neighborhood intergenerational mobility fixed effect from Chetty et al. (2016)

Table 8: Automation, Career Values, and 18+ School Enrollment

	Δ Career Values 2000-2016			Δ Wage 2000-2015	Δ Employment 2000-2015
	All	Below College	College or Higher		
	(1)	(2)	(3)	(4)	(5)
EU Instrument '04-'16	-0.086***	-0.245***	-0.053**	-0.000	-0.049**
	(0.021)	(0.037)	(0.020)	(0.001)	(0.023)
18+ School Attendance '00	1.255	-15.315***	6.374	0.422***	12.178***
	(3.959)	(5.588)	(4.421)	(0.135)	(4.446)
EU Instrument '04-'16 x 18+ School Attendance '00	0.392*	2.239***	-0.033	-0.013**	0.015
	(0.225)	(0.357)	(0.218)	(0.007)	(0.240)
Mean of D.V.	-0.139	-0.232	-0.262	0.135	0.036
R-squared	0.489	0.257	0.445	0.535	0.751
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 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, France, Finland, UK and Germany during 2004-2016. Observations are weighted by commuting zone population.

5 Mechanisms

In this section, we look into mechanisms behind the main findings, as summarized in Tables 3, 4, 5, and 6. Our results so far suggest that expected lifetime incomes and upward mobility of workers declined as a result of automation, and more so for low-skilled workers. However, automation effects could be so noticeable and pronounced due to a number of reasons. It could happen because of spillover effects to other industries, especially non-tradable ones (supply-side effects), or general equilibrium changes in the patterns of consumption and consumer expectations (demand-side effects). In this section, we summarize some evidence pointing towards the mechanisms. We furthermore look at whether other sources of mobility mitigate the negative effects of automation and robotization on career values and compare it with the effect on current employment and wages.

5.1 Spillovers from Manufacturing to Other Industries

Our focus on career values makes the interdependence between different industries in a given location more visible. Table 9 summarizes how exposure to robots affects career values in different industry groups. We combine all manufacturing, trade, and service NAICS categories to simplify exposition. The coefficients are all statistically significant and close in magnitudes. This happens since career values look at all employment options workers have, instead of focusing only on their current industry. In fact, different industries are affected differentially by automation shocks (see e.g., Table A.9 or Table A.10 in the appendix), but the variation across industries in these shocks is attenuated from the perspective of workers when one takes into account all *possible* career transitions.[17] [18]

Table 9: Exposure to Robots and Change in Career Values, by Industry Group. IV Lasso

	Manufacturing (1)	Retail and Wholesale (2)	Services (3)	Management (4)	Other Industries (5)
U.S. Robot Exposure '04-'16	-0.354***	-0.346***	-0.415***	-0.232**	-0.389***
	(0.043)	(0.038)	(0.040)	(0.097)	(0.039)
Mean of D.V.	-0.235	-0.405	-0.390	0.348	-0.138
F-stat.	93.875	80.315	103.167	7.348	106.558
Census Division FE	Yes	Yes	Yes	Yes	Yes
A&R Controls	Yes	Yes	Yes	Yes	Yes
Observations	722	722	722	616	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). 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. Industrial classification is based on 2-digit NAICS. Observations are weighted by commuting zone population.

5.2 Consumer Responses

In this subsection, we look at whether automation had any impact on consumption and economic expectations. In particular, we tested whether automation exposure results in a change in average household spending on groceries and household items. To this end, we use the Nielsen Consumer Panel data on household-level consumption. The earliest data in this panel go back to 2004, and we use data from households common to both the 2004 and 2016 panels to control for unobserved household characteristics. In Table 10, we present the IV specifications, regressing the logged difference between 2016 and 2004 aggregate household spending, and adjusting for inflation. Running specification 5 with the change in total household spending on grocery and household items shows that, with greater exposure to robotization, household consumption saw a greater and statistically significant decline. The magnitude of the effect implies that one additional robot per 1000 workers resulted in a 2.5% decline in the overall consumption between 2004 and 2016, and more so in high-manufacturing commuting zones. Table A.21 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, and provides practically the same results.

[17] Respective results for wages are summarized in Tables A.11 and A.12

[18] In the online appendix section A.9, we also check the patterns of business creation and destruction in different sectors. We follow Mian and Sufi (2014), who use 4-digit NAICS codes to define tradable vs. non-tradable establishments, to estimate this effect. We find a negative but insignificant direction on the number of establishments in places with higher exposure to robots in the construction sector. Non-tradable establishments in regions with higher robot exposure also have a significantly smaller number of employees. Overall, these results are suggestive of some negative effects of automation on local business growth, consistent with declining demand for goods and services.

Table 10: Automation Exposure and Household Retail Consumption. IV Lasso

	Log (Δ Total Household Spending)	Log (Δ Total Spending)	
	All	High Manuf. CZ	Low Manuf. CZ
	(1)	(2)	(3)
U.S. Robot Exposure '04-'16	-0.025***	-0.036***	-0.017
	(0.004)	(0.003)	(0.041)
Mean of D.V.	-0.300	-0.309	-0.290
F-stat.	14.100	11.407	0.003
Census Division FE	Yes	Yes	Yes
A&R Controls	Yes	Yes	Yes
Observations	11146	5620	5498

Notes. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Robust standard errors are in brackets and clustered by state. The source of household spending data is NielsenIQ Consumer Retail Panel, made accessible by the Kilts Center at the University of Chicago. Panels are from 2004 and 2016. The outcome compared the log of the difference in household spending. The analysis is based on the households that are common between 2004 and 2016, and uses the difference in spending of each household. Household spending in inflation-adjusted. 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.

Next, we report what happens to people's economic expectations. In Table 11, we check if greater exposure to robotization altered people's perceptions of the economic conditions in any way. As a proxy for the perception of the economy, we use a question from the Gallup Poll Social Series (GPSS) surveys measuring economic confidence/economic outlook: "Right now, do you think that economic conditions in the country as a whole are getting better or getting worse?" and the possible answers are Getting Better; Getting Worse; Same; Don't Know; Refused to answer. We code two variables, one is coded $better = 1$ if the answer is "better" and 0 otherwise, and the other variable is coded $worse = 1$ if the answer is "worse" and 0 otherwise. The response to the survey question employed as an outcome was recorded in 2016. In local markets that have experienced greater robot exposure, individuals are less likely to state that the economy is getting better, suggesting that the worsening of people's perceptions correlates with greater robotization. These results, furthermore, imply that automation and robotization can affect people's long-term decisions, as examined in Section 6.

6 Career Value and Long-term Outcomes

Results in sections 4 and 5 suggest that automation affects future mobility, expected lifetime incomes, and economic expectations. These changed expectations can, in turn, affect people's long-term decisions. In this section, we aim to estimate the causal effects of expected career values, our measure of expected lifetime income, on schooling, housing, and voting.

Table 11: Automation and Perception of the Economy, Gallup. IV Lasso

	(1) Economy has gotten better	(2) Economy has gotten better	(3) Economy has gotten worse	(4) Economy has gotten worse
U.S. Robot Exposure '04-'16	-0.004***	-0.004***	-0.001	-0.000
	[0.001]	[0.001]	[0.001]	[0.001]
Mean of D.V.	0.04	0.04	0.05	0.05
F-stat.	639	632	639	632
Census Division FE	Yes	Yes	Yes	Yes
A&R Controls	Yes	Yes	Yes	Yes
Individual Controls	No	Yes	No	Yes
Observations	10,165	9,960	10,165	9,960

Notes. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Robust standard errors are in brackets and clustered by commuting zone. An observation is an individual in 2016. Data on perceptions are from the Gallup Poll Social Series (GPSS) surveys from 2016. 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). Columns (2) and (4) include individual-level controls for gender, age group, educational status, hispanic origin, marital status, employment status and religious preferences. 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 and the survey weight.

6.1 Estimating the effect of career value changes

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, we employ an additional instrumental variables strategy to identify the effect of career values on college education, housing permits, and voting. 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. At 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:

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

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.

6.2 Implications of career value changes

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 study in places with higher career values. To test which of these effects prevails, in what follows, we summarize how career values affect people's average levels of education.

Next, 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 the association to career values.

Finally, we also take a look at political behavior by checking 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 one can see in columns (3), (5), and (7), career values have significant effects on long-term decisions in the predicted direction, for IV Lasso estimates. Columns (2), (4), (6) report the results for OLS estimation for comparison. Numerically, higher career values led to higher shares of people getting higher education over the corresponding time period, with one standard deviation of career values leading to 1.1 p.p. increase in the share of those getting higher education. In a similar vein, the coefficient in column (4) implies that one standard deviation of career values led, on average, to a decline of 379.6 in the number of new permits, which constitutes 13.2% of the initial number of permits in 2004.[19] Columns (6) and (7) demonstrate that in regions where the local market career values, instrumented by the average market career values of nearby CZz, were lower, Trump vote shares were higher in the 2016 Presidential Election, controlling for the GOP vote share of the 2012 Presidential Election. Numerically, one standard deviation increase in career values led to a 0.68 p.p. decrease in Trump's vote share in 2016. We will focus on this outcome more closely in the following section.

[19]To get this number, we multiplied the coefficient, 6.56 with one standard deviation of career values change, 1.51. Noting that all housing permits are divided by the population of the CZ and multiplied by 10,000, we derive the number 6.56*1.51*381,634/10,000= 379.6.

Table 12: Career Value Effects on College Education, Housing Permits, and Voting

	Δ LMCV, 04-16	Δ College % 00-15		Δ ln Housing Permits		GOP Vote Share 2016	
	First-Stage	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Predicted Δ LMCV '04-'16	3.462***						
	(0.308)						
Δ LMCV '04-'16		0.297***	0.719***	6.563***	13.745***	-0.055	-0.448**
		(0.068)	(0.138)	(1.987)	(4.562)	(0.128)	(0.228)
Mean of D.V.	-0.139	4.805	4.805	-60.920	-60.920	65.368	65.368
KP F-stat.			126.407		124.970		127.464
R-Squared	0.564	0.585	0.522	0.358	0.335	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.

