Missing Routine Work: Automation and the Life Cycle

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Abstract

I study the effect of automation on workers at different stages of the life cycle. Using a difference-in-difference design, I estimate earnings outcomes by age following an expansion in automatic machines. The analysis exploits variation in the use of routine manual tasks across occupations. I estimate that earnings losses for young workers are four times as large as for old workers. I develop a model to answer why young workers' earnings are more affected by machines. The model incorporates the effect of automatic machines on non-wage amenities. Following automation, young workers move to lower-wage but higher-amenity occupations. While young workers see larger earnings declines, older workers see larger amenity declines. A model withut amenities declines accounts for only 23 percent of the estimated earnings decline for young workers.

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1 Introduction

The expansion of automatic machines has the potential to reshape both labor markets and the nature of work. Automation has varying consequences across occupations but in general reduces the need for workers to perform routine tasks. While automatic machines offer the possibility of enhancing worker productivity, these machines can also be disruptive and lead to periods of labor market transition that may be difficult for certain workers. In this paper, I study how missing routine work in the labor market brought on by automation affects workers' earnings across the life cycle.

I focus on the expansion of automatic machines in 1980s Germany and these machines' role in replacing routine manual tasks previously performed by workers. It is well documented that older workers see larger earnings losses than young workers when forced to switch occupations. Based on this fact, we might conclude that older workers will face larger earnings declines following an expansion in automation that leads workers to reallocate across occupations. However, using administrative data from Germany and a difference-in-difference design, I show that it is young workers in highly routine occupations whose earnings decline the most after the expansion of automatic machines. This runs counter to what we might have initially expected, and the question then remains as to why the earnings of young workers are more negatively affected by automatic machines. To answer this question, I turn to a model that can rationalize the pattern of earnings declines by age and quantify the sources of earnings losses observed in the data.

I begin by documenting evidence of how automatic machines affect earnings by age. Using a difference-in-difference analysis, I use variation in exposure at the occupation level to estimate the effect of automatic machine expansion in 1980s Germany on earnings.[1] For each occupation, I create a measure of treatment intensity that captures exposure to automatic machines using information on the shares of routine manual tasks from survey data. I then combine these occupation-level measures with worker employment histories in administrative data to analyze the labor market outcomes for workers at different stages of the life cycle. I find that the relative earnings decline between higher- and lower-treatment intensity workers was four times larger for the youngest cohort than for the oldest cohort. This result is perhaps surprising at first, given that we typically think of young workers as more resilient to labor market shocks. I turn to a model to answer why young workers face larger earnings

[1]Note that my main results are for the sample of men in Germany. In my full analysis, I will also present and discuss differences in the results for women.

declines.

I incorporate a new mechanism to prior models of automation to reconcile the patterns observed in the empirical exercise. In the model, I allow automation to affect amenities as well as wages. Amenity values reflect non-wage characteristics of an occupation that may also be affected by the adoption of automatic machines. This mechanism is supported by work that documents how the adoption of industrial robots leads to lower job satisfaction (Schwabe and Castellacci, 2020). Amenities are difficult to measure directly, so I follow prior work to use a model to quantify the importance of this mechanism. With declining amenities, young workers in highly exposed occupations are more willing to move to lower-wage occupations that are now relatively better in terms of amenities. I find that accounting for changes to amenities is quantitatively important, and without them, the model fails to replicate the pattern of earnings losses by age.

I develop a life-cycle model with automation in order to replicate my empirical exercise. As in the data, I want the model to have two main features: (1) occupations that vary in their use of routine manual tasks and (2) workers with a finite life cycle who make occupation choices. For the first component, I extend the task-based automation framework of Acemoglu and Restrepo (2018) to incorporate variation in the use of routine manual tasks across occupations. For routine manual tasks, machines and workers are substitutes. Other tasks require only labor inputs. Occupation goods producers decide how to allocate tasks to workers or machines based on factor prices. For the life-cycle component, I adapt the dynamic Roy model developed by Dvorkin and Monge-Naranjo (2019) to my setting. Workers accumulate human capital and choose their occupation in each period based on occupation-level wages, mobility frictions, amenity values, and their idiosyncratic comparative advantage. The amenity value in each occupation is determined by the level of automation. Beyond wages, workers find it less appealing to work in an occupation where automatic machines do more of the tasks.

I use the model to replicate my empirical exercise and quantify the importance of declining amenities. I calibrate the model to 1970s Germany and target the level of routine manual tasks in the model occupations to match corresponding occupations in the data. This gives me a measure of treatment intensity in the model that corresponds with my empirical measure. The model also replicates the lifetime career trajectories of workers in different occupations. I use the model to simulate the employment histories of workers following an automation shock. Following an expansion in automatic machines, machines replace some of the routine manual tasks previously done by workers. This leads to wage declines in occupations that require more routine manual tasks relative to other occupations. At the same time, these same occupations also see a relative decline in amenity values. Both of these effects make working in a highly automated occupation less attractive, and workers can escape through occupation switching. The model generates a worker panel comparable in structure to my data. The structure of the model panel allows me to run a difference-in-difference analysis similar to my empirical exercise. The model replicates the pattern observed in the data of larger earnings declines for young workers following an expansion in automatic machines.

The model helps answer why young workers see larger earnings declines following an expansion in automatic machines. It is the higher mobility of young workers that leads to their larger earnings declines. Mobility is costly in terms of human capital but allows workers to escape the wage and amenity consequences of being in a highly automated occupation. As we would expect, young workers escape these occupations at a higher rate. When young workers move, however, they move to new occupations that pay a lower wage. While these occupations do pay lower wages, they also offer relatively higher amenity values following automation. For older workers, who face higher switching costs than young workers, moving costs would outweigh what they gain in amenities. Thus, older workers stay in their occupations and see twice as large a decline in amenity values compared to young workers. These results highlight the need to take a holistic approach when examining the consequences of automation and consider both wage and non-wage implications.

I then quantify the importance of amenity declines following automation. To do this, I have a counterfactual model where automation only affects wages, and amenity values remain fixed. The counterfactual model does not replicate the patterns of earnings losses by age observed in the data, particularly for young workers. It can account for only 23 percent of the effect on earnings for young workers. Even with a robust model with human capital accumulation, variation in the cost of switching occupations with age, and other life cycle features, I cannot rationalize the data patterns when automation only affects the tasks workers perform. Without amenities, mobility is lower and earnings declines are more similar across the life cycle. While quantitatively important, amenity declines do capture something closer to a residual. Future work can explore whether these declines in amenity values reflect a reduction in enjoyment for the work itself or other non-wage benefits that may decline alongside the rise in automatic machines.

My findings have important implications for how we evaluate the consequences of expanded automation and potential policy solutions. Prior work typically models automation as a labor demand shock that changes relative wages. As my work shows, if we do not account for changes in amenity value as well, we will fail to properly measure the distributional consequences of automation by age. My findings also have implications for policymakers deciding how to target policies aimed at workers affected by automation. Programs that try to assist workers affected by automation by replacing lost wages will fail to sufficiently account for the value of non-wage amenity declines caused by automation. For instance, policy directed at subsidizing workers to stay in routine occupations may not provide enough of an incentive to keep workers in a now lower-quality work environment. Similarly, policies targeted at those who switch occupations may over-subsidize workers.

This paper proceeds as follows. Section 2 discusses this paper's contribution to the literature. Section 3 contains the reduced-form analysis. Section 4 details the model, section 5 discusses the model calibration and section 6 contains the quantitative exercises. Section 7 concludes.

2 Related Literature

This paper falls within a long line of work focusing on the labor market consequences of automation. This literature has highlighted the role of automation technologies, and how they replace routine tasks, as a driver of earnings inequality and job polarization in the employment distribution (Autor et al., 2003; Acemoglu and Autor, 2011; Autor and Dorn, 2013; Goos et al., 2014).[2] Much of the literature on the labor market consequences of automation has been devoted to modeling the role of routine-biased technological change in accounting for shifts in the cross-sectional wage and employment structure (see Autor (2022) for a recent review). This paper builds on the prior literature by bringing new evidence and understanding of how automation affects workers across the life cycle and the importance of considering the non-wage consequences of automation.

There is a large empirical literature examining the labor market consequences of automation. The results from these studies vary with some finding earnings losses, particularly for lower-education workers (Akerman et al., 2015; Humlum, 2021), some finding earnings gains (Aghion et al., 2021; Hirvonen et al., 2022), and some finding no effect (Doms et al., 1997). Methodologically, by focusing on occupational exposure, my empirical strategy has

[2]Job polarization refers to the shift in employment away from occupations in the middle of the earnings distribution and into occupations in the upper and lower tails of the distribution.

elements similar to those of the strategy in Acemoglu and Restrepo (2022). They study the exposure of different demographic groups to routine tasks to measure the wage impacts of labor-replacing technologies in cross-sectional data starting in the 1980s from the United States. While they consider variation in exposure by gender and education, I document new evidence of the effect of automation on workers by age.

My reduced-form exercise provides evidence of the differential consequences of automation across the life cycle. Other work analyzing the effects of automation by age is scarce. My finding that young workers saw larger relative earnings declines than older workers is similar to the findings of Dauth et al. (2021), who empirically study the labor market implications of exposure to industrial robots across local labor markets also using data from Germany. My empirical approach differs from theirs in terms of methodology and treatment measure. They use direct measures of industrial robot adoption at the industry-level and employ a shift-share approach. My empirical results may seem out of sync with the findings of another related paper Kogan et al. (2019), which emphasize that the loss of specific human capital leaves older workers facing larger consequences from technological change. However, Kogan et al. (2019) focus on highly displacing technologies and are thus more likely to select on workers forced to switch occupations.

My work also relates to the literature in labor economics and macroeconomics that uses theoretical models to examine the consequences of automation. My model is one of several that build on the task-based automation framework of Acemoglu and Restrepo (2018). I extend their framework to consider multiple occupations, and similar to Guerreiro et al. (2022) I also consider both routine and non-routine tasks. For the life-cycle component of the model, I rely on the innovations of Dvorkin and Monge-Naranjo (2019) to keep the model tractable once incorporating dynamic occupation choices. They develop a model that incorporates dynamic occupational choices and also analyze the implications of automation. Compared to their work, I extend the model to incorporate a finite worker life cycle. One main component of their model is a Roy-style occupation assignment problem. Other papers using this Roy-style assignment model to consider reallocation following technological change include Bárány and Siegel (2018) and Adão et al. (2022). The Roy model structure itself builds on the insights from Eaton and Kortum (2002). Papers that have made methodological advances with this framework in static settings include Costinot and Vogel (2010), Lagakos and Waugh (2013) and Hsieh et al. (2019). These papers relate to the literature comparing exposure to trade shocks and automation (Burstein et al., 2019; Galle and Lorentzen, 2021).

Turning to implications, my work uncovers an important role of declining amenity values of working in highly automated occupations. The research on automation highlighted above tends to focus only on the implications of automation via wages and ignore the possibility of non-wage consequences. There is an extensive literature documenting the importance of amenities for how workers choose jobs and for understanding inequality (Hamermesh, 1999; Dey and Flinn, 2005; Nosal and Rupert, 2007; Hall and Mueller, 2018; Sorkin, 2018; Taber and Vejlin, 2020) Given the importance of non-wage amenities for the value workers' derive from their jobs, it is perhaps less surprising that automation would also affect non-wage characteristics. One study using evidence from Norway does find that the adoption of industrial robots leads to lower job satisfaction for workers most at risk of replacement (Schwabe and Castellacci, 2020). There is a related literature from technologist, who also work on developing new automatic machines, documenting incidences of robot sabotage (Mutlu and Forlizzi, 2008; Bršćić et al., 2015). Future work can be done to analyze which amenities are affected by automation. Declining amenities due to automation may also help account for why work has become more stressful and less meaningful for men over time (Kaplan and Schulhofer-Wohl, 2018).