7 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. (2020a), Autor et al. (2016), and Colantone and Stanig (2018b) 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 suggest that career prospects 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., 2020b; Colantone and Stanig, 2018a; Guiso et al., 2019, 2020; Dippel et al., 2017; Fetzer, 2019; Anelli et al., 2019, etc.). Moreover, low levels of trust, identity politics, and growing hostility towards immigrants also contributed to the growth of populism (Algan and Cahuc, 2013; 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.

7.1 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 13, 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 Romney and McCain, the Republican candidates in the previous general elections. 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.[20]

In columns (4)-(6) of the table, we report what happens if voting is predicted by local labor market career values, again using commuting zones beyond 100 miles circle 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 increase 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,

[20]Note that we can extend the robot exposure part of the table back to 1988 in online appendix Table A.17, where the effect of exposure on Republican Presidential candidate vote share is insignificant in each year.

Table 13: 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				-0.448**	-0.106	0.081
				(0.228)	(0.158)	(0.195)
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.

2019). Further analysis in this section is aimed at understanding a more nuanced picture of what's going on.

7.2 Distributional Effects of Automation and Voting Preferences

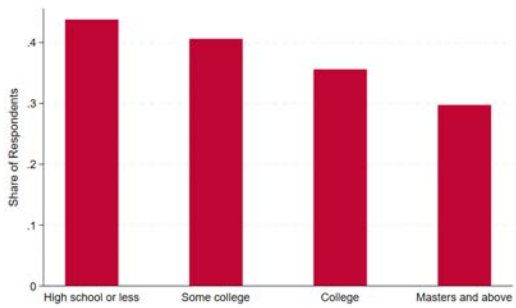
The hypothesis that economic changes affect voting is almost as old as the modern political economy literature. However, this hypothesis implies important heterogeneity: people who are the most affected by the shock should be people who change their voting behavior in response. This is a sanity check 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 A.13, we look at the distributional effects of robotization employment. We confirm that even for contemporary effects, the low-skilled are more likely to be affected (and those with education at the master's level and above were placed into more jobs in manufacturing, as column (8) of Table A.13, Panel A implies).

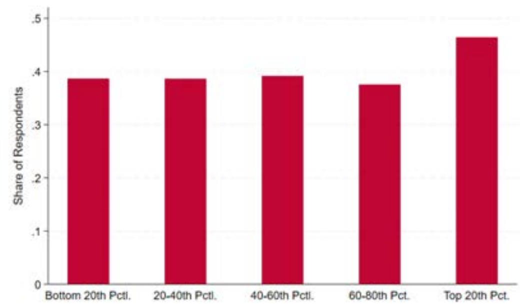
Now, we study whether those who are most likely to be affected are also more likely to vote for Trump. Figure 8 shows the shares of self-reported Trump voters by their levels of education. We find that in parallel to the results in Table 6 and Table A.13, the least educated people had the highest share of Trump voters. Furthermore, as Figure 8 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.[21]

Figure 8: Voting Intentions by Education and Share of Manufacturing, 2016 Presidential Elections

(a) By Educational Attainment

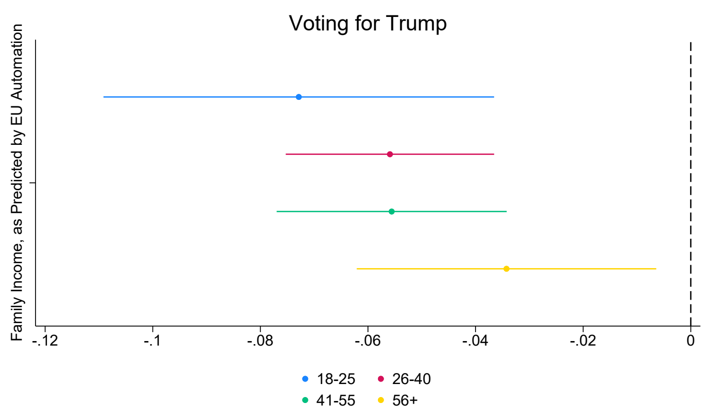


(b) By Share of Employment in Manufacturing



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.

Figure 9: 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.

[21] In the appendix, we repeat this analysis by race. We cannot estimate career values by race, but we can look at employment. We report CCES-based Trump vote intentions by race in Figure A.9. By comparing the columns in Figure A.9, we conclude that African American and Hispanic voters support Trump less than their economic situation predicts. White low-skilled voting behavior in this election is, thus, well explained by economic logic. At the same time, the behavior of African-American and Hispanic voters is not mostly driven by their economic interests. In other words, for people of other races, their economic situation was less important for their decision to vote for a particular candidate in the 2016 Presidential elections. These findings are consistent with the studies on sociodemographic drivers of populist voting based on OLS estimates from electoral survey data (Inglehart and Norris, 2016; Mocan and Raschke, 2016; Serani, 2016).

7.3 Automation, Income, Age, and Voting

In this subsection, 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 9. The figure suggests that the association between income and voting for Trump seems to be numerically strongest for the youngest people, while, at the same time, it becomes numerically smaller and statistically insignificant for 56+. This (albeit suggestive) 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 should care the most about their career values and associated opportunities for upward mobility.

7.4 Automation and the Supply-Side of Politics

In this subsection, we study whether increased demand for populism triggered some changes in the behavior of politicians.

Table 14: Automation and Campaign Visits, 2016. IV Lasso

	Republicans			Democrats		
	All	November 2016	October 2016	All	November 2016	October 2016
	(1)	(2)	(3)	(4)	(5)	(6)
U.S. Robot Exposure '04-'16	1.129	0.376*	0.818*	-0.917	-0.532	-0.289
	(1.021)	(0.207)	(0.423)	(1.609)	(0.366)	(0.689)
Mean of D.V.	1.924	0.293	0.823	1.708	0.334	0.655
KP F-stat.	1.072	1.780	4.332	0.605	2.194	0.411
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 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 and UK in the same time periods. Observations are weighted by commuting zone population.

In Table 14, we check if the automation exposure of a CZ is correlated with the number of campaign visits to that location, looking separately at the visits by the Republican and Democratic Presidential candidates while campaigning for the 2016 Presidential Election.[22] In panel A, we find no significant evidence of higher campaign visits to CZs with higher automation exposure by the Democratic candidates. Still, we find a positive association for the Republican candidate. One standard deviation increase in

[22]The source of campaign visit data is Devine (2018). We were not able to obtain similar data for 2012 or 2008.

robot exposure is associated with 0.81 additional visits to a CZ for the Republican candidate in October 2016 and 0.37 additional visits in November. [23]

8 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 earning 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 by $2,100 between 2000 and 2008, which corresponds to an 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 $3,820, or 1.7% 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.

Our analysis also points to a possible spillover effect of automation: We find that in local labor markets with higher automation exposure, employment shares and wages decline in a multitude of industries, including those that are not directly facing automation themselves. We find lower employment or a wage decline for industries such as retail, wholesale trade, healthcare, construction, professional and technical services. The negative labor market outcomes observed in these industries could be because workers whose own industries are impacted by automation may have to or want to migrate to other industries, increasing competition, particularly among less-than-college educated workers. Increased supply of workers may reduce their bargaining power for wages and result in a decline in wages if the demand for workers in non-manufacturing industries cannot accommodate these workers. However, increasing supply does not necessarily imply a decline in employment rates in other industries. Therefore, displacement of workers in manufacturing jobs and their migration to jobs in other industries is not sufficient to explain all observed patterns in the data.

We focus on a number of possible explanations for the decline in career values, consistent with the spillover effects of automation. A second channel through which automation can influence career values

[23] We also ask whether exposure to automation and robotization translated into differential policies. Table A.22 presents roll call votes by politicians as well as the Nokken and Poole scores for the US House of Representatives for the year 2016 (Nokken and Poole, 2004; Lewis et al., 2023). Here, a score of -1 indicates a far-left ideology and a score of 1 indicates a far-right ideology, and 0 represents moderate ideologies. Panel A in the table finds no correlation on average between a CZ's robot exposure and the score of the candidates representing it in the House of Representatives. Panels B and C break down the CZs by high and low manufacturing labor shares. We see that in CZs with higher manufacturing intensity, greater exposure to automation is associated with a more conservative record of the politician representing the CZ, whereas there is no statistically significant relationship in low manufacturing-intensity regions. Specifically, in high manufacturing areas, a one-unit increase in automation exposure of labor is associated with a 0.026 p.p. increase in the roll call score, controlling for the score in 2012. This implies a more conservative roll-call voting behavior.

and result in declines in employment and wages is through reduced spending and long-term investments in local markets. If future career value expectations decline in regions which have been more exposed to automation, the spending in items such as retail and hospitality industry may decline. We find that higher exposure to automation results in an increase in the new permits issued for traditional and manufacturing establishments, but there is also a decline in the number of employees per establishment. We see that locally-consumed industries suffer from automation whereas others (e.g., mining, utilities) do not.

Finally, we document several changes in the political area. We show that both robot adoption and expected career values affect voting for Trump but not for other Republican Presidential candidates. We find that the heterogeneity of the effect of robotization by education and age is consistent with career value explanation for voting. We furthermore document changes in the campaign visits and policy voting, i.e., that the supply side of politics also responds to the changes in political demands.

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—focusing on industries beyond those that are most immediately impacted and beyond the immediate occupation of workers. 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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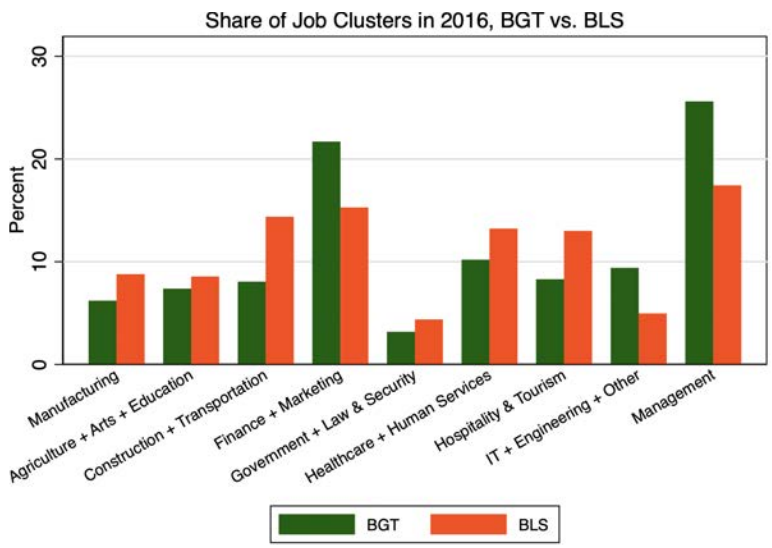
A ONLINE APPENDIX: Additional Figures & Tables (Not for Publication)

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).