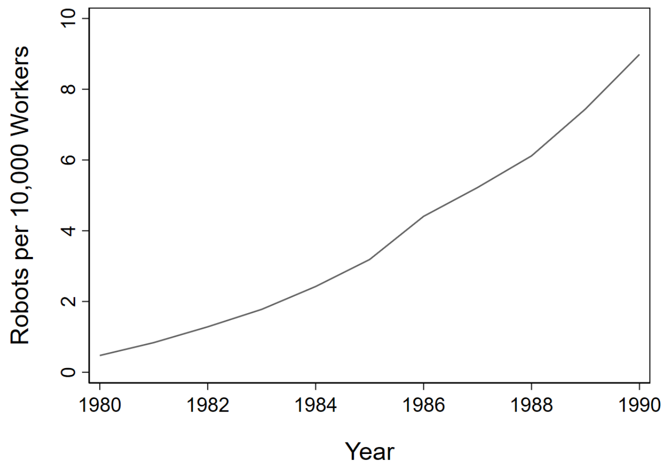
Finally, my work brings new insights into our understanding of age and reallocation outcomes following automation or other shocks. Prior work highlights that young workers account for an important share of workers who reallocate during periods of structural change (Cociuba and MacGee, 2018). In models, it is not uncommon to consider young worker's mobility as a means by which they can more easily avoid the earnings consequences of automation (Guerreiro et al., 2022; Kogan et al., 2019). My results highlight that higher mobility is not always a guarantee that young workers will escape the *earnings* consequences of automation. In the presence of amenity shocks, higher mobility may come alongside higher earnings losses as workers move to higher-amenity occupations. Again, my findings highlight the need to take a holistic approach and consider wage and non-wage consequences of automation.

3 Reduced-Form Analysis

3.1 Background

In my reduced-form analysis, I use the expansion in the use of automatic machines in the 1980s as exogenous variation that allows me to study the effect of automation. At this time, there was an acceleration in the adoption of machines that incorporated computer-related

Figure 1: Expansion of industrial robots in Germany



This figure plots the number of industrial robots in operation per 10,000 workers in Germany from 1980 to 1990. The data are based on the author's calculations from IFR and UNECE (2004).

technologies. The computerization of machines improved the range of tasks that machines could accomplish and made such machines more affordable. Automatic machines in the 1980s had advances such as sensors, and personal computer-based technologies improved information storage, retrieval, and analysis. Figure 1 shows how the number of operational industrial robots per 10,000 workers in Germany expanded starting in the 1980s. While industrial robots receive a lot of attention in the discussion of automatic machines, computer numerical control machines were also expanding at this time. Automatic machines in production led to the replacement of routine tasks requiring manual dexterity (Groover et al., 1986). I exploit variation in the degree to which occupations involved these types of routine manual tasks in my analysis.

3.2 Data

For the reduced-form exercise, I combine occupation-level measures of exposure to automatic machines with administrative data from Germany.[3] For the worker panel, I use the Sample of Integrated Labor Market Biographies (SIAB) provided by the Research Institute of the Federal Employment Service (IAB) (Antoni et al., 2019). The SIAB is a 2-percent random sample of all individuals in Germany who were employed and subject to social security over

[3] I refer to the country of study here as Germany, but more specifically, during the time period that I study, it was the Federal Republic of Germany (or West Germany, as it was known colloquially).

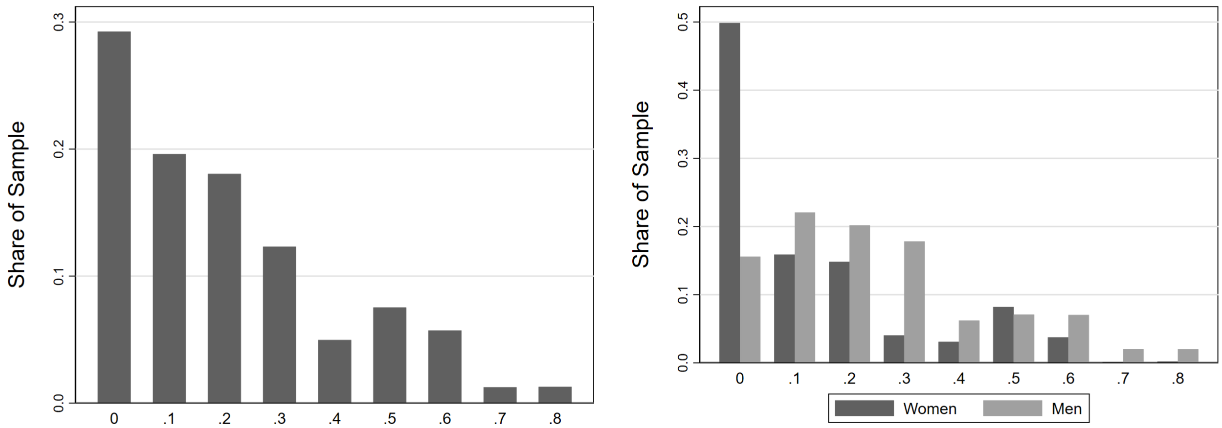
my sample period. It provides information on a worker's employment history along with key demographic variables. For my occupation-level measure of exposure, I use the Qualification and Career Survey from 1979 provided by the German Federal Institute for Vocational Training (BIBB) and the IAB (BIBB and IAB, 1983). Further description of how the I use the SIAB to construct an annual panel and how variables are constructed including sample restrictions can be found in Appendix A. A comparison of the demographic composition of each data set can be found in Appendix B.

The administrative data provides me with key information on workers' labor market outcomes. I focus on workers over the period from 1975 to 1989. Focusing on this time period allows me to analyze the consequences of the rise in automation in the 1980s.[4] I focus on workers aged 25–50 in 1979. This means that the youngest workers will have spent some time in the labor force prior to the 1980s and older workers will be less likely to retire over the sample period, making for better comparisons across age groups. My restriction to this time period also helps me avoid potential issues in the data related to the reunification of Germany in the early 1990s. The main outcome variable that I am interested in is annual earnings. I follow Dauth and Eppelsheimer (2020) and construct an annual data set from the original employment spell data. Earnings are censored above the social security contribution threshold, so I impute wages above this threshold. My main outcomes of interest is log annual earnings. Annual earnings is calculated as the average daily wage times the number of days employed in a given year. This measure includes spells of full-time and part-time employment. I do not observe hours worked.

To analyze the consequences of automation, I need a measure of exposure to the expansion in automatic machines. I create an occupational measure of exposure to automatic machines–which I refer to as *treatment intensity*–using information on occupation tasks included in the BIBB survey. To determine potential exposure in the 1980s, I use the survey from 1979. Since automation alters the composition of job tasks over time, using the 1979 survey gives me a measure of treatment intensity based on information only on tasks performed before the arrival of new technologies in the 1980s. The survey covers approximately 30,000 individuals. In the survey, respondents are asked to report from a list which activities they do in their job. There were changes to the task list in the later surveys that make cross-year analysis of occupational task content difficult. The data set does not include information about how

[4] Acemoglu and Restrepo (2022) use a similar cut-off date in their analysis. Although their data are from the United States, they have data prior to the 1970s, which I do not, and show that there was no significant differences between wage patterns for routine versus other workers prior to the 1980s.

Figure 2: Measures of Treatment Intensity by Occupation and Gender



(a) Distribution of Treatment Intensity (b) Distribution of Treatment Intensity by Gender

Figure (a) plots the distribution of employment over by each occupation's treatment intensity measure (D_j) Figure (b) reports the same by gender. Source: SIAB and BIBB.

much time workers devote to the different activities in their jobs. The survey also records what tools and machines the worker uses in her job from a set list, which I use to validate my measure.

3.3 Measuring Treatment Intensity

For my difference-in-difference analysis, I exploit differences in treatment intensity across occupations. The goal is to relate outcomes to occupation-level exposure across age groups. I observe 115 occupations in the SIAB. Since I do not observe measures of automatic machine adoption directly, I use information on tasks from the BIBB survey data to measure each occupation's treatment intensity.

I start by categorizing the tasks in the BIBB data. I focus on the 1979 survey, which records the use of 84 distinct tasks ranging from conducting research to operating machines to performing care activities. In the data, workers report from a list which tasks they perform. I first categorize which of these tasks can be considered routine manual, nonroutine manual, routine cognitive, nonroutine cognitive, and nonroutine interpersonal. I then construct the measure of treatment intensity. I follow the work of Spitz-Oener (2006) and Mihaylov and Tijdens (2019) to categorize the tasks. Appendix C contains the full mapping of tasks to categories. Respondents can choose multiple tasks, and the median number of reported tasks is 3. Since many workers report only a small numbers of tasks, I aggregate the tasks to the

Table 1: Top and Bottom Routine Manual Share Occupations

Rank	Occupation	Share (D_j)
1	Drillers up to borers	.84
2	Metal producers, melters, other mold casting occupations	.81
3	Turners	.74
4	Welders, oxy-acetylene cutters	.71
5	Sheet metal pressers, drawers, stampers, metal molders	.67
	...	
113	Stenographers, typists	.05
114	Social workers, care workers	.05
115	Cost accountants	.05
116	Nursery teachers, pediatric nurses	.04
117	Technical draftsperson	.04

This table reports the top and bottom 5 occupations by routine manual task share. Source: Based on author's calculations from BIBB data.

occupational level to construct the measures of treatment intensity.

I define the treatment intensity in each occupation as the share of routine manual (RM) tasks performed by workers in each occupation:

$$D_j = \frac{\text{\# of RM tasks performed by workers in occupation j}}{\text{total \# of tasks performed by workers in occupation j}}$$

Figure 2a plots the employment shares across the measures of treatment intensity. It is interesting to note that we do observe that men and women differ in their average exposure because of the difference in their occupational choices. Figure 2b plots the employment shares by gender across routine manual tasks shares. We see that women are less represented than men in occupations with high shares of routine manual tasks. These differences in exposure lead me to separately consider outcomes by gender as well as age.

Table 1 reports the occupations with the highest and lowest shares of routine manual tasks. The occupations with the highest treatment intensity tend to be production occupations, but all occupations use routine manual tasks to some degree. This motivates my decision to use a difference-in-difference design with a continuous treatment. To validate the use of these measures, I analyze how well they correspond with the future use of automatic machines. Appendix D reports how the shares of routine manual tasks correspond with higher eventual adoption of industrial robots by workers in these occupations. I also perform a validation exercise where I regress my measure of treatment intensity on the level of adoption of industrial robots by the 1990s, following Autor et al. (2003).

3.4 Difference-in-Difference Specification

I exploit the variation in treatment intensity as measured by routine manual task shares to analyze the effect of increased automation on earnings for workers across occupations. To do this, I adopt a DID-with-continuous-treatment strategy considering the 1980s an unanticipated event from the perspective of workers in the 1970s. I designate a worker's treatment group by her 1979 occupation. The DID design compares outcomes of workers across treatment occupation groups before and after 1980. To analyze consequences by age, I divide workers into 5-year bins based on their year of birth. I restrict the sample so that the oldest workers were 50 and the youngest 25 in 1980. This is to avoid exit due to early retirement, which in Germany could effectively start at age 60 due to its generous unemployment system during this time period. After implementing these restrictions on my sample, I am left with 3,149,817 person-year observations.

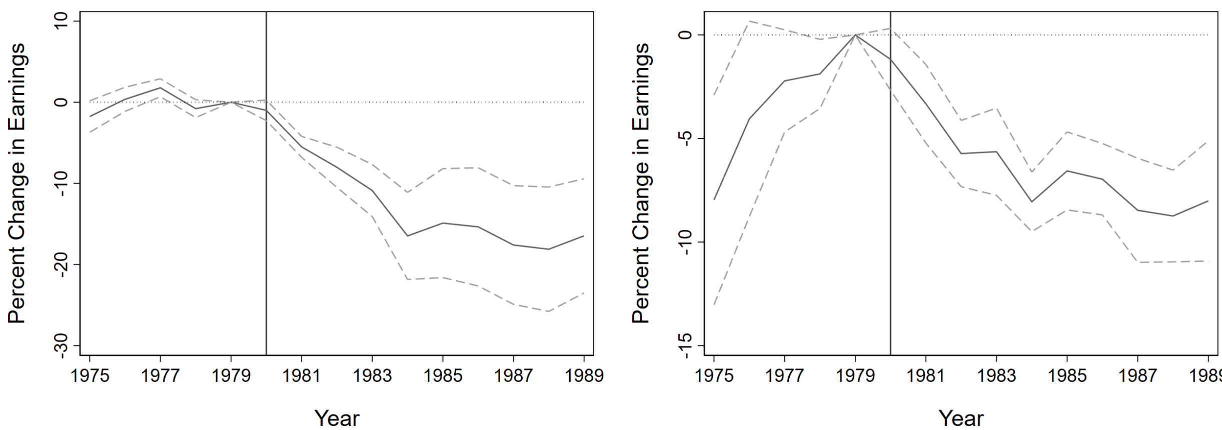
In my main analysis, I estimate a difference-in-difference model with continuous treatment using a two-way fixed effect (TWFE) specification. The main estimated coefficient from this specification is typically interpreted as the average causal response (ACR). That is, the estimated coefficient is taken to represent the causal effect of a unit change in treatment intensity. However, recent work by Callaway et al. (2021), shows that the estimated coefficient is equivalent to the ACR only when a strong parallel trends assumption holds; otherwise, the estimate is susceptible to what they call "selection bias." In my case, for the strong parallel trends assumption to hold, workers in both less routine and more routine occupations would have to have seen the same evolution of outcomes as they would have had they been in the less routine occupation. As Callaway et al. (2021) discuss, there is no test for the strong parallel trend assumption, so I am left to test for "normal" parallel trends. In this case, the parallel trends test examines whether the lower-dose units have the same evolution of untreated potential outcomes as that of higher-dose units. Before running my main specification, I focus on this test.

3.4.1 Parallel Trends

I test for parallel trends by means of an event study. This allows me to examine how well 1980 captures the beginning of the treatment period. I run the following specification:

$$Y_{it} = \sum_{t=1975, t\neq 1979}^{1989} \beta^t \cdot D^t_{j(i)} + x'_{it}\gamma + \alpha_i + \theta_t + \varepsilon_{it} \tag{1}$$

Figure 3: Estimated Average Causal Responses from the Event Study by Gender



(a) Men (b) Women

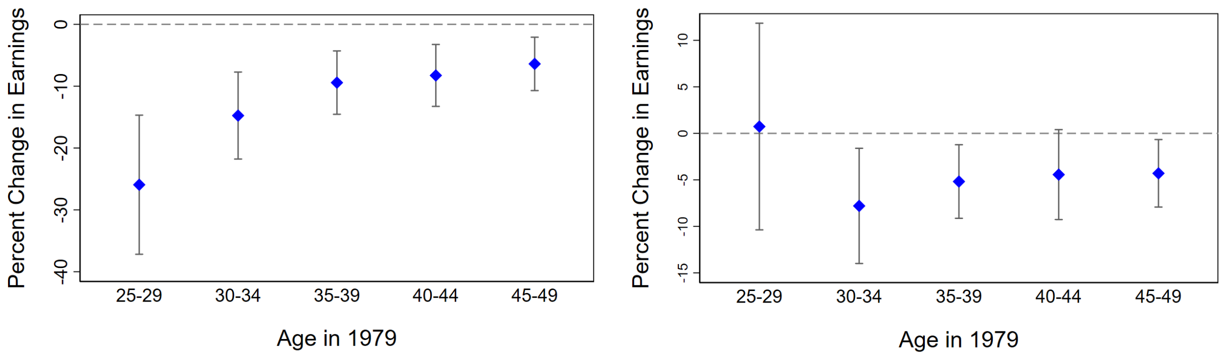
These figures plot the estimated ACR as a percent change in earnings ($\beta \times 100$) from the event study specification in equation (1) with log earnings as the outcome variable and the routine manual task share as the measure of treatment intensity. The ACR is the effect of a one unit change in treatment intensity. The dotted lines represent the 95-percent confidence intervals. Panel (a) reports the results for men, and panel (b) reports the results for women.

In the specification, Y_{it} is log annual earnings for worker i in year t. $D^t_{j(i)}$ is the measure of the worker's treatment intensity determined by her occupation $j(i)$ in 1979.[5] This measure is equal to zero prior to 1980, and all results are in reference to 1979. The variable x_{it} is a vector of individual-level controls including experience, experience squared, and education. Finally, α_i is individual fixed-effects, which will absorb the treatment group fixed-effects based on the worker's occupation in 1979, and θ_t is year fixed effects. I also run the specification separately for men and women. This is equivalent to a specification where I interact gender with each variable. I cluster standard errors at the treatment occupation level.

Figure 3 plots the results of the event study separately for men and women with routine manual tasks as the measure of treatment intensity. The units of the coefficient when multiplied by 100 give us the ACR as a percent of annual earnings, which I plot in Figure 3a. We see that, for men, 1980 is a good proxy for the start of the treatment period for exposure to automation of routine manual tasks. In Figure 3b, the estimated coefficients prior to 1980 suggest that women in highly exposed occupations were already receiving lower earnings than workers in less exposed occupations. This informs my decisions to consider

[5]For robustness, I also run a similar specification designating treatment shares based on each worker's occuaption in 1975 and get similar results.

Figure 4: Estimated Average Causal Response by Age and Gender



(a) Men

(b) Women

Panel (a) plots the estimated ACR as a percent change in earnings ($\beta \times 100$) for men by age from the TWFE specification in equation (2) with log annual earnings as the outcome variable and the routine manual task share as the measure of treatment intensity. The ACR is the effect of a one unit change in treatment intensity. The lines represent the 95-percent confidence intervals. Panel (b) plots the same for women.

men and women separately in my analysis. We also see that the magnitude of losses for men is approximately twice as large as for women at its peak.

3.4.2 Heterogeneity by Age

To compare outcomes across age groups, I split the sample into five-year cohort bins. I run the specification separately for each cohort and for men and women. This is equivalent to a specification where I interact cohort and gender with each variable. I estimate a DID with a two-way fixed effects regression:

$$Y_{it} = \beta D_{j(i)} \cdot Post_t + x'_{it}\gamma + \alpha_i + \theta_t + \varepsilon_{it} \tag{2}$$

In the specification, Y_{it} is the log annual earnings of worker i in year t. D_j is the measure of the worker's treatment intensity determined by her occupation $j(i)$ in 1979. $Post_t$ is a dummy for the post-treatment period, which is 1980–1989. The variable x_{it} is a vector of individual-level controls including experience, experience squared, and education. Finally, α_i is individual fixed-effects, which will absorb the treatment group fixed-effects, and θ_t is year fixed effects. I cluster standard errors at the treatment occupation level.

I start by reporting the results for men. Figure 16 reports estimates of β for each cohort of men, which–if the proper assumptions hold–we can consider the ACR. The units of the coefficient when multiplied by 100 give us the ACR as a percentage of annual earnings, which is what I plot in Figure 16. We see differences in outcomes by age when comparing the results for the oldest and youngest cohorts. A one-standard-deviation increase in treatment intensity equals a 19 percentage point increase in the routine manual task share. This is approximately similar to a worker's moving from a being a locksmith (routine manual share of 52 percent) to a welder (routine manual share of 71 percent). The point estimate implies that a one-standard-deviation increase in treatment intensity leads to a 4-percent relative decline in annual earnings for the youngest cohort of workers (25–30) and closer to a 1-percent relative decline for the oldest cohort (45–50).

I next consider the patterns by age for women. Figure 4b reports the results. For the oldest four cohorts, women see losses with a similar pattern to those of men, but the magnitude of the losses is more muted. However, we do not see the same declines in earnings for the youngest cohort of women that we do for the youngest cohort of men. This result could reflect that, for a given dose, men and women have different responses, or it may reflect other differences in how men and women adjust to following exposure to automation.

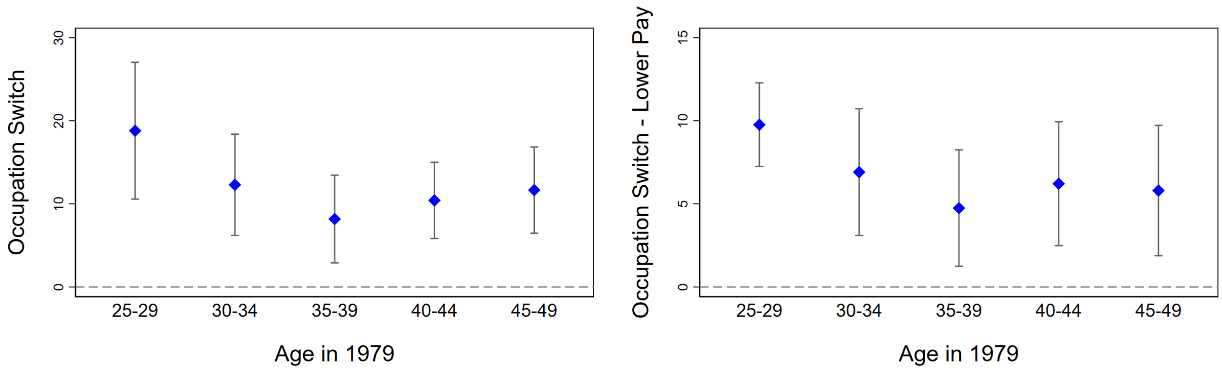
These results could also reflect limitations of the data or selection into the sample. Women make up a smaller portion of the sample and work more in part-time or marginal positions. For approximately 20 percent of women, the primary employment spell reported corresponds to a part-time position, while the same is true for only 1 percent of men. The reporting requirements for these marginal positions varied over my treatment period, making the observations for women more subject to selection bias. Young women, around the age of having children, may have even less labor force attachment. Further analysis with better data would be required to completely tease out the heterogeneity in the consequences of automation across gender.

3.4.3 Mobility

Macroeconomic models of automation often highlight the importance of worker mobility for "escaping" the consequences of automation. Thus, it is of additional interest to understand whether and where workers move following technological change. For this analysis, I focus on the sample of men.

First, I consider the effect of technological change on occupational moves. I create an indicator equal to one when the worker is in an occupation that differs from his occupation in 1979. I then run the same TWFE regression to estimate the DID. Figure 5a reports the

Figure 5: Analysis of Mobility Outcomes



(a) Leave 1979 occupation

(b) Move to lower paying occupation

Panel (a) plots the estimated ACR ($\beta \times 100$) for men from the TWFE specification in equation (2) with an indicator equal to one if the worker is in an occupation different from the one he was in in 1979 and the routine manual task share as the measure of treatment intensity. The lines represent the 95-percent confidence intervals. Panel (b) plots the estimated ACR for men from the TWFE specification in equation (2) with an indicator equal to one if the worker is in an occupation with a lower average wage than the one he was in in 1979 and the routine manual task share as the measure of treatment intensity. The lines represent the 95-percent confidence intervals. Source: SIAB and BIBB.

resulting coefficients across cohorts. Workers in routine manual occupations do have higher rates of occupational mobility across all cohorts, with slightly higher occupational exits from the youngest cohort.

I can also observe some characteristics of the occupations that workers move to. I first rank occupations based on the average earnings of workers in the occupation in 1979. I then create an indicator for when a worker's current occupation was ranked lower in terms of average earnings from the occupation that she was in when I designate the treatment in 1979. Running the main specification with this indicator as the outcome, as reported in Figure 5b, I see that highly routine manual workers tended to move into lower-paying occupations than those that they started in. While these moves to lower-paying occupations could be a reason for the higher earnings losses of young workers, they do not explain why young workers move to these lower-paying occupations to begin with.

3.5 Possible Mechanisms

Are there observable factors that can account for the patterns of losses following automation that I observe in the data? I consider the possible role of differences in task composition by age and the role that German labor markets may play through unions or encouragement of early retirement. For this analysis, I focus on the sample of men, for whom young workers see the largest earnings losses.