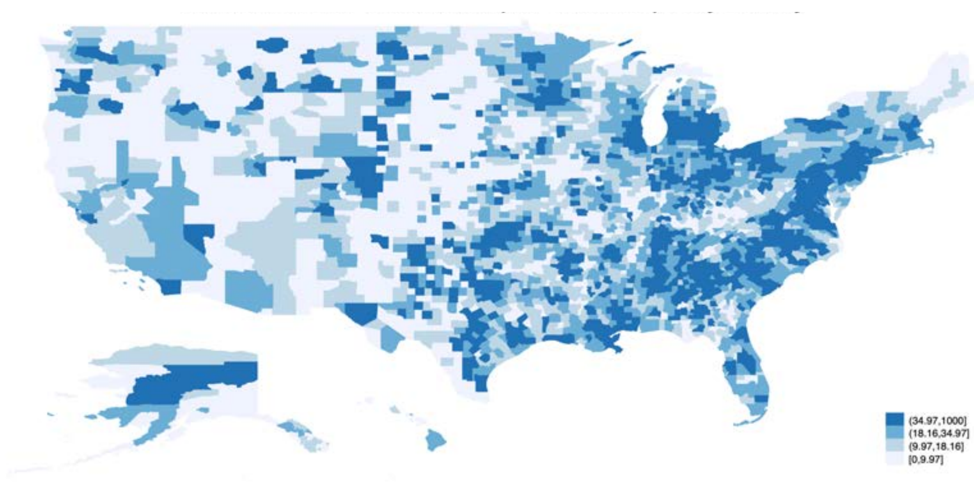
Figure A.2 maps the shares of resumes in the BGT data by county.

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

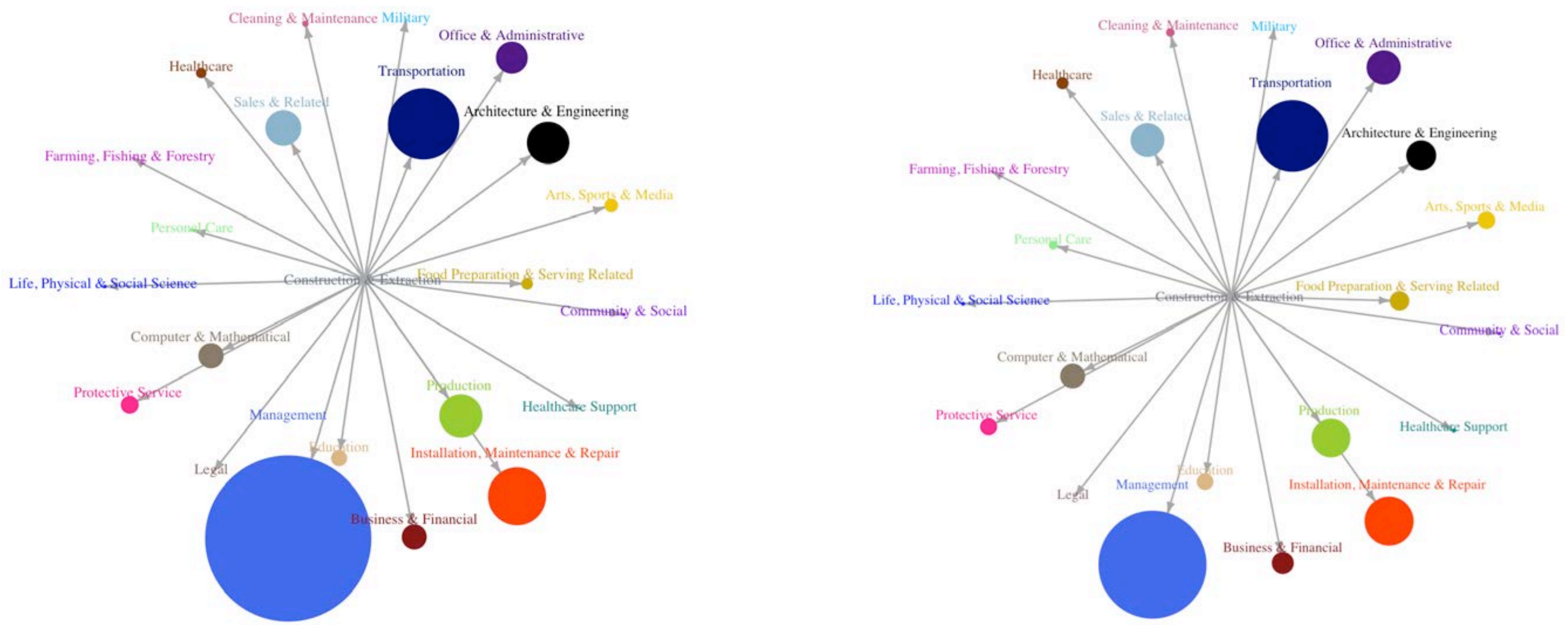


Notes. The figure represents the share of resumes in the BGT dataset per 100 people in each county. County population data is obtained from American Community Survey 5-yearly estimates. Only candidates with a job between 2004 and 2016 are plotted in the figure.

A.2 Occupational Transitions

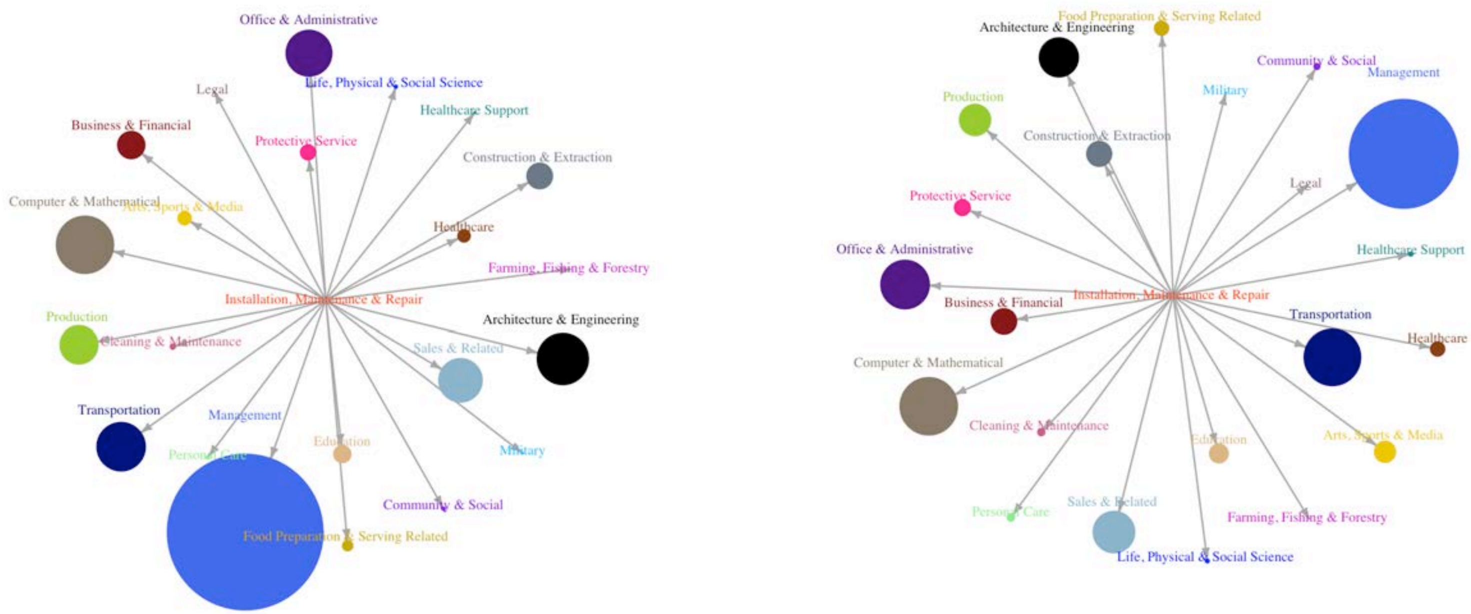
Figures A.3 and A.4 replicate Figure 3 of the paper for construction and installation occupations, respectively, based on the BGT sample.