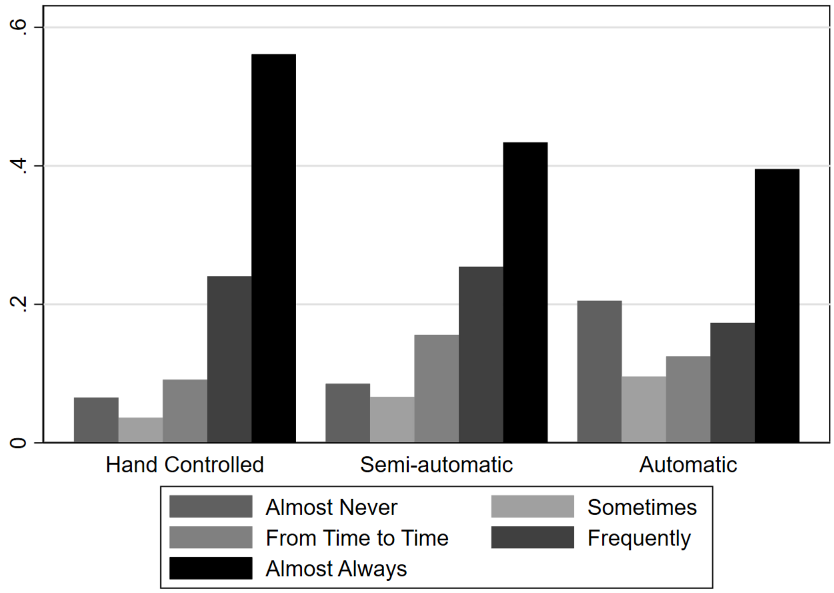
3.5.1 Exposed Tasks by Age

I first return to the BIBB survey data and consider variation in the types of tasks done by workers across age groups within occupations. If young workers perform more of the tasks performed by automatic machines this could be one reason for young workers seeing higher earnings losses. It could suggest that they are closer substitutes with automatic machines in production. Figure 6 shows responses to the question "How often does your daily work require good manual dexterity?" that workers report by the type of industrial machine that they report using at work. It plots the skill requirements reported by workers using hand-operated machines (e.g., lathes), semi-automatic machines, and fully automated machines (e.g., industrial robots). The share of workers reporting that they "frequently" or "almost always" require manual dexterity in their job declines as the level of automation of the industrial machine increases.

Next, I analyze how these affected tasks vary across age groups. To do this, I create an indicator variable for workers who report "almost always" or "frequently" requiring manual dexterity in their job. I then run a simple ordinary least squares (OLS) regression of these indicators on age and control for occupation, gender, and education.

The results are reported in Table 2. They show that the share of workers reporting that they require high manual dexterity in their jobs declines with age. That older workers are in jobs with lower manual dexterity requirements is not entirely surprising given that manual strength can decline with age. This could suggest that one reason for young workers seeing higher earnings losses is because they are closer substitutes with automatic machines in production. However, the magnitudes of the estimated coefficients are relatively small. Even without controls or fixed effects, the estimated coefficient suggests that, with 10 additional years of age, the share of workers reporting being in high-dexterity jobs declines by only 2 percentage points.

Figure 6: Manual Dexterity Requirements across Industrial Machines



This figure plots the distribution of responses to the question "How often does your daily work require good manual dexterity?" for workers who report using industrial machines with different degrees of automation. Source: BIBB.

Table 2: Manual Dexterity Requirements and Age

	(1)	(2)	(3)
Age	-0.0022***	-0.0014***	-0.00087**
	(0.00026)	(0.00024)	(0.00026)
Constant	0.55***	0.53***	0.48***
	(0.010)	(0.0093)	(0.012)
Occ. FE	No	No	Yes
Controls	No	Yes	Yes
Adj. R2	0.0024	0.22	0.24
N	27,359	27,359	23,666

Standard errors in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table reports the coefficients of regressions of manual dexterity across age. The outcome variable is an indicator for whether the worker reports "almost always" or "frequently" requiring manual dexterity in her job. Column (1) reports the results without occupation fixed effects and worker controls, column (2) adds worker controls, and column (3) adds both worker controls and occupation fixed effects.

3.5.2 Collective Bargaining

Germany has certain labor market institutions that may play a role in determining the differential earnings responses to automation by age. I focus on the role of collective bargaining.

Collective bargaining can prioritize incumbent workers, who tend to be older, over outsiders. I draw from Abraham and Houseman (1993) for background on the German labor market features described in this section.

Wages for many workers in Germany fall under collective bargaining agreements. In the 1980s, approximately 40 percent of wage and salary earners in Germany belonged to a union. Industry-level agreements determine minimum wages in the respective industries. In the 1980s, when Germany's unemployment rate was elevated, some of these wages were considered "too high" and were cited as a potential reason for longer unemployment duration. In the 1980s, hours were also an issue addressed by collective bargaining. Collective bargaining agreements apply to all workers in a sector.

To test whether collective bargaining affected the response to technological change, I use data on German union coverage provided by the Institute of Economic and Social Research (WSI).[6] I test the importance of unions by comparing earnings and wage outcomes when I interact occupational exposure with union density. For union density, I create an indicator for industries that have above-median union density and interact that with the continuous treatment variable. Tables in Appendix F report the results. When interacted with the routine manual treatment, workers in sectors with higher union density do not have statistically different outcomes from those in low-density sectors. The data on union coverage are quite coarse, but they do not seem to indicate that unions are strong enough to drive the results across age groups.

3.5.3 Early-Retirement Incentives

During the 1980s, Germany implemented several plans to reduce excess unemployment via early retirement schemes that started at age 60. The duration of unemployment benefits for older workers was also expanded during this period, effectively allowing a worker starting at age 57 to use unemployment benefits as a bridge to early retirement.

Early retirement would affect my analysis if it led to selection into employment for the older workers whom I observe. Once workers retire, I do not observe them in my sample, although I do continue to observe individuals collecting unemployment benefits. I choose the dates and cohorts in my analysis such that workers over 60 are excluded from the sample. In Appendix F, I report the levels of attrition by cohort in the sample. I measure attrition based on the share of workers whom I observe in 1979 and also observe at the end of my

[6] I thank Tommaso Porzio for pointing me to these data.

sample period in 1989. I do see slightly higher attrition for the oldest cohort, which may reflect these early retirements. Attrition for the other cohorts is similar those, so I conclude that early retirement is not a main contributor to my differential results by age.

3.6 Analysis of Other Tasks

In Appendix G, I provide additional analysis using the same framework to consider exposure to other types of tasks. I focus on nonroutine cognitive tasks, which may have benefited from the expansion of labor augmenting technologies, and on the interaction between nonroutine cognitive tasks and routine manual tasks.

4 Model

I now turn to a model that I will use to examine the consequences of automation for worker's lifetime earnings outcomes. As in Acemoglu and Restrepo (2018), automatic machines compete with workers to perform certain tasks. Occupations vary in their use of automatic machines a feature that allows for the expansion of automation to have heterogeneous effects on wages across occupations. Workers are allocated to occupations according to their comparative advantage following Dvorkin and Monge-Naranjo (2019).

4.1 Environment

The model has two types of producers, a representative final goods producer that produces the final consumption good and representative occupational good producers that produce intermediate occupation goods. Occupation goods are used in the production of the final good and are produced by combining labor and automatic machines. Automatic machines are owned by a representative machine owner who competitively supplies them to the market. Labor is supplied by finitely lived workers who each choose an occupation in which to supply their human capital. Both machine owners and workers use their earnings to purchase units of the final good for consumption. Time in the model is discrete with an infinite horizon. In this section, I suppress time subscripts because production is static (i.e., producers do not make dynamic choices like investment), and my focus is on steady state equilibrium where workers dynamic choices depend only on their age.

4.2 Final Goods Producers

In the economy, there is a single final good Y that acts as the numeraire good. The representative final good producer purchases occupation goods Y_j, $j \in \{1, ..., J\}$. Aggregate production follows a CES production function defined over multiple occupations:

$$Y = \left[\sum_{j=1}^{J} \pi_j Y_j^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{3}$$

where $\pi_j \in (0, 1)$ and $\sum_j \pi_j = 1$. $\sigma \in [0, \infty)$ is the elasticity of substitution across occupation goods.

4.3 Occupational Goods Producers

Each occupational good Y_j is competitively produced by a representative occupation good producer. Each representative occupation good producer hires efficiency units of labor L and purchases units of automatic machines K, which are then allocated to tasks. Production of the occupation good requires both routine manual (M) and other (N) tasks, which are combined to produce the occupation good according to a Cobb-Douglas production function. Output from routine manual tasks follows the task-based production framework of Acemoglu and Restrepo (2018) where there is a unit interval of routine manual tasks $i \in [0, 1]$ and automatic machines and labor are perfect substitutes for any given task. Other tasks can only be done using labor. Occupations vary in the intensity to which they require routine manual versus other tasks. By considering multiple tasks types and multiple occupations, I extend Acemoglu and Restrepo (2018)'s original production framework.

I define $\tilde{Y}_j(K, L)$ as the level of occupation good output associated with the optimal task allocation given factor inputs K and L:

$$\tilde{Y}_j(K, L) = \max_{k(i), \ell^M(i), L^N} \left[\int_0^1 \left(\kappa(i)k(i) + \ell^M(i)\right)^{\frac{\rho-1}{\rho}} di\right]^{\frac{\rho}{\rho-1}(\eta_j)} \left(L^N\right)^{(1-\eta_j)} \tag{4}$$

$$\text{s.t.} \int_0^1 k(i)di \leq K$$

$$\int_0^1 \ell^M(i)di + L^N \leq L$$

where $\eta_j \in (0, 1)$ is the share of routine manual tasks and $\rho \in (1, \infty)$ is the elasticity of substitution across routine manual tasks. $\kappa(i)$ denotes the relative productivity of automatic machines compared to labor at a given routine manual task i and is the same for all occupations. Each occupation good producer chooses how to assign factors to tasks: $k(i)$ is the total units of automatic machines purchased to perform routine manual task i, $\ell^M(i)$ is the total number of efficiency units of labor employed to produce routine manual task i, and L^N is the total number of efficiency units of labor employed to perform other tasks. Note that the only variation across occupations comes from differences in the Cobb-Douglas shares η_j while the relative productivity of labor to automatic machines $\kappa(i)$ is constant across occupations.

To characterize the allocation of factors to tasks, I need additional structure on the occupation producer problem. I follow Acemoglu and Restrepo (2018) and assume, without loss of generality, that $k(i)$ is strictly decreasing in i. This assumption implies that labor will be relatively more efficient at performing higher index routine manual tasks and automatic machines will be relatively more efficient in low indexed tasks. Then each occupational good producer will choose thresholds I_j such that:

$$i \in [0, I_j) \text{ performed using automatic machines}$$

$$i \in [I_j, 1] \text{ performed using labor}$$

where tasks at the threshold I_j are assigned to labor. This threshold also allows us to re-characterize the expression for occupation good output:

$$\tilde{Y}_j(K, L) = \max_{k(i),\ell^M(i),L^N,I_j} \left[\int_0^{I_j} \kappa(i)k(i)^{\frac{\rho-1}{\rho}} + \int_{I_j}^1 \ell^M(i)^{\frac{\rho-1}{\rho}} di\right]^{\frac{\rho}{\rho-1}(\eta_j)} (L^N)^{1-\eta_j} \tag{5}$$

$$\text{s.t.} \int_0^{I_j} k(i)di \leq K$$

$$\int_{I_j}^1 \ell^M(i)di + L^N \leq L$$

This functional form illustrates the relationship between the endogenous task threshold I_j and the intensity of labor versus automatic machines in the production of routine manual tasks.

4.4 Automatic Machine Owners

Automatic machines are owned by a separate set of agents from workers who supply labor. These agents have a constant unit measure of population. Automatic machine owners are endowed with K units of automatic machines, which they sell competitively at price p_k. They have linear utility and earnings from the sales of automatic machines are used to purchase units of the final good for consumption. There is no savings, and they consume all of their earnings.

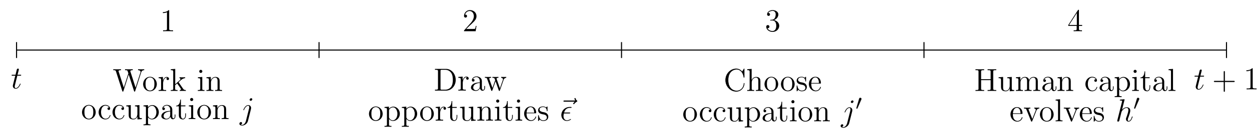
4.5 Workers

There is also a unit mass of workers who purchase units of the final good using earnings derived from supplying their human capital. Workers are in the labor market for a finite number of periods $t = 1, ..., T$. In each period, workers decide on an occupation in which to work given a time-invariant vector of wages per unit of human capital. Each worker's occupation choice is also affected by how her available human capital will evolve based on her occupation choice and some random idiosyncratic forces. Solving for wages in general equilibrium with this type of set-up can be difficult; determining wages requires aggregation of individual labor supplies in each occupation which in turn involves characterizing the dynamic evolution of aggregate labor supplies to each occupation. I follow Dvorkin and Monge-Naranjo (2019) by incorporating additional structure to the model in order to make it tractable. The key ingredients are 1) homogeneity in the utility function of workers and in the law of motion of their human capital and 2) a Markov structure for the comparative advantage of workers across occupations. With these ingredients in place, we can characterize workers' occupation choices and aggregate labor supplies at the occupation level for general equilibrium.

Workers choose consumption each period to maximize lifetime utility where utility is CRRA where $\gamma \geq 0$ is the coefficient of relative risk aversion. Workers do not save, or borrow, and the budget constraint is $c_t = w_{j(t)} h_t$ where $w_{j(t)}$ is the price per efficiency unit of labor in the worker's chosen occupation j at age t and h_t is the worker's human capital at age t. Wages are taken as given and are constant across workers of different ages.

Entrants begin in the labor market with a positive amount of human capital and decide in which occupation $j \in \{1, ..., J\}$ to work in the first period. Then, in each subsequent period of the worker's career, $t = 1, ..., T$, the worker starts attached to an occupation. Figure 7 describes the stages of each period. At the start of the period, production occurs

Figure 7: Incumbent worker timing



and the worker receives (and consumes) her earnings. Next, the worker draws a vector of idiosyncratic opportunities in each occupation $\vec{\epsilon} = [\epsilon_1, ..., \epsilon_J] \in \mathbb{R}^J_+$. Each element, denoted $\epsilon_{j'}$, corresponds with labor market opportunities in potential occupation j' and determines the amount of human capital h' the worker can carry into the next period. Then, the worker decides whether to stay in her current occupation or to move to a new occupation j'. The worker's choice is affected by the pecuniary, represented by elements that affect h', and non-pecuniary costs of switching occupations. After a choice is made, human capital evolves and then the same process is repeated. In the last period of the life cycle, the worker simply consumes her earnings and does not make occupation choices. In the rest of this section, I focus on the problem of incumbent workers. The entrant problem is similar aside from adjustments made to account for the fact that entrants do not start attached to an occupation as incumbent workers do. I describe the entrant problem in Appendix H.

I start by describing the human capital process. The vector $\vec{h'} = h\tau^t \circ \vec{\epsilon} \in \mathbb{R}^J_+$ describes how much effective human capital the worker can supply to each occupation she is choosing over. Here $\circ$ denotes element-by-element multiplication. After choosing an occupation, the worker's available human capital for the next period is correspond to the elements of the vector $\vec{h'}$:

$$h' = h\tau^t_{j,j'}\epsilon_{j'} \tag{6}$$

The amount of human capital the worker has available in the following period after making an occupation choice is based on the worker's current human capital h, the labor market opportunity in her chosen occupation $\epsilon_{j'}$, and the *human capital transferability* matrix τ^t. The *human capital transferability* matrix τ^t is a $J \times J$ matrix with strictly positive entries, $\tau^t_{j,j'}$. Each entry $\tau^t_{j,j'}$ captures the fraction of human capital h that can be transferred from the current occupation j to a new occupation j' by a worker with age t. On-diagonal represent terms for stayers and off-diagonal elements reflect terms for switchers. If $\tau^t_{j,j'} < 1$ it represents skill depreciation and if $\tau^t_{j,j'} > 1$ it implies skills appreciate. *Human capital transferabiltiy* can vary with age t, which allows me to capture variation in earnings growth over the life cycle. With this form, the level of human capital comes to represent both the worker's absolute advantage that she can carry across occupations, but also as a record of the worker's past occupation choices and idiosyncratic shock realizations.

A worker's occupation choice is also influenced by the *amenity value* matrix χ, also a $J \times J$ matrix. Elements of χ denoted by $\chi_{j,j'}(I_{j'})$ are positive and represent the non-pecuniary value of choosing occupation j' for a worker in occupation j. The *amenity value* parameters vary with the level of automation in each destination occupation $I_{j'}$, which allows me to incorporate both pecuniary and non-pecuniary costs of automation. Values of χ affect occupations choices but do not affect the evolution of human capital. When taking to the model to the data, I assume that the cost of choosing a certain occupation is increasing in the level of automation. This could represent a decline in enjoyment from performing an occupation once it is more automated or it could represent a decline in other characteristics such as job security or enjoyment working from coworkers that may also be affected by automation.

Finally, the Bellman Equation of the worker during her career can be characterized, written from the point of view of the start of period t:

$$V_t(j,h) = \frac{(w_j h)^{1-\gamma}}{1-\gamma} + \beta \mathbb{E}_{\vec{h'}} \left[\max_{j'} \left\{ \chi_{j,j'}(I_{j'}) V_{t+1}(j',h') \right\} \right] \tag{7}$$

where the expectation is over the worker's vector of potential human capital realizations $\vec{h'}$, which in turn depends on her idiosyncratic labor market opportunities $\vec{\epsilon}$. Following Dvorkin and Monge-Naranjo (2019), I make the further assumption that labor market opportunities ϵ_t^j in each occupation j are draw iid from the Fréchet distribution each period with scale parameter $\lambda = 1$ and shape parameter α. This is a key step in characterizing workers' occupation choices and aggregate labor supplies at the occupation level for general equilibrium. [7] The h' in the continuation value denotes the human capital in the chosen occupation as expressed in equation (6).

4.6 Competitive Equilibrium

I assume labor, automatic machine, and goods markets are perfectly competitive. Firms and automatic machine owners maximize current profits and workers maximize expected lifetime utilities given prices. I start by first characterizing the problems of workers and

[7] When taking the model to the data, τ and λ are not separately identifiable. I choose $\lambda = 1$ and simplify the notation of the worker's problem.

firms and outlining the market clearing conditions before formally defining the competitive equilibrium.

4.6.1 Firms' Optimization and Factor Demand

Occupation goods are sold at price P_j. Each representative occupation goods producer optimizes revenue net of factor costs. Each representative occupation goods producer hires efficiency units of labor at wage w_j, which varies across occupations, and purchases automatic machines at price p_k, which is constant across occupations. In equilibrium profits are zero. The profit maximization problem of the representative occupation good producer is:

$$\Pi_j = \max_{K,L} \left[P_j \tilde{Y}_j(K, L) - w_j L - p_k K \right] \tag{8}$$

I can then characterize the optimal choice of automation threshold I_j. Since, for any given routine manual task i, machines and labor are substitutes, we can derive that the unit cost of production of task i with automatic machines is $p_k/\kappa(i)$. The unit cost of production of task i with labor is simply the wage per efficiency unit w_j. The unique threshold I_j is characterized as:

$$\kappa(I_j) = \frac{p_k}{w_j} \tag{9}$$

At the threshold, the marginal product is the same regardless of whether it is produced by automatic machines or labor. Labor will perform tasks above the threshold and automatic machines with perform tasks below the threshold. Note that the thresholds I_j vary across occupations due to variation in wages w_j.

Finally, the final good producer maximizes profits taking the occupation producers' optimal choices into consideration. Let $Y_j = \tilde{Y}_j(K^*, L^*)$ be defined as the output of the occupation good at the optimal choices of labor and automatic machines. Then, the representative final goods producer's profit maximization problem is:

$$\Pi = \max_{\{Y_j\}_{j=1}^{J}} \left[Y - \sum_{j=1}^{J} P_j Y_j \right] \tag{10}$$

The results of this profit maximization follow standard CES results. Derivations of the occupation and final goods producer problem can be found in Appendix H.

4.6.2 Workers' Optimization and Labor Supply

Dvorkin and Monge-Naranjo (2019) show that once exploiting the characteristics of the Fréchet distribution, the worker's policy function becomes a simple probabilistic model that does not rely on the worker's level of human capital. I assume that $\gamma > 1$ in the quantitative exercise, which leads to the characterization of $\mu(j, j')$, the proportion of workers switching from occupation j to occupation j' each period from each, defined as:

$$\mu_t(j, j') = \frac{[\tau^t_{j,j'}(-\chi_{jj'}(I_{j'})v^{j'}_{t+1})^{1/(1-\gamma)}]^\alpha}{\sum_{k=1}^{J}[\tau^t_{jk}(-\chi_{jk}(I_k)v^k_{t+1})^{1/(1-\gamma)}]^\alpha} \tag{11}$$

where v^j_t solves the recursion problem:

$$v^j_t = \frac{(w_j)^{1-\gamma}}{1-\gamma} - \beta\Gamma(1 - \tfrac{1-\gamma}{\alpha})\left[\sum_{j'=1}^{J}(-\chi_{jj'}(I_{j'})v^{j'}_{t+1})^{\alpha/(1-\gamma)}(\tau^t_{j,j'})^\alpha\right]^{\frac{1-\gamma}{\alpha}} \tag{12}$$

Derivation and proofs can be found in Dvorkin and Monge-Naranjo (2019). Note that while the worker's problem and proofs in Dvorkin and Monge-Naranjo (2019) are written with an infinitely lived worker, the key assumptions of the model, the homogeneity in the utility function and human capital low of motion as well as the assumption on the idiosyncratic shocks, are also met by the finitely lived worker case.

We can now characterize the allocation of workers to occupations and distribution of human capital over the life cycle in order to characterize aggregate labor supply in each occupation. First, we characterize the decision of new entrants. Then, the initial employment shares across occupations is:

$$\theta_0(j) = \frac{[\tau^0_j(-\chi^0_j(I_j)v^j_1)^{1/(1-\gamma)}]^\alpha}{\sum_{k=1}^{J}[\tau^0_k(-\chi^0_k(I_k)v^k_1)^{1/(1-\gamma)}]^\alpha} \tag{13}$$

where χ^0 and τ^0 are $1\times J$ vectors and are the entrant equivalent to the incumbents *amenity value* and *human capital transferability* matrices respectively. Then we can characterize the evolution of the distribution of workers across the life cycle by employing the characterization of worker's occupational choices:

$$\theta_t = \mu_t\theta_{t-1}$$

.

where μ is defined as in (11).

Next, I characterize human capital provided to each occupation j at each age t, in the form of the $J \times T$ matrix H. We start by characterizing the initial distribution of human capital. From the entrant shares we can determine the amount of human capital provided to each occupation in the first period:

$$H_0(j) = \Gamma(1 - \tfrac{1}{\alpha})\tau_j^0[\theta_0(j)]^{1-\frac{1}{\alpha}} \tag{14}$$

To characterize the evolution of human capital, we first characterize the transition matrix of aggregate human capital M. M is a $J \times J \times T$ matrix. The elements of M are defined by:

$$M_t(j, j') = \Gamma(1 - \tfrac{1}{\alpha})\tau_{j,j'}^t[\mu_t(j, j')]^{1-\frac{1}{\alpha}} \tag{15}$$

.