Figure A.3: 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.4: Occupational Transitions From Installation Occupations, 2004 vs 2016

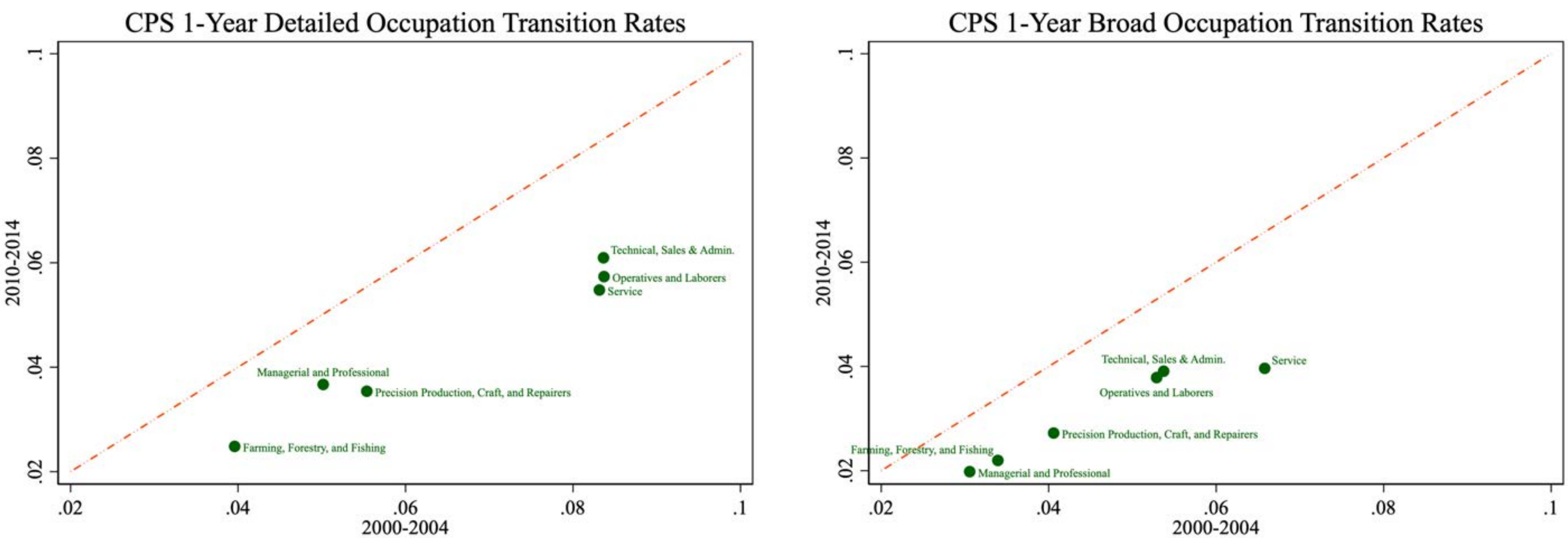


Notes. The figures show the normalized probabilities of transitioning from installation occupations to various other occupation groups. The left figure demonstrates the transitions for the year 2004 and the right figure demonstrates the transitions for 2016. Size of each bubble indicates the likelihood 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 CPS Data

Figure A.5 shows the likelihood of transitioning into a job with higher, lower, or similar wage to the previous job, conditional on moving between detailed occupations, for 1981-2020 using CPS data. Figure A.6 shows occupational mobility among male workers age 20-64 measured biannually using the CPS Employee Tenure and Occupational Mobility Supplement. Figure A.7 demonstrates the transitions to occupations at higher/similar/lower wage levels using CPS data.

Figure A.5: Probabilities of Transition Out of Occupations in the CPS

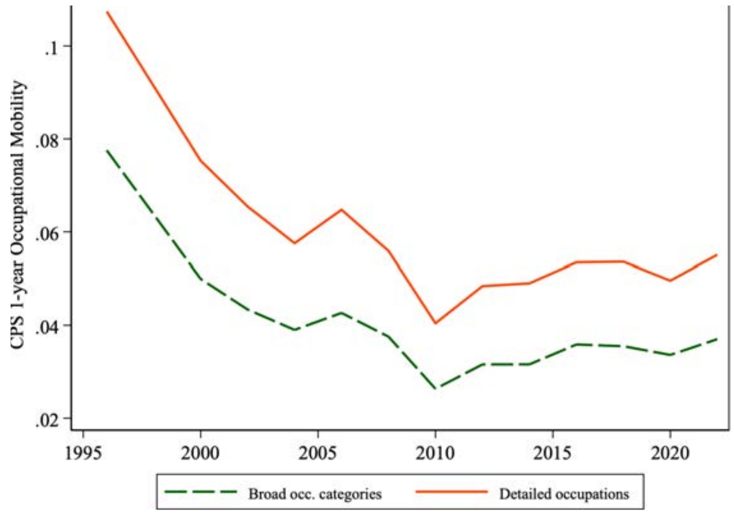


(a) Detailed occ. mobility

(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.6: Occupational 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.

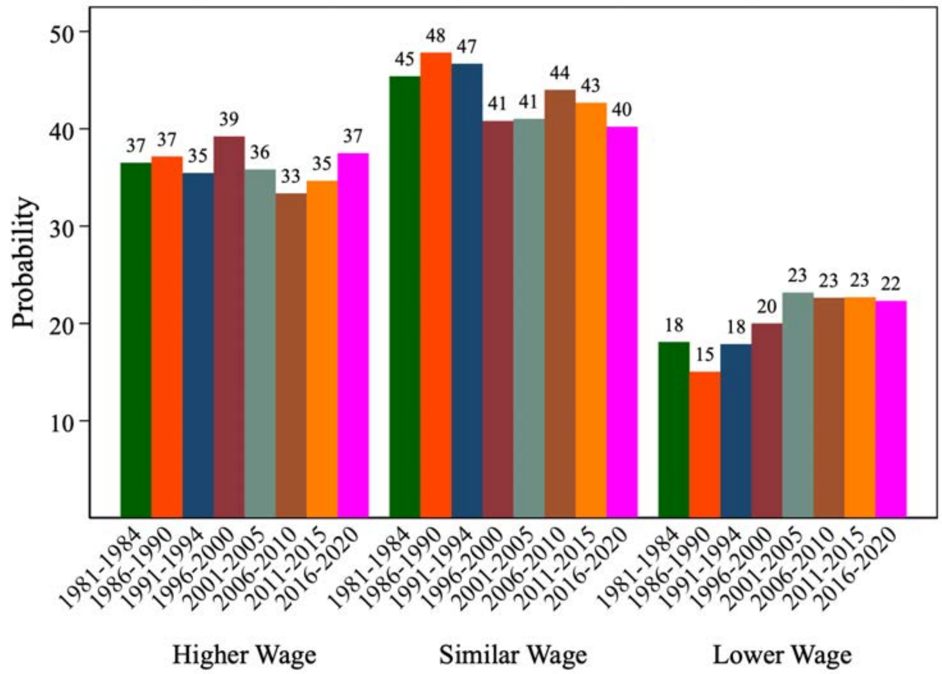
A.4 Career Values and Automatability of Occupations

Figure A.8 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).

A.5 Voting Intentions

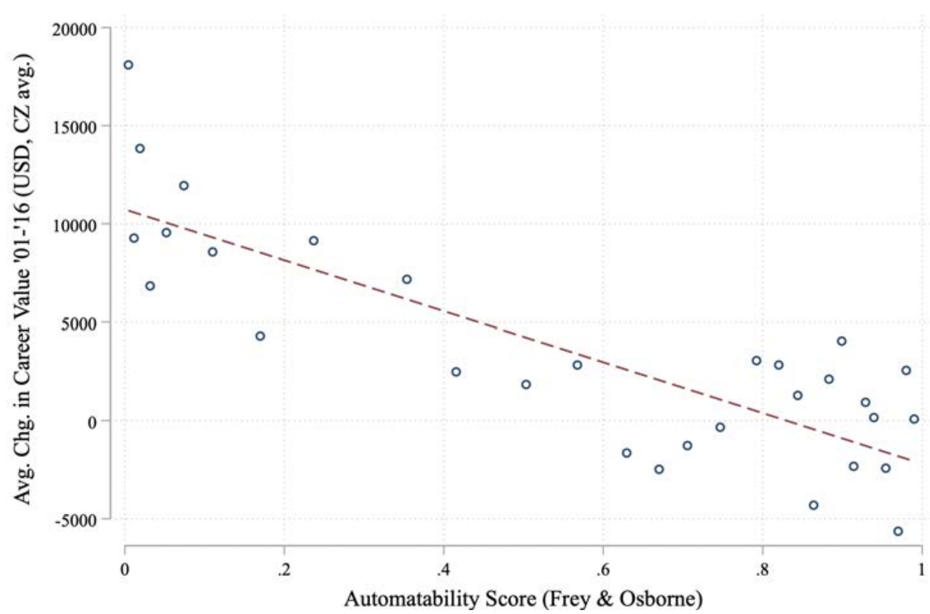
Using data from the Congressional Cooperative Election Survey, Figure A.9 breaks down the stated voting intention for Trump in the 2016 Presidential Race. The voting intentions are highest among the whites and non-Hispanics.

Figure A.7: Transitions to Different Types of Occupations in CPS data, by Time Period



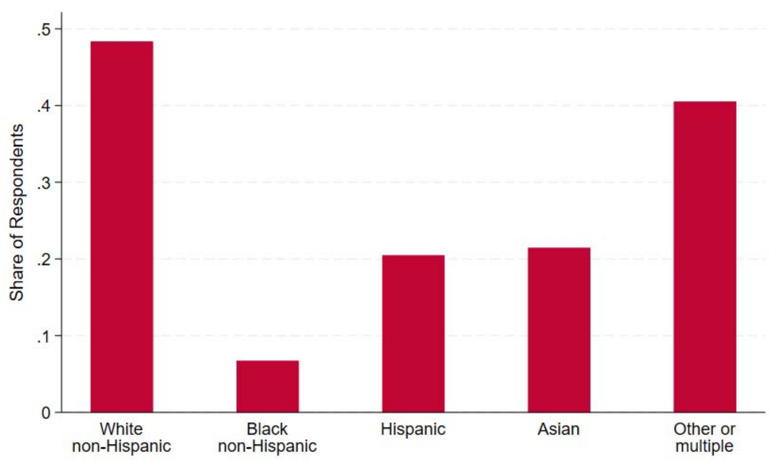
Notes. Figure shows the probability in % that hourly wages increase by more than 10% (left), decline by more than 10% (right), or experience a smaller absolute change (middle) at a 1-year horizon in longitudinally linked CPS March Surveys, conditional on the worker experiencing a change in detailed harmonized 1990 Census occupation. The sample consists of male workers age 20-64 who are employed at the time of the survey.

Figure A.8: 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.

Figure A.9: Voting Intentions by Race, 2016 Presidential Elections



Notes. The source of data is the Congressional Cooperative Election Survey (2016). Numbers indicate the share of individuals by race out of those intending to vote for Trump.

Additional Tables

A.6 Summary statistics

Table A.1: Summary Statistics, 2004-2016

Variable	Obs	Mean	Std. Dev.	Min	Max	P25	P75
Local Market Career Values, 04-08	741	-.088	1.091	-4.179	3.892	-.786	.652
Local Market Career Values, 04-16	741	-.103	1.516	-4.943	4.273	-1.115	.857
Local Market Career Values, 08-16	741	-.015	1.254	-3.161	3.625	-.879	.821
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
Empl. Change, High School Degree, 2000-2015	722	-.241	3.064	-8.675	8.113	-2.538	1.816
Empl. Change, College Degree, 2000-2015	722	-2.658	2.328	-9.8	4.615	-4.171	-1.285
Empl. Change, Some College Degree, 2000-2015	722	-2.317	2.301	-9.476	4.425	-3.875	-.784
Empl. Change, Master Degree, 2000-2015	722	-3.594	3.502	-16.916	4.977	-5.755	-1.26
Wage Change, High School Degree, 2000-2015	722	.083	.093	-.131	.416	.02	.126
Wage Change, College Degree, 2000-2015	722	.083	.095	-.121	.441	.021	.129
Wage Change, Some College Degree, 2000-2015	722	.117	.092	-.132	.439	.056	.159
Wage Change, Master Degree, 2000-2015	722	.106	.109	-.231	.556	.034	.171

A.7 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 and other occupations, however, the magnitude of the decline is much larger for the other, future occupations.

Table A.3 summarizes the effect of robotization on the change in the probability of moving away from an occupation (conditional on moving away from an occupation), mapped to classifications of occupations based on whether the occupation is considered manual (column 1) vs. cognitive (column 2) and routine (column 3) vs. non-routine (column 4), as well as the combinations of the two dimensions (columns 5-8) according to the definitions from Autor et al. (2003). The change in the conditional probability of transitioning away from manufacturing occupations is also provided as a reference in column 9. The table indicates a positive change in the likelihood of moving away from manual job categories (column 4) for both routine (column 5) and non-routine manual (column 6) occupations in regions that were more exposed to robotization. We observe a positive and significant effect of similar magnitude for the manufacturing occupations (column 9). The effect on cognitive occupations is not significant.

Table A.4 decomposes the effects of exposure to robots on the likelihood of changing occupations (column 1), changing employers (column 2), changing employers while keeping one's occupation (column 3), and changing occupation while staying with one's firm (column 4). The table then breaks down the likelihood of occupational movements to and from management (columns 5 and 6), engineering (columns 7 and 8), construction (columns 9 and 10), maintenance (columns 11 and 12), and production occupations (columns 13 and 14). The estimates in this table suffer from weak identification and survivorship bias. However, focusing on the two columns with higher F stats, we can conclude that higher robot exposure in a region results in higher horizontal mobility—changing employer while keeping a job within the same occupation family (column 3). In addition, higher exposure to robots implies a higher movement from production occupations (column 13).

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	Δw	$\Delta\psi$	$\Delta\psi \times \Delta$w	Total	Δw	$\Delta\psi$	$\Delta\psi \times \Delta$w
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
U.S. Robot Exposure '04-'16	-0.043***	-0.060***	0.022**	-0.004***	-0.292***	-0.144***	-0.138***	-0.009
	[0.010]	[0.013]	[0.010]	[0.001]	[0.035]	[0.032]	[0.022]	[0.007]
Mean of D.V.	-0.319	0.244	-0.540	-0.024	0.076	0.828	-0.600	-0.152
F-stat.	23.135	90.346	12.527	24.101	66.811	44.452	25.712	4.907
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)

	Δ Conditional Probability Occupational Transition From								
	Manual	Cognitive	Non-Routine	Routine	Manual Routine	Manual Non-Routine	Cognitive Routine	Cognitive Non-Routine	Manufacturing
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
U.S. Robot Exposure '04â'16	0.01691**	0.00087	0.01421	0.01157	0.01601*	0.01871***	0.00658	0.00860	0.01249*
	(0.00752)	(0.01080)	(0.01154)	(0.00806)	(0.00886)	(0.00607)	(0.01138)	(0.00969)	(0.00649)
Mean of D.V.	-0.013	0.008	0.022	-0.029	0.011	-0.024	0.024	-0.014	-0.034
F-stat.	1344.537	1344.537	1344.537	1344.537	1344.537	1344.537	1344.537	1344.537	1344.537
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. 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.

Table A.4: Exposure to Robots and Job Transitions (Change in Occupations within and between Firms. IV Lasso)

	(1) Change occupation	(2) Change firm	(3) Change firm within occupation	(4) Change occupation within firm	(5) Change occupation from management	(6) Change occupation to management	(7) Change occupation from engineering
U.S. Robot Exposure '04-'16	-0.002**	0.002***	0.003***	0.000	0.001	0.002**	0.007*
	[0.001]	[0.001]	[0.001]	[0.000]	[0.001]	[0.001]	[0.004]
Mean of D.V.	.67	1.08	.17	.04	.65	.24	.86
F-stat.	3.99	5.19	14.35	.2	.06	4.13	1.97
Observations	722	722	722	722	721	722	696
	(8) Change occupation to engineering	(9) Change occupation from construction	(10) Change occupation to construction	(11) Change occupation from maintenance	(12) Change occupation to maintenance	(13) Change occupation from production	(14) Change occupation to production
U.S. Robot Exposure '04-'16	0.001***	-0.011***	-0.000	0.001	0.000	0.014***	-0.000
	[0.000]	[0.004]	[0.000]	[0.003]	[0.000]	[0.004]	[0.000]
Mean of D.V.	.03	1.02	.02	.93	.03	.98	.04
F-stat.	4.43	4.9	.27	.03	.4	13.35	.44
Observations	722	683	722	697	722	685	722
A&R Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census Division FE	Yes	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.

A.8 Heterogeneity of Automation Effects with Respect to Upward Mobility

In this section, we repeat the estimation of equation (8) using alternative proxies for opportunities for upward mobility, more specifically, the average level of education (Table A.5) and local intergenerational mobility (Table A.6). The measure of the latter are the neighborhood intergenerational mobility effects from Chetty et al. (2016) The results are qualitatively similar to the results in Table 8.

Table A.5: Automation, Career Values, and Education

	Δ Career Values 2000-2016			Δ Wage 2000-2015	Δ Employment 2000-2015
	All	Below College	College or Higher		
	(1)	(2)	(3)	(4)	(5)
EU Instrument '04-'16	-0.086*	-0.200**	-0.051	-0.003*	-0.020
	[0.049]	[0.092]	[0.035]	[0.002]	[0.060]
College Rate '00	7.803	-4.304	12.754*	0.853**	-3.479
	[6.289]	[9.088]	[6.778]	[0.340]	[7.137]
EU Instrument '04-'16 x College Rate '00	0.170	0.836	-0.059	0.006	-0.184
	[0.286]	[0.513]	[0.221]	[0.010]	[0.378]
Mean of D.V.	-0.139	-0.232	-0.262	0.135	0.036
R-squared	0.491	0.242	0.447	0.545	0.746
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, France, Finland, UK and Germany during 2004-2016. Observations are weighted by commuting zone population.

A.9 Creative Destruction in Tradable/Non-Tradable Sectors

In this subsection, we ask what happens to the patterns of business creation and destruction in different sectors. If demand for services/products are shrinking in a region, we may also anticipate the number of establishments in an area to go down. We follow Mian and Sufi (2014) (MS from here on), who use 4-digit NAICS codes in defining tradable vs. non-tradable establishments, to estimate this effect. Accordingly, an establishment is classified as tradable "if it has imports plus exports equal to at least $10,000 per worker, or if total exports plus imports for the NAICS 4-digit industry exceeds $500M." For example, retail and restaurant industries are non-tradable, while manufacturing, mining, or agriculture – i.e. industries that appear in global trade data—are tradable.[24] These results are reported in Table A.7.

Although we cannot separate business entries from business exits, we see negative signs in the overall number of establishments in places with higher exposure to robots, while the effects are not statistically significant. Both trade-able and non-tradable establishments have fewer number of employees (columns 4 and 5), with the numbers of employees in non-tradable sectors more negatively impacted. We see a higher average number of employees in the construction sector, which, together with the negative signs for the number of businesses, may imply a trend toward monopolization. Overall, these results suggest

[24]We also use a more restricted version of non-tradable industries that includes only grocery retail stores and restaurants.

Table A.6: Automation, Career Values, and Intergenerational Mobility

	Δ Career Values 2000-2016			Δ Wage 2000-2015	Δ Employment 2000-2015
	All	Below College	College or Higher		
	(1)	(2)	(3)	(4)	(5)
EU Instrument '04-'16	-0.155***	-0.175**	-0.165***	-0.001	-0.032
	[0.052]	[0.068]	[0.056]	[0.002]	[0.043]
Intergenerational Mobility	10.048**	6.435	12.993***	0.819***	37.634***
	[4.287]	[5.793]	[4.694]	[0.177]	[4.571]
EU Instrument '04-'16 x Intergenerational Mobility	1.459*	1.486	1.647*	-0.016	-0.258
	[0.862]	[1.197]	[0.924]	[0.030]	[0.735]
Mean of D.V.	-0.162	-0.246	-0.286	0.133	-0.013
R-squared	0.418	0.179	0.384	0.556	0.759
Census Division FE	Yes	Yes	Yes	Yes	Yes
A&R Controls	Yes	Yes	Yes	Yes	Yes
Observations	712	712	712	712	712

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, France, Finland, UK and Germany during 2004-2016. Intergenerational mobility measures are the neighborhood mobility measures from (Chetty et al., 2016). Observations are weighted by commuting zone population.

that, there may be some negative effects of automation on local business growth, consistent with declining demand for goods and services.

A.10 Automation, Career Value, Employment, and Wages by Industry

Table A.8 regresses the change in career values in broad 2-digit NAICS industry sectors (and selected sub-sectors) on exposure to robots, where columns (3) to (15) correspond to the manufacturing related industries. We find that the change in career value is not only confined to manufacturing jobs. In regions more exposed to automation, career values also declined in utilities (16), research (18), and services (19). Put differently, there is a broad decline in the future labor market conditions. The magnitude of the decline in these categories is comparable to that in a number of manufacturing categories.