Then, we can define how human capital evolves across age:

$$H_{t+1} = H_t M_t \tag{16}$$

Finally, to characterize labor market clearing and for determining wages in general equilibrium, we can characterize total labor supply at the occupation level as:

$$L_j^S = \sum_t^T H_t \tag{17}$$

4.6.3 Definition of the Competitive Equilibrium

Given a stock of robots K and initial human capital of entrants h_0, an equilibrium consists of (i) a price system p_k, $\{w_j, P_j\}_{j=1}^J$, (ii) individual worker occupation choices $\{v_t^j, \mu_t\}_{j=1}^J$, (iii) occupation good firms' task allocation choices $\left\{\{k_j(i), \ell_j^M(i)\}_{i=0}^1, I_j, L_j^N\right\}_{j=1}^J$, (iv) aggregate vectors of workers and human capital across occupations $\{\theta_t, H_t\}_{t=1}^T$, and (v) aggregate and occupation output Y, $\{Y_j\}_{j=1}^J$ such that:

(a) Given wages and an occupation choice, each worker chooses $\{c_t\}_{t=1}^T$ to maximize utility subject to the respective constraint

(b) Given wages, each individual chooses the occupation, given by equations (11) and (12), that maximizes utility

Table 3: External Parameters

Parameter	Description	Value	Source
Occupation Production:			
ρ	Manual task elasticity	1.28	Karabarbounis and Neiman (2014)
A	Robot Productivity	.8	-
Final good Production:			
π_j	Occupation shares	[.22, .47, .31]	Wage shares (SIAB)
σ	Occupation elasticity	1.34	Caunedo et al. (2023)
Worker parameters:			
γ	CRRA parameter	2	Dvorkin and Monge-Naranjo (2019)
β	Discount rate	.95	Dvorkin and Monge-Naranjo (2019)
α	Fréchet shape	13	Dvorkin and Monge-Naranjo (2019)

(c) Given prices, occupation producers optimally allocate factors to tasks and threshold conditions are satisfied (equation (9))

(d) Automatic machine producers maximize their consumption

(e) Factor and good markets clear: $L_j^D = L_j^S$, $\sum_{j=1}^J K_j^D = K$, $Y_j^D = Y_j^S$

(f) Aggregate resource constraint holds $Y = C + p_k K$, where C is aggregate consumption of all workers $C = \sum_{j=1}^J w_j L_j$.

5 Model-to-Data

Next, I turn to taking the model to the data. I divide the occupations in the German data into three broad occupations: professional ($j = 1$), service and construction ($j = 2$), and production ($j = 3$). Occupation categories correspond with the occupation's rankings based on the routine manual task share. These groupings are based off of the broad categories from the International Classification of Occupations. Professional occupations consist of managers, professionals, and technicians. Production occupations include craft and related trades as well as plant and machine operators, assemblers, and engineers. I combine construction with service occupations including clerical support workers, service and sales workers, and elementary occupations.

5.1 External Parameters

Table 3 summarizes the parameter values that are chosen outside the model. Starting with the parameters governing final goods production, occupation shares π_j are set equal to the share of total earnings for each occupation calculated in the German administrative data. The elasticity across occupations σ is equal to 1.34 from Caunedo et al. (2023).

Moving to occupational production the elasticity $\rho = 1.28$ is set to match estimates of the elasticity between robots and workers in Karabarbounis and Neiman (2014). I then need to assume a functional form for κ. I choose $\kappa(i) = e^{A(\frac{1}{2}-i)}$ with $A > 0$. This ensures that $\kappa(i)$ is decreasing in i and is normalized so that $\kappa(1/2) = 1$. [8]

On the worker side, I also set some parameters outside the model based on values from the literature. I set $\beta = .95$ as the annual discount rate, the risk aversion parameter $\gamma = 2$, and the Fréchet distribution parameters $\alpha = 13$ is from Dvorkin and Monge-Naranjo (2019).

5.2 Internal Calibration

Table 4 reports the parameters that are jointly calibrated in the model and the respective model targets. On the production side, the initial machine stock is targeted to match the capital share (1 minus the labor share) in Germany in 1979 (Feenstra et al., 2015).[9] The Cobb-Douglas shares occupational goods production are targeted to match the routine manual shares in each occupation. The routine manual share in the model are defined to be proportion of all labor units in an occupation assigned to routine manual tasks ($\frac{\int_{I_j}^{1} \ell_j^M}{L_j}$).

The remaining parameters to calibrate are related to the *human capital transferability* matrices. Each of these matrices has a potentially large number of elements. For instance, τ^t would have $J \times J \times T$ elements. To simplify the calibration, I add additional structure to these matrices. I focus on targeting matrix elements that capture differences in employment, earnings, and mobility across occupations and age.

First, I target elements of the *human capital transferability* vector for entrants τ^0 to capture differences in initial earnings across occupations for entrants. The elements of the matrix are normalized so that that element corresponding with services τ_3^0 is equal to one.

[8] In steady state, the slope of $\kappa(i)$, A, governs the routine manual share along with η_j. In the model, higher η_j corresponds with a higher routine manual shares in the occupation and a higher exposure to changes in the level of machines. However, if the slope parameter of $\kappa(i)$ were instead used to target treatment intensity, we get a relationship where occupations with lower routine manual shares would have the highest exposure to changes in the level of automatic machines. This is the opposite of what I observe in the data, therefore, I decide to target η_j to capture treatment intensity across occupations and fix the slope parameter. I perform sensitivity analysis to test whether the slope parameter affects my findings. The slope parameter I choose is arbitrary, and I choose a value that implies relatively similar productivity between machines and workers.

[9] The total capital share is not a perfect match for the share of automatic machines that I highlight in my model, but disaggregated data on the capital structure that allow me to target the automatic machine share are not available.

Table 4: Internal Calibration

Parameter	Description	Value	Target	Model	Data
K	Machine supply	46.0	Capital share	0.33	0.33
η_1	Routine manual weight	0.27	Routine manual shares	0.13	0.16
η_2		0.27		0.18	0.19
η_3		0.76		0.53	0.5
τ_1^0	Entry matrix	0.8	Relative earnings: entrants	1.0	1.06
τ_3^0		0.94		1.2	1.15
τ_{11}	Human capital: Stayers	1.0	Earnings ratio Age 40/21	2.3	2.5
τ_{22}		0.98		1.3	1.36
τ_{33}		0.99		1.6	1.26
τ_{12}	Human capital: Switchers	0.91	Occupation mobility	0.014	0.029
τ_{13}		0.81		0.017	0.013
τ_{21}		0.68		4.6e-5	0.012
τ_{23}		0.9		0.033	0.02
τ_{31}		1.1		0.0052	0.007
τ_{32}		1.1		0.0099	0.022
ζ_1	Human capital w/Age	0.0022	Earnings ratio Age 55/40	0.974	0.99
ζ_2		0.0018		0.79	0.98
ζ_3		0.0009		1.0	0.91
ϕ_0	Switching cost young	0.78	Occupation mobility age 21-25	0.0038	0.04
ϕ	Switching cost with age	0.0025	Occupation mobility age 40-55	0.0021	0.019
χ_1^0	Amenity value entrants	2.0	Entrant employment shares	0.16	0.16
χ_2^0		0.73		0.57	0.54
χ_3^0		1.4		0.28	0.3
χ_1	Amenity value	1.0	Employment share	0.13	0.16
χ_2		0.95		0.54	0.54
χ_3		0.98		0.33	0.3
c_0		1.1	Earnings declines by age	Figure 10a	
ΔK		1.4			

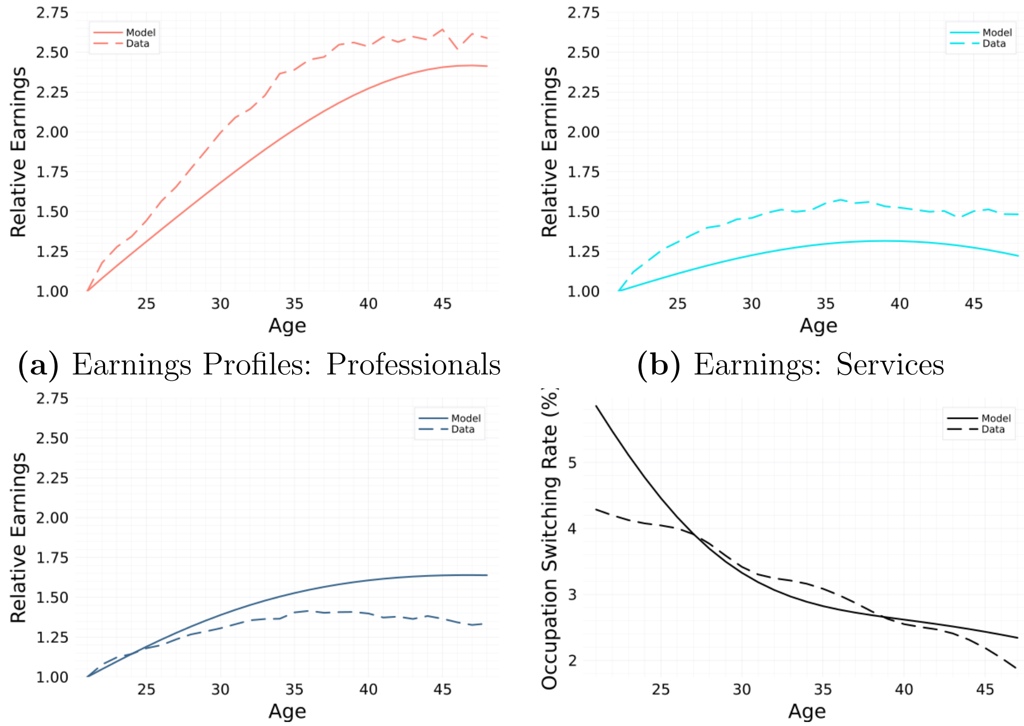
The other elements are targeted to the ratio of earnings of entrants in those occupations relative to entrants in services from the German administrative data.

Moving on to the *human capital transferability* matrix for incumbents, I add structure to capture earnings and mobility differences across age and occupation. I decompose $\tau^t = \tau^t \circ \tau$. I consider elements that capture differences by age τ^t and occupation τ.

Starting with the matrix τ, a $J \times J$ matrix, is used to capture key differences in earnings across occupations. The on-diagonal elements $\tau_{j,j'}$ capture occupation specific earnings growth. I targeted each $\tau_{j,j'}$ to match the earnings ratio for workers in occupation j at age 45 relative to age 25. The off-diagonal elements capture the costs, or gains, of a worker switching occupations. In the data, the corresponding moment is calculated by measuring rates of occupation switching between each occupation category.

Next, I use elements of τ^t to capture differences in earnings and mobility by age. The

Figure 8: Earnings and Mobility Profiles: Model vs. Data



(a) Earnings Profiles: Professionals **(b)** Earnings: Services

(c) Earnings Profile: Production **(d)** Mobility Profile

Panels (a)–(c) compare the relative earnings in the model and data for professionals, services, and production respectively. Both model and data series are normalized relative the earnings of entrants in Services. Panel (d) compares the occupation switching rate for workers in the model and data. Data series is plotted as three-year moving average. Data Source: SIAB.

matrix τ^t is also $J \times J$ matrix. The on-diagonal elements capture the age-earnings profile. I let $\tau^t_{j,j'} = 1 - \zeta_{j'}t$, where $\zeta_{j'}$ governs the decline in human capital accumulation with age. $\zeta_{j'}$ is targeted to match the log earnings ratio of workers age 55 to age 50 in each occupation. The off-diagonal elements capture variation in occupational mobility with age. Let $\tau^t_{j,j'} = (1 - \zeta_{j'}t)(\phi_0 - \phi t)$ where ϕ_0 is targeted to match occupation mobility of young workers age 20-25 and ϕ is targeted to match occupation switching for old workers age $50-55$.

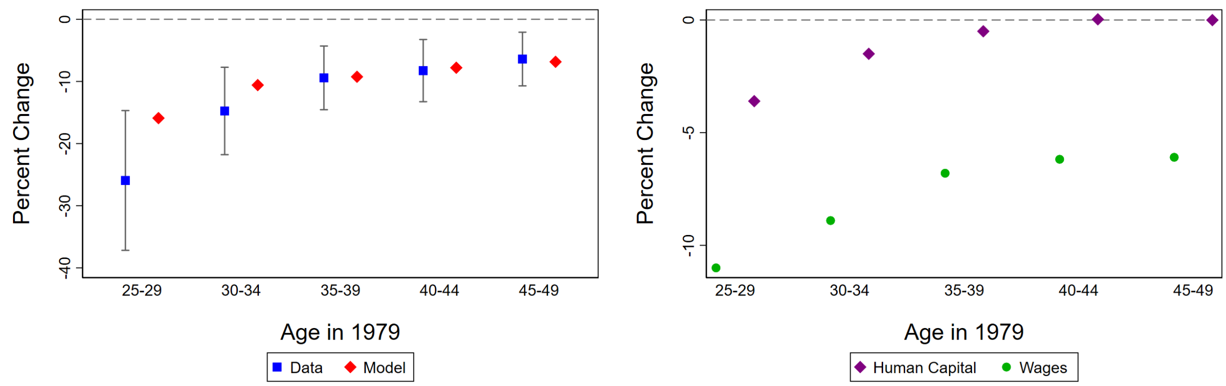
Then *amenity value* matrices χ^0 and χ are given structure to target the distribution of workers across occupations. I assume that the amenity value of entering an occupation is constant regardless of origin occupation. This implies that $\chi_{j,j'} = \chi_{j'} \ \forall \ j'$ and $\chi^0_j = \chi_j \ \forall \ j$. For each element of χ, I assume it can be decomposed into two components $\chi_{j'}(I_j) = \chi_{j'} \circ \chi(I_{j'})$. Each element of $\chi_{j'}$ is targeted to match the employment shares in each respective occupation. The other elements $\chi(I_{j'})$ will vary with the level of automation. I choose the functional form $\chi(I_{j'}) = \frac{c^{I_{j'}\eta_j}}{c^{.5\eta_{j'}}}$. This functional form centers the value of amenities at 1 when half of the task are automated. It also implies that changes in the task threshold lead to larger declines in amenities in occupations with higher levels of automation. This curvature is needed to match the empirical moments.