Table A.9 regresses the change in employment in a CZ for all, private, and public jobs, and then specifically for manufacturing and service occupations. The takeaway from the table is that, increasing robotization goes hand in hand with a decline in employment in all five categories (Panel A), and the overall effect is driven by the declines in the manufacturing intensive CZs (Panel B).

Table A.10 regresses the change in employment in all sectors classified according to the 2-digit SOC classification. We again find that the change in employment is not only confined to manufacturing jobs (Panel A, columns (5)-(7)). In regions that were more exposed to automation, employment in a number of occupation categories decline, including retail (Panel B, columns (1) and (2)), transportation and warehousing (Panel B, column (3)), as well as jobs that are of more white collar nature (professional, scientific, technical services (Panel B column (8)). Put differently, there is a broader job decline in the labor market conditions in the regions that are more exposed to automation beyond manufacturing jobs.

We report the aggregate wage changes in regions exposed to automation in Table A.11. Accordingly, with increasing automation exposure, wages in all reported sectors decline. On average, the hourly wages

Table A.7: Automation and Establishments, by Sector. IV Lasso

	No. of Establishments			No. of Employees Per Establishment		
	Tradable	Non-tradable	Construction	Tradable	Non-tradable	Construction
	(1)	(2)	(3)	(4)	(5)	(6)
U.S. Robot Exposure '04-'16	0.000	0.010	-0.001	-0.010**	-0.022***	0.017***
	[0.003]	[0.008]	[0.003]	[0.005]	[0.003]	[0.004]
Mean of D.V.	-0.082	-0.013	-0.119	0.128	-0.078	0.037
F-stat.	0.007	2.212	0.515	18.018	51.354	15.233
Census Division FE	Yes	Yes	Yes	Yes	Yes	Yes
A&R Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	716	712	722	721	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). 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.Sectoral classification is based on 4-digit NAICS. Observations are weighted by commuting zone population.

decline by $0.01 with 1 additional robot per 1000 workers (column (1)). A breakdown of the CZs into high manufacturing (columns (4)-(6)) and low manufacturing (columns (7)-(9)) areas demonstrate that most of the wage declines are observed in the manufacturing intensive zones.

Table A.12 reports how the average hourly wage in different industries changes with automation exposure between 2004 and 2016 and paints a similar picture to Table A.11 in that automation exposure results in wage declines in a number of industries, even in the ones that are not directly impacted by industrial robots.

Table A.8: Exposure to Robots vs Sector Career Values, by Industry Groups. IV Lasso

	(1) Agriculture	(2) Mining	(3) Food	(4) Textiles	(5) Furniture	(6) Paper	(7) Petrochemicals	(8) Mineral	(9) Metal Basic	
U.S. Robot Exposure '04-'16	-0.397***	-0.290***	-0.453***	-0.479***	-0.229***	-0.367***	-0.364***	-0.227***	-0.448***	
	[0.051]	[0.090]	[0.066]	[0.058]	[0.043]	[0.046]	[0.060]	[0.086]	[0.040]	
Mean of D.V.	-0.278	0.422	-1.019	-1.01	-0.023	-1.077	-0.202	-0.368	0.306	
F-stat.	82.03	31.31	111.71	72.42	25.71	83.55	62.8	8	56.45	
	(10) Metal Machinery	(11) Metal Products	(12) Electronics	(13) Automotive	(14) Vehicles (Other)	(15) Manufacturing (Other)	(16) Utilities	(17) Construction	(18) Research	(19) Services
U.S. Robot Exposure '04-'16	-0.166***	-0.816***	-0.342***	-0.068	-0.837***	-0.111	-0.388***	-0.406***	-0.490***	-0.366***
	[0.045]	[0.087]	[0.063]	[0.068]	[0.152]	[0.122]	[0.031]	[0.042]	[0.051]	[0.039]
Mean of D.V.	-0.715	0.217	0.357	-0.638	2.057	-0.893	0.154	-0.358	-0.345	-0.192
F-stat.	23.57	90.82	38.83	4.26	29.89	3.07	99.37	134.7	120.88	90.55
Census Division FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
A&R Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	722	526	722	722	440	681	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). 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. Industrial classification is based on 2-digit NAICS. Observations are weighted by commuting zone population.

Table A.9: Employment by Industry and Automation Shocks, 2004-2016. IV Lasso

Employment and Automation Shocks, 2004-2016. IV Lasso					
Panel A. Full Sample	Change in employment 2000-2015 (log), ACS				
	Aggregate	Private	Public	Manufacturing	Services
	(1)	(2)	(3)	(4)	(5)
U.S. Robot Exposure '04-'16	-0.009**	-0.010**	-0.004	-0.001	-0.009**
	[0.004]	[0.004]	[0.004]	[0.006]	[0.004]
Mean of D.V.	0.073	0.107	0.044	-0.152	0.162
F-stat.	8.53	9.370	1.07	0.004	6.99
Census Division FE	Yes	Yes	Yes	Yes	Yes
A& R Controls	Yes	Yes	Yes	Yes	Yes
Observations	722	722	722	722	722
Panel B. Employment in manufacturing intensive areas	Change in employment 2000-2015 (log), ACS % manufacturing above the median				
	Aggregate	Private	Public	Manufacturing	Services
	(6)	(7)	(8)	(9)	(10)
U.S. Robot Exposure '04-'16	-0.008***	-0.009***	-0.007*	-0.011*	-0.006**
	[0.002]	[0.003]	[0.004]	[0.006]	[0.002]
Mean of D.V.	0.037	0.056	0.032	-0.259	0.155
F-stat.	9.29	9.69	4.21	4.18	4.69
Census Division FE	Yes	Yes	Yes	Yes	Yes
A& R Controls	Yes	Yes	Yes	Yes	Yes
Observations	722	722	722	722	722
Panel C. Employment in other areas	Change in employment 2000-2015 (log), ACS % manufacturing below the median				
	Aggregate	Private	Public	Manufacturing	Services
	(11)	(12)	(13)	(14)	(15)
U.S. Robot Exposure '04-'16	0.082	0.075	0.318	0.375	0.056
	[0.137]	[0.144]	[0.198]	[0.373]	[0.136]
Mean of D.V.	0.108	0.158	0.056	-0.044	0.168
F-stat.	0.78	0.64	7.60	4.56	0.31
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). 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. Change in logarithms for employment is computed as the difference of logarithms in numbers of those employed in a given sector in between 2015 and 2000. Observations are weighted by commuting zone population.

Table A.10: Exposure to Robots vs Sector Employment, by Industry Groups

	Change in Employment by Industry (log), ACS, 2000-2015							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Agriculture, Forestry, Fishing & Hunting	Mining, Quarring, Oil & Gas Extraction	Utilities	Construction	(NAICS 31)	Manufacturing (NAICS 32)	(NAICS 33)	Wholesale Trade
Panel A								
U.S. Robot Exposure '04-'16	0.022*	-0.001	0.002	-0.026***	-0.013	0.028***	-0.005	-0.022***
	[0.013]	[0.023]	[0.011]	[0.006]	[0.008]	[0.011]	[0.006]	[0.006]
Mean of D.V.	0.136	0.459	0.072	0.046	-0.078	-0.187	-0.112	-0.151
F-stat.	9.366	0.038	0.206	27.462	1.728	14.338	0.015	
	Retail Trade (NAICS 44)	(NAICS 45)	Transportation & Warehousing (NAICS 48)	(NAICS 49)	Information	Finance & Insurance	Real Estate & Rental & Leasing	Professional, Scientific, & Technical Serv.
Panel B								
U.S. Robot Exposure '04-'16	-0.016***	-0.015*	-0.011*	-0.009	-0.005	-0.004	-0.005	-0.023***
	[0.004]	[0.009]	[0.007]	[0.016]	[0.009]	[0.006]	[0.006]	[0.008]
Mean of D.V.	0.066	0.066	0.08	0.135	-0.159	0.07	0.097	0.276
F-stat.	9.568	14.3	4.063	1.559	0.483	0.907	0.375	
	Mgmt of Companies & Enterprises	Admin. & Support & Waste Mgmt & Remediation Serv.	Educational Serv.	Health Care and Social Assist.	Arts, Entertainment, & Recreation	Accommodation Food Serv.	Other Serv. (except Public Admin.)	
Panel C								
U.S. Robot Exposure '04-'16	-0.004	0.001	-0.007	-0.002	0.010*	-0.004	-0.006	
	[0.010]	[0.006]	[0.006]	[0.005]	[0.006]	[0.005]	[0.004]	
Mean of D.V.	0.338	0.426	0.107	0.339	0.331	0.236	-0.013	
F-stat.	0.908	16.816	0.04	0.35	1.115	0.394	0.737	
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

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. Industrial classification is based on 2-digit NAICS. Change in logarithms of employment is computed as the difference in logarithms for the numbers of those employed in a given industry between 2015 and 2000. Observations are weighted by commuting zone population.

Table A.11: Exposure to Automation and Wages, 2004-2016. IV Lasso

	ACS Average Hourly Wage Percentage Change, 2000-2015								
	All areas			% Manufacturing above the median			% Manufacturing below the median		
	All	Manufacturing	Services	All	Manufacturing	Services	All	Manufacturing	Services
U.S. Robot Exposure '04-'16	-0.010***	-0.008***	-0.008**	-0.010***	-0.008***	-0.008***	-0.018	-0.142	-0.032
	[0.003]	[0.003]	[0.003]	[0.002]	[0.003]	[0.002]	[0.091]	[0.150]	[0.114]
Mean of D.V.	0.135	0.164	0.149	0.103	0.124	0.12	0.166	0.203	0.179
F-stat.	35.15	7.051	18.258	33.92	5.821	17.319	.112	1.865	.292
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	362	362	360	360	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). 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.12: Exposure to Automation and Wages by Industry, 2004-2016. IV Lasso

Wages by Industry and Automation Shocks, 2004-2016. IV LASSO Estimates. ACS Average Hourly Wage Percentage Change, 2000-2015								
	Agriculture, Forestry, Fishing & Hunting	Mining, Quarring, Oil&Gas Extraction	Utilities	Construction	Manufacturing (NAICS 31)	Manufacturing (NAICS 32)	Manufacturing (NAICS 33)	Wholesale Trade
U.S. Robot Exposure '04-'16	0.022	0.013	0.003	-0.013***	-0.001	0.015**	-0.017***	-0.012***
	[0.014]	[0.015]	[0.007]	[0.003]	[0.006]	[0.006]	[0.004]	[0.004]
Mean of D.V.	0.138	0.372	0.145	0.139	0.192	0.221	0.195	0.218
F-stat.	4.405	0.771	0.366	15.299	0.397	6.979	23.048	7.891
Observations	722	721	722	722	722	722	722	722
	Retail Trade (NAICS 44)	Retail Trade (NAICS 45)	Transportation & Warehousing (NAICS 48)	Transportation & Warehousing (NAICS 49)	Information	Finance and Insurance	Real Estate and Rental and Leasing	Professional, Scientific, & Technical Services
U.S. Robot Exposure '04-'16	-0.011***	-0.009*	0.006	-0.035***	0.012**	-0.009**	0.008	-0.007
	[0.004]	[0.005]	[0.004]	[0.013]	[0.005]	[0.004]	[0.010]	[0.007]
Mean of D.V.	0.082	0.072	0.123	0.185	0.04	0.267	0.109	0.321
F-stat.	17.453	6.068	1.443	16.383	3.916	2.525	0.516	1.004
Observations	722	722	722	722	722	722	722	722
	Management of Companies & Enterprises	Administrative & Support & Waste Management & Remediation Services	Educational Services	Health Care and Social Assistance	Arts, Entertainment, & Recreation	Accommodation & Food Services	Other Services (except Public Admin.)	
U.S. Robot Exposure '04-'16	-0.003	-0.009	-0.011**	-0.002	-0.006	-0.019***	-0.012***	
	[0.020]	[0.006]	[0.005]	[0.002]	[0.006]	[0.003]	[0.003]	
Mean of D.V.	0.505	0.155	0.055	0.201	0.126	0.042	0.145	
F-stat.	0.01	2.362	7.608	0.242	1.418	36.426	13.071	
Observations	711	722	722	722	722	722	722	
A&R Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census Division FE	Yes	Yes	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. Change in wages is calculated as the difference between average wages between 2015 and 2000 years in a given industry, divided by the average wages in 2000 in the same industry. Industrial classification is based on 2-digit NAICS. Observations are weighted by commuting zone population.

A.11 Distributional Effects of Automation by Education and Race

The effects of automation on employment and wages can vary by educational attainment. In Table A.13 Panel A, we see that there is a negative relationship between automation exposure and employment in private sector jobs for all educational levels. This relationship is modified slightly for the sample comprising manufacturing jobs only. For this subsample, while a standard deviation increase in automation exposure continues to be negatively associated with employment in manufacturing for levels of education up to high school, there is a positive relationship with employment for individuals with college and higher levels of education. In Panel B of the table, we see in the regression of wages for private sector and manufacturing jobs, higher automation exposure has a negative and statistically significant relationship on wages for all levels of education for all jobs except for those with masters and above.

Table A.14 replicates the same table, focusing on the employment and wage effects for different races. In Panel A, we see that the negative effects of automation in all private sectors is felt mostly by the whites, whereas the effects are more positive for the workers of Asian origin. We see the direction of the estimates to be similar for manufacturing-only occupations, but the effect for the whites is no longer precisely estimated. In Panel B, we look at the wage changes with higher robot exposure for all jobs, as we do not have the wage data broken down by race and manufacturing. Here too we see negative signs on the estimates for all races, with the estimate of the Asian worker population being insignificant. The F-statistics provided in both tables suggest that, for several sub-populations, we may suffer from weak instruments.

Table A.13: 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	Masters and Above	High School or below	Some College	College	Masters and Above
U.S. Robot Exposure '04-'16	-0.344***	-0.299***	-0.194***	-0.235**	-0.120***	-0.099*	0.101**	0.225***
	[0.054]	[0.066]	[0.075]	[0.118]	[0.022]	[0.058]	[0.040]	[0.043]
Mean of D.V.	.53	-.06	2.542	2.241	-1.472	-1.617	-.664	-.242
F-stat.	39.36	30.844	8.903	4.763	19.622	10.112	9.491	24.17
Observations	722	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	Masters and Above	High School or below	Some College	College	Masters and Above
U.S. Robot Exposure '04-'16	-0.011***	-0.014***	-0.007***	-0.002	-0.018***	-0.017***	-0.005**	0.002
	[0.003]	[0.003]	[0.002]	[0.003]	[0.003]	[0.004]	[0.003]	[0.007]
Mean of D.V.	.087	.081	.136	.21	.102	.093	.225	.262
F-stat.	37.974	48.348	8.743	.276	42.969	28.067	.68	.001
Observations	722	722	722	722	722	722	722	694
Census Division FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
A&R Controls	Yes	Yes	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.

Table A.14: Distributional Effects of Automation by Race. IV Lasso

Panel A. Employment	**ACS Change in Employment, 2000-2015**							
	All Private Sector				Manufacturing Only			
	Black	White	Asian	Hispanic	Black	White	Asian	Hispanic
U.S. Robot Exposure '04-'16	0.050	-0.263***	0.565***	-0.052	0.144**	-0.048	0.576***	0.060
	[0.187]	[0.044]	[0.201]	[0.158]	[0.071]	[0.039]	[0.115]	[0.067]
Mean of D.V.	4.685	.808	2.874	2.467	.039	-1.421	-.007	-2.503
F-stat.	.285	29.757	5.246	.027	3.53	3.381	33.711	1.103
Observations	722	722	722	722	722	722	722	
Census Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census Division FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B. Wages	**ACS Change in Wages, 2000-2015**			
	Black	White	Asian	Hispanic
U.S. Robot Exposure '04-'16	-0.014**	-0.011***	-0.015	-0.008**
	[0.005]	[0.003]	[0.010]	[0.003]
Mean of D.V.	.075	.145	.27	.08
F-stat.	3.391	38.502	.862	3.306
Observations	722	722	722	722
Census Controls	Yes	Yes	Yes	Yes
Census Division FE	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.

A.12 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.15 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. We only find statistically significant effects for areas with a high concentration of manufacturing. In these regions, an increase in career values is associated with a positive increase in education levels.

Table A.15: Career Values, Schooling, and Manufacturing

Panel A. *High % Manufacturing CZs*	ΔCollege Share 2000-15 (1)	ΔSome College Share 2000-15 (2)	ΔCollege Share 2000-15 (3)	ΔSome College Share 2000-15 (4)	ΔCollege Share 2000-15 (5)	ΔSome College Share 2000-15 (6)
ΔCareer Values, 2004-08	0.564***	0.358*				
	[0.213]	[0.195]				
ΔCareer Values, 2008-16			0.977*	0.704*		
			[0.530]	[0.414]		
ΔCareer Values, 2004-16					0.340***	0.187*
					[0.130]	[0.107]
Observations	361	361	361	361	361	361
1st Stage F-Stat	11	11	2	2	25	25
Census Division FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B. *Low % Manufacturing CZs*	ΔCollege Share 2000-15 (1)	ΔSome College Share 2000-15 (2)	ΔCollege Share 2000-15 (3)	ΔSome College Share 2000-15 (4)	ΔCollege Share 2000-15 (5)	ΔSome College Share 2000-15 (6)
ΔCareer Values, 2004-08	1.262	-2.479				
	[2.738]	[5.884]				
ΔCareer Values, 2008-16			0.580	0.404		
			[0.449]	[0.494]		
ΔCareer Values, 2004-16					2.046	-0.603
					[2.136]	[1.186]
Observations	361	361	361	361	361	361
1st Stage F-Stat	0	0	2	2	0	0
Census Division FE	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), and industry fixed effect.

A.13 Voting and Political Activity

In this last subsection, we analyze the effects of robotization on a number of political activity outcomes during the presidential races from the last decade. First, in Table A.16, we look at the number of campaign visits by the Republican and the Democratic presidential candidates to the commuting zones, regressing visits on the robot exposure in the region. Panel A suggests that robot exposure of the regions were not correlated with higher campaign visits from the Democratic candidates, but there were higher campaign visits for the Republican candidates. One standard deviation increase in robot exposure is associated with 0.44 additional visits to a CZ in November 2016 and 0.84 in October 2016. Panel B shows that the effects are similar for the high-manufacturing regions.

In addition, regressing the vote share of the GOP candidate on the robot exposure measure in Table A.17 for the earlier elections (1988-2004) does not suggest any effects.

Table A.16: Automation and Campaign Visits, 2016. IV

	Republicans			Democrats		
	All	November 2016	October 2016	All	November 2016	October 2016
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All Commuting Zones						
U.S. Robot Exposure '04-'16	1.126	0.396*	0.803*	-0.926	-0.528	-0.300
	(1.083)	(0.206)	(0.454)	(1.675)	(0.373)	(0.719)
Mean of D.V.	1.924	0.293	0.823	1.708	0.334	0.655
KP F-stat.	1344.537	1344.537	1344.537	1344.537	1344.537	1344.537
Observations	722	722	722	722	722	722
Panel B: High-Manufacturing Commuting Zones						
U.S. Robot Exposure '04-'16	0.687	0.547***	0.430	-0.871	-0.623	-0.098
	(1.298)	(0.143)	(0.577)	(1.765)	(0.524)	(0.731)
Mean of D.V.	2.790	0.332	1.293	2.237	0.458	0.861
KP F-stat.	657.494	657.494	657.494	657.494	657.494	657.494
Observations	359	359	359	359	359	359
Panel C: Low-Manufacturing Commuting Zones						
U.S. Robot Exposure '04-'16	1.701	3.319	0.982	22.714	5.120	10.947
	(15.324)	(8.216)	(2.352)	(42.733)	(6.814)	(19.359)
Mean of D.V.	1.076	0.257	0.361	1.193	0.213	0.452
KP F-stat.	8.805	8.805	8.805	8.805	8.805	8.805
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 and UK in the same time periods. Observations are weighted by commuting zone population.