I calibrate c as well as the change in the level of automatic machines ΔK to target the outcomes of the empirical regression by age. I use the model to analyze the impact of an expansion in automation on workers at different stages of the life cycle. To do this, I first simulate a panel of worker labor market histories.[10] Finally, I discuss how well the model accounts for the patterns of earnings declines by age for workers in highly routine manual occupations. Following the expansion of machines, workers observe the new prices and amenity values and make new occupation decisions. This gives me a panel of simulated workers where I observe occupation, age, wages, and earnings around the time of the shock, which I benchmark to 1980. Appendix J documents how occupation and employment moments vary in response to the shock for the full sample. I take this panel data and use it to replicate the difference-in-difference specification in equation (2) with log earnings of the model as the outcome variable and the routine manual shares for each model occupation as the measure of treatment intensity.

From table 4 we see how well the model can matching the targeted moments. The model does well with most moments. The model misses slightly on some of the earnings targets, but still captures the key career earnings and mobility profiles. Figure 18 plots how well the model matches lifetime earnings profiles and mobility profiles by age. Even with the simplifications of the human capital and utility matrices, the model can match these profiles. Workers' earnings profile are hump shaped, and the profiles also capture the ordinal ranking of earnings across occupations. The model also captures the declining rate of mobility with age, although workers have slightly higher mobility that in the data at the end of their careers. Figure 10a plots the main results and compares them with the empirical results in the data. The model also does a good job matching the overall profile of earnings declines across cohorts although slighty underestimates the earnings declines for the youngest cohort of workers.

[10] I simulate 230,000 workers, approximately the number of individuals I observe in 1979 of the German employment panel. See Appendix I for how I characterize the individual policy function.

Figure 9: Model DID Results



(a) Earnings

(b) Wages and Human Capital

Panel (a) plots the estimated ACR as a percent change in earnings ($\beta \times 100$) from the model by age from the TWFE specification in equation (2) with log annual earnings as the outcome variable and the routine manual task share as the measure of treatment intensity. The ACR is the effect of a one unit change in treatment intensity. The lines represent the 95-percent confidence intervals. Panel (b) plots the results of the same exercise with log wages and log human capital as the outcome variables.

6 Quantitative Analysis

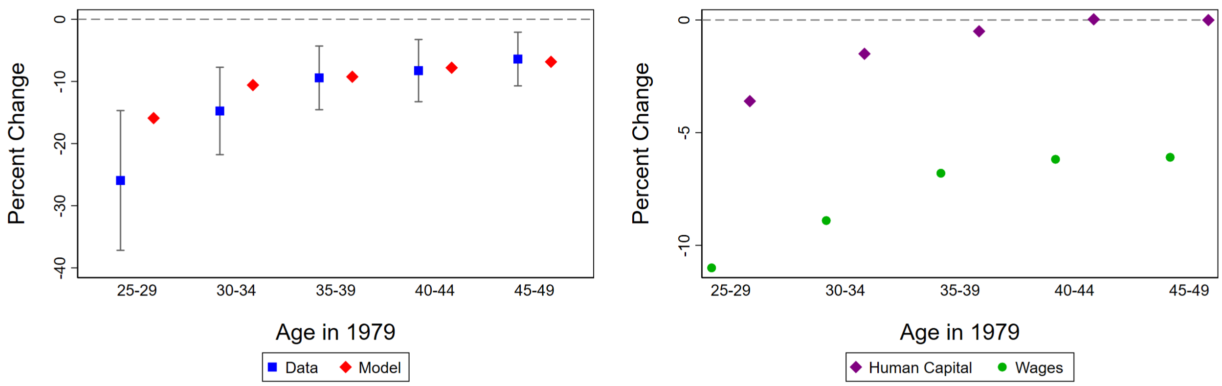
I now move on to the quantitative analysis. The purpose of the quantitative model is to shed light on the sources of losses by age following an expansion in automation machines, and in particular to answer why young workers see the largest earnings decline following automation. In this section, I detail how I simulate data from the model to replicate my difference-in-difference design and discuss the insights from the model. I also compare model steady states and discuss potential model extensions.

6.1 Model Impact of Automation across the Life Cycle

I then use the model to analyze the sources of earnings losses for workers across cohorts. I run the same specification with log wages and log human capital as the outcomes variables. Figure 10b plots the results for both outcomes variables. We see that the bulk of the earnings losses for young workers come from young workers seeing larger declines in wages than older worker, but we also see that the cost of switching leads to lower human capital as well.

I next perform additional analysis to understand why young workers see larger earnings declines. While all workers face mobility costs, this cost is smaller for young workers, and they

Figure 10: Model DID Results

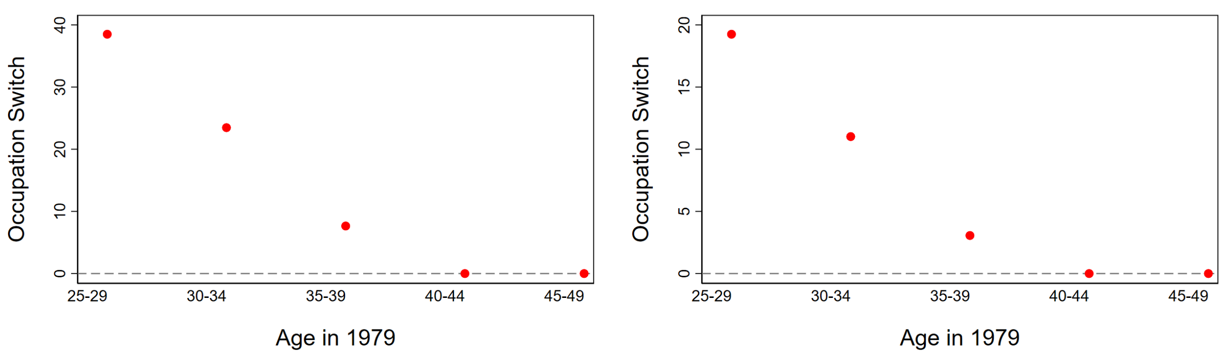


(a) Earnings

(b) Wages and Human Capital

Panel (a) plots the estimated ACR as a percent change in earnings ($\beta \times 100$) from the model by age from the TWFE specification in equation (2) with log annual earnings as the outcome variable and the routine manual task share as the measure of treatment intensity. The ACR is the effect of a one unit change in treatment intensity. The lines represent the 95-percent confidence intervals. Panel (b) plots the results of the same exercise with log wages and log human capital as the outcome variables.

Figure 11: Model DID Results: Amenity and Mobility Outcomes



(a) Amenity Values

(b) Worker Mobility

Panel (a) plots the estimated ACR as a percent change in amenities ($-\beta \times 100$) from the model by age cohort from the TWFE specification in equation (2) with log annual earnings as the outcome variable and the routine manual task share as the measure of treatment intensity. The ACR is the effect of a one unit change in treatment intensity. Panel (b) plots the results of the same exercise with occupation switching as the outcome variables.

have a longer horizon to regain any costs of switching. Young worker then switch more often, and they move to low-wage occupations that are now relatively higher in quality. Figure 11a performs the same DID specification using log amenity values, χ that workers get from their occupations. Note that high values of χ correspond with lower amenity occupations, so plot $-\beta$ for clarity. Amenities decline more for older workers than younger workers.The estimated coefficients suggest that older workers amenity declines are almost twice as large as those of young workers. Figure 11b compares the effect of automation on mobility across cohorts in the model. The magnitude of mobility is not targeted, and while higher that in the data, does show a similar profile with a larger mobility response for young workers.

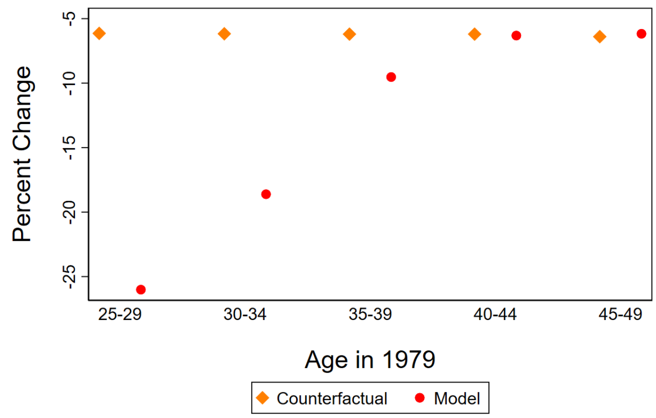
6.1.1 Amenity vs. Wage Costs

Next, I want to determine the quantitative importance of accounting for amenity declines. To do this, I use a counterfactual model where χ does not change following an increase in automation. I then run the DID specification on the model cohorts. Figure 12 compares the results from the model exercise with the reduced-form results. The counterfactual model, while capturing the overall levels of earnings declines, does not replicate the patterns of earnings losses by age. In fact, we see a relatively flat pattern of earnings declines across cohorts. The counterfactual model gives an approximately 50 percent lower overall effect of automation on earnings. For old worker, the effect on earnings is essentially the same, but for young workers the model without amenities only accounts for 23 percent of the effect on earnings.

6.2 Model Impact of Automation on the Labor Market

I next analyze and compare steady states under different levels of automatic machine supply. In the model, occupations vary in their exposure to automatic machines due to heterogeneity in their use of routine manual versus other tasks in production. These share are governed by the parameter η_j. Figure 19 plots the comparative statics for the model for different outcomes over different level of automatic machines. Panel (a) plots the changes in the routine manual share in each occupation for different levels of automatic machines. As the amount of machines available for production increases, the routine manual share in each occupation declines. However, it declines more in production where the intensity of routine manual tasks was highest. Interestingly, this does not correspond directly with changes in the automation threshold I_j. Panel (b) plots changes in the threshold in each occupation

Figure 12: Counterfactual: No Amenity Changes



This figure plots the estimated ACR as a percent change in occupation switching ($\beta \times 100$) from the model by age cohort from the TWFE specification in equation (2) with log annual earnings as the outcome variable and the routine manual task share as the measure of treatment intensity. The ACR is the effect of a one unit change in treatment intensity. The lines represent the 95-percent confidence intervals.

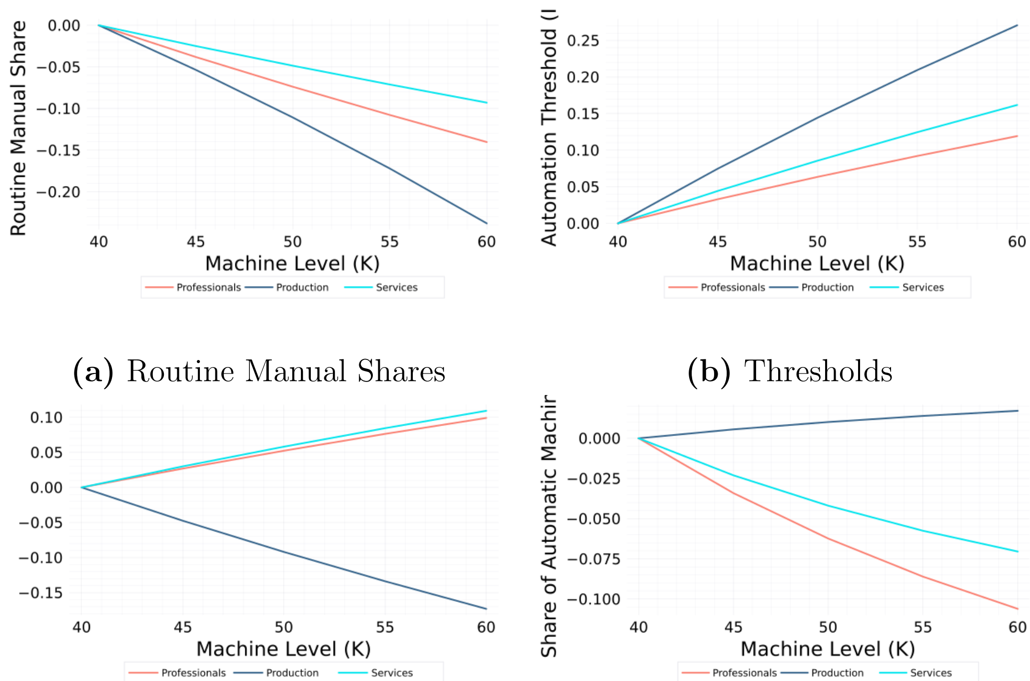
over different levels of the supply of automatic machines. As automatic machines expand, production occupations also see larger increases in automation.

The model also has implications for the structure of employment and how automatic machines are allocated across occupations. Panel (c) plots changes in the employment share for each occupation. Employment moves out of production as the level of automatic machines increases. This corresponds with the changes in routine manual shares. Panel (d) plots changes in the share of automatic machines in each occupation. Again, here we see that a larger share of total automatic machines are allocated to production occupations relative to services and professional occupations. .

In Appendix K, I document the comparative statics examining the distribution of human capital across occupations and tasks, which affects relative wages. These plots show that when the level of automatic machines increases, the level of human capital utilized in routine manual tasks declines for all occupations and the level of human capital utilized in other tasks increases in all occupations. However, while the total level of human capital used in services and professional occupations increases, the there is decline in overall level of human capital used in production. Lower wages reflect this decline in overall labor utilization in production occupations.

Appendix K also documents the sensitivity of outcomes under different choices of the

Figure 13: Steady State Comparisons



(a) Routine Manual Shares

(b) Thresholds

(c) Employment Shares

(d) Share of Automatic Machines

The figures plot the comparative statics for different outcome variables for different levels of automatic machines. Panels (a) plots changes in routine manual shares across occupation. Panel (b) plots the changes in the automation thresholds I_j. Panel (c) plots changes in the employment shares across occupations. Panel (d) plots changes in the share of automatic machines in each occupations.

slope parameter for $\kappa(i)$. When the relative productivity of robots compared to labor declines, the routine manual share increases, the capital share decreases. What is of more concern when moving to analyze worker outcomes is how $\kappa(i)$ affects the relative changes in prices. When the relative productivity of robots declines, then for the same increase in machines, the relative wage decline in production is of smaller magnitude and the relative shift out of production in terms of employment is also of smaller magnitude.

6.3 Model Extensions

While the model does well in matching the first-order data facts from my analysis, it misses on two potentially important second-order data fact. First, mobility in the simulated data is higher than in the data. Secondly, the model does not fully capture heterogeneity by age in earnings losses for workers who stay in their occupations following automation. I discuss how the model might be extended to consider these additional data features.

6.3.1 Switching Rate

Starting with mobility, in the simulation, after the shock, mobility in the model goes up significantly and outpaces what I observe in the data. Appendix shows the response in terms of mobility. In order to match the data, it would imply a rise in mobility costs that is relatively large. These additional costs restricting mobility may be due to congestion or search frictions associated with a larger degree of reallocation. Another explanation for the higher mobility costs is that the 1980s in Germany was a time of high unemployment, so this may reflect differences in switching costs over the business cycle. They could also be addressed by solving for a smoother transition path of wages.

I do consider a counterfactual exercise where in addition to facing different wages, workers also face higher mobility costs in the transition period. The results in this exercise depend on the magnitude of the mobility increase. If it increases but not so much as to hinder mobility, it can lead to larger human capital declines due to costly switching, which increases the overall magnitude of the earnings losses for exposed workers. However, if the mobility costs increase is high enough that it limits mobility, then workers would actually see smaller earnings losses since they stay in their occupations. This implies a non-monotonic effect of mobility costs on earnings once we allow for changes in amenities.

6.3.2 Heterogeneity by Age: Stayers

There are two alternative explanations that might account for the why young workers also do worse among stayers as I observe in the data. First, automation might have an affect on human capital accumulation τ^t. If automation is accompanied by a human capital shock for stayers or a decline in opportunities to learn new skills stayers might also see earnings declines. Alternatively, young and old workers could vary in how well machines substitute for them in production. If young workers are closer substitutes with machines, then they would be more affected by automation. In this case, we could consider an alternative model where production incorporates heterogeneity by age, such as allowing the relative productivity of machines to vary with age $\kappa_t(i)$. Future work can consider additional sources of heterogeneity in the effect of automation by age.

7 Conclusion

In this paper, I examine how the automation of routine manual tasks affects workers across the life cycle. Using administrative data from Germany, I exploit variation in exposure to automatic machines across occupations to estimate the effect of automation on earnings by age. I find important new evidence that it is the earnings of young workers that are the most negatively affected by machines. These losses follow young workers even when they escape high-exposure occupations.

To answer why the earnings of young workers were more negatively affected by automation, I develop a quantitative life-cycle model. The model incorporate the automation of routine manual tasks and workers' occupation choices over their careers. I propose a new mechanism, the effect of automation on amenities, to reconcile the empirical findings. I use the model to replicate the earnings losses by age observed in the empirical exercise. The model uncovers the quantitatively important role of declining amenity values in highly exposed occupations as a source of larger earnings declines for young workers.

The model points to a potential linkage between the tasks that workers perform in their occupations and the value they derive from their work. As my work shows, if this channel is unaccounted for we will fail to identify the distributional consequences of automation by age. These results suggest that reallocation to occupations less affected by automation is not always enough to help workers escape the consequences of automation in terms of wages. My results have implications for policymakers deciding where to target redistribution policies to affected workers following automation. The model points to the fact that automation doesn't just affect wages, but can alter non-wage amenities as well. Without considering changes in the total value of work, policies that only consider wages will be ineffective in addressing the true consequences of automation.

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A SIAB sample construction

In this section I describe how I prepare the SIAB data for analysis. The SIAB data comes in spell format, which I convert to an annual data. To convert the spell data to annual, I use the code provided by Eberle and Schmucker (2017) and Dauth and Eppelsheimer (2020). I also reference code from Burdett et al. (2020) and Jarosch (2023) in preparing the data sample.[11]

I keep spells subject to social security in the reference year. This excludes trainees, employees in partial retirement, interns and student trainees. The sample includes part-time workers whose earnings match a certain threshold. The reporting threshold for part-time work varies across my sample. Part-time workers needed to exceed 20 hours from 1975-1978, the threshold was lowered to 15 hours until 1987, and since 1988 it as been at 18 hours a week. The occupation codes follow the 1988 German Classification system and are groups to protect worker anonymity by the FDZ in my sample. I further drop workers in occupations related to agriculture and security along with politicians. I restrict to workers age 20-50 in 1979. To construct the education variables I reference Fitzenberger et al. (2005) and Thomsen et al. (2018). In the German system, there is a less clear hierarchy over traditional schooling and vocational degrees than in the United States. I designate workers as low-education if they have no vocational training or only an Upper Secondary School leaving certificate. I designate workers as medium-education if they have vocational training or both a Upper Secondary School leaving certificate and vocational training. Finally, I designate workers as high education if they have a degree from a University of Applied Sciences or a traditional University degree. Similar to Burdett et al. (2020), I also restrict to workers in West Germany, since East German workers did not start reporting until 1991. Since I do not have a good measure of labor market experience for workers who enter the labor market prior to 1975 I focus on a measure of experience as age net time spend in education, assuming that those with low education enter at 18, those with medium education enter at 20, and those with high education enter at 22. These values correspond with the typical entry ages of new workers in the sample by education type.

Next, I designate periods of employment in the monthly panel. I observe incidences where I consider a worker to be employed if they work full-time or part-time and non-employed otherwise. When employed, I assign the average daily wage. Wages are reported in Euros, or the Euro equivalent prior to the introduction of the Euro. For wages during employment, I

[11] Special thanks to both Gregor Jarosch and Carlos Carillo-Tuedela for sharing their code with me.

convert the reported value to 2015 euros using the CPI for Germany reported by the OECD. [12] Annual earnings is defined as the average daily wage multiplied by the number of days employed in a given year. The reported data is censored at the social security contribution ceiling, and I follow Dauth and Eppelsheimer (2020) and use imputed wages to correct for this. This mainly affects high education workers. I also consolidate parallel observations, when the employee has more than one observation in a given year, and restrict to the main spell.

B Summary Statistics

Table 5: Comparison of Demographic Characteristics in the BIBB and SIAB

	BIBB	SIAB
Demographics		
Share low education	.21	.30
Share med. education	.72	.65
Share high. education	.09	.05
Share women	.34	.39
Average Experience (Age-Edu)	17.8	19.25
Person Observations in 1979	23,939	396,255

[12] https://data.oecd.org/price/inflation-cpi.htm

C Classification of job tasks

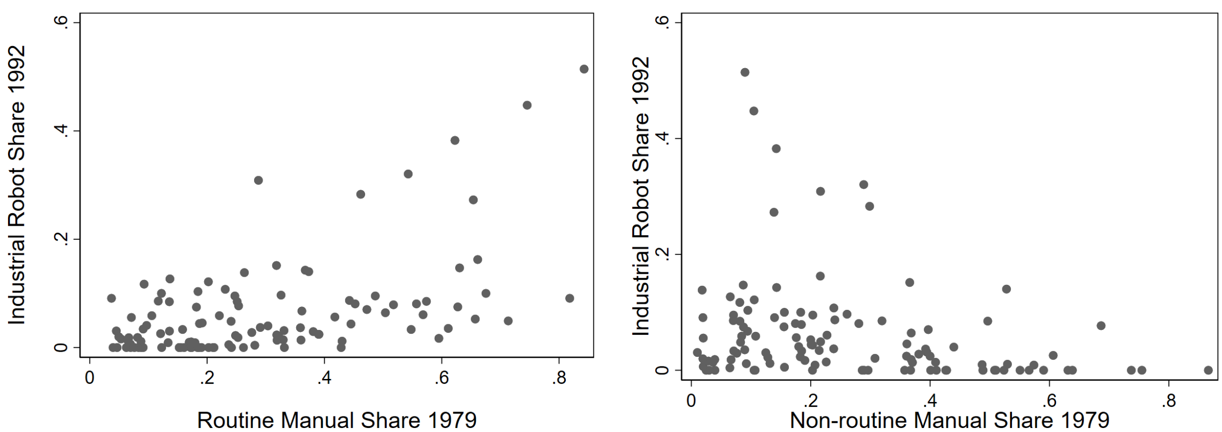
Category	Tasks
Non-routine cognitive:	Analyze (chemical, medical), research, test, interpret (statistics, statements)
	Plan, design, create
	IT activities, programming, Statistics,
	Publish, Literary work, provide legal advice, lead
Non-routine interpersonal:	Entertain, artistic work,
	Buy/sell, advise customers, negotiate, advertise,
	Apply laws or regulations, certify
	Educate, teach, advise
	Instruct, train staff
	Coordinate, organize, lead (management)
Non-routine manual	Repair, maintain
	Mend, restore, renew
	Clean or dispose of waste,
	Baking, cooking, brewing,
	Transporting, delivering, storing,
	Secure, protect
	Care (medical, cosmetic)
	Construction (Build, install, pain)
Routine Cognitive	Paperwork, correspondence, complete forms,
	Shorthand, typing
	File, sort, edit text,
	Calculate, bookkeeping, inventory
Routine Manual	Assemble
	Setting-up, using machines
	Operate machines, systems
	Production