Table A.17: 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. 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.

A.14 Robustness Checks with Additional Controls

Table A.18: 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	Δ LMCV	Δ LMCV	Δ LMCV	Δ LMCV	Δ LMCV
	(1)	(2)	(3)	(4)	(5)	(6)
U.S. Robot Exposure '04-'08	-0.362***			-0.382***		
	(0.076)			(0.084)		
U.S. Robot Exposure '08-'16		-0.164			-0.267***	
		(0.121)			(0.093)	
U.S. Robot Exposure '04-'16			-0.311***			-0.339***
			(0.044)			(0.038)
Mean of D.V.	-0.124	-0.015	-0.139	-0.124	-0.015	-0.139
F-stat.				44.603	5.662	63.753
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.19: 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	0.077***	-0.065***	0.055**	0.171***	1.670*	-0.065***	-0.158	0.104***	0.412
	(0.028)	(0.010)	(0.024)	(0.019)	(0.971)	(0.024)	(0.220)	(0.017)	(0.341)
Mean of D.V.	0.007	0.008	0.008	0.260	0.073	0.263	0.073	0.263	0.074
F-stat.	31.308	96.810	14.372	161.036	32.102	36.522	1.031	44.053	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	359	360	359	360	359	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 and France in the same time periods. Observations are weighted by commuting zone population.

Table A.20: 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***	0.009***	0.009***
	(0.001)	(0.001)	(0.002)	(0.003)
Mean of D.V.	1.212	1.278	1.309	1.588
F-stat.	0.041	16.368	27.204	19.753
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). In addition, we include share of employment in routine occupations and change exposure to imports from China from 1990 to 2007 as controls. 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, and France 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.

Table A.21: Automation Exposure and Household Retail Consumption. IV Lasso

	Log (Δ Total Household Spending)	Log (Δ Total Spending)	
	All	High Manuf. CZ	Low Manuf. CZ
	(1)	(2)	(3)
U.S. Robot Exposure '04-'16	-0.026***	-0.036***	-0.014
	(0.004)	(0.003)	(0.038)
Mean of D.V.	-0.300	-0.309	-0.290
F-stat.	15.039	10.970	0.001
Census Division FE	Yes	Yes	Yes
A&R Controls	Yes	Yes	Yes
Observations	11146	5620	5498

Notes. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Robust standard errors are in brackets and clustered by state. The source of household spending data is NielsenIQ Consumer Retail Panel, made accessible by the Kilts Center at the University of Chicago. Panels are from 2004 and 2016. The outcome compared the log of the difference in household spending. The analysis is based on the households that are common between 2004 and 2016, and uses the difference in spending of each household. Household spending in inflation-adjusted. 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. 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.22: Automation and Roll Call Votes. IV Lasso

	Nominate Scores (House of Representatives)				Nokken Poole (House of Representatives)			
	2016 Score	2016 Score	2016 Abs Score	2016 Abs Score	2016 Score	2016 Score	2016 Abs Score	2016 Abs Score
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: All Commuting Zones								
U.S. Robot Exposure '04-'16	0.017	0.015	0.012	0.011	0.013	0.012	0.009	0.008
	(0.023)	(0.023)	(0.014)	(0.014)	(0.026)	(0.025)	(0.016)	(0.015)
Ideology '12		-0.087		-0.055		-0.092		-0.098
		(0.128)		(0.107)		(0.132)		(0.114)
Mean of D.V.	0.311	0.313	0.351	0.353	0.317	0.319	0.359	0.362
F-stat.	2.330	1.885	3.699	3.285	1.135	0.885	1.994	1.616
Observations	719	714	719	714	719	714	719	714
Panel B: High-Manufacturing Commuting Zones								
U.S. Robot Exposure '04-'16	0.036**	0.032**	0.028**	0.027***	0.033*	0.029*	0.027**	0.026**
	(0.017)	(0.016)	(0.011)	(0.010)	(0.019)	(0.018)	(0.012)	(0.011)
Ideology '12		-0.264*		-0.139		-0.287*		-0.188
		(0.158)		(0.119)		(0.163)		(0.124)
Mean of D.V.	0.287	0.288	0.335	0.336	0.292	0.293	0.343	0.343
F-stat.	8.649	6.989	12.942	11.607	6.719	5.330	10.190	9.078
Observations	359	358	359	358	359	358	359	358
Panel C: Low-Manufacturing Commuting Zones								
U.S. Robot Exposure '04-'16	0.070	0.089	0.755	0.801	0.140	0.171	0.864	0.940
	(0.490)	(0.540)	(0.459)	(0.530)	(0.570)	(0.640)	(0.542)	(0.657)
Ideology '12		0.088		0.360		0.106		0.415
		(0.150)		(0.299)		(0.174)		(0.358)
Mean of D.V.	0.336	0.338	0.369	0.372	0.342	0.346	0.377	0.381
F-stat.	0.091	0.132	18.650	19.096	0.323	0.424	21.732	22.566
Observations	357	353	357	353	357	353	357	353
Census Division FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
A&R Controls	Yes	Yes	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). We also control for the scores from 2012 in columns (2), (4), (6) and (8). U.S. Robot Exposure is instrumented using robot exposure in Denmark, Italy, Sweden, Finland, France, Germany and UK in the same time periods. Observations are weighted by commuting zone population.

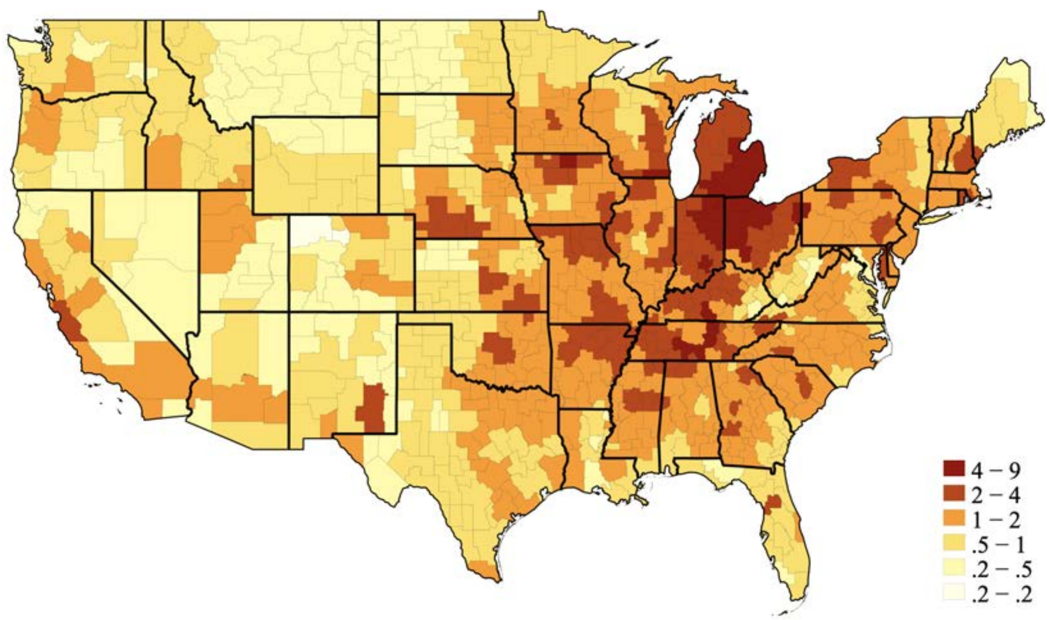
B Online Data Appendix (Not for Publication)

B.1 Industrial Robots Data

The data collected by IFR is obtained via yearly 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).

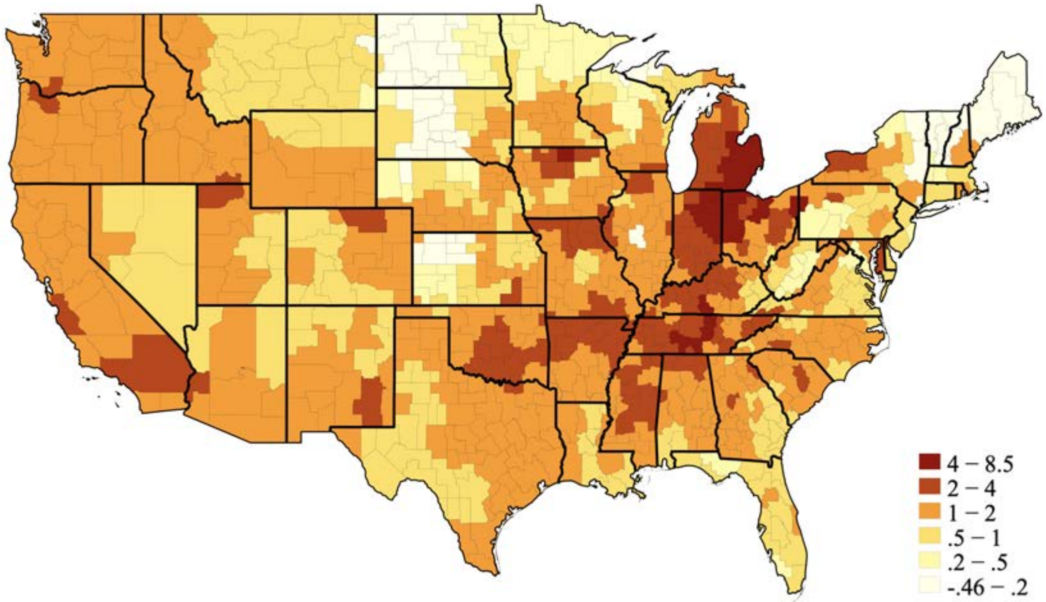
Figures B.1 shows the distribution of robots per 1000 workers in the US between 2004 and 2016. Figure B.2 shows exposure after taking into account census division fixed effects. Figures **??** and **??** summarize the accumulation of robots in various different industries across the years. From these figures, it is clear that there were higher levels of robotization in automation, food and beverages industry, metals, plastic and chemical goods.

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



Notes. Source of Data: International Federation of Robotics.

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



Notes. Source of Data: International Federation of Robotics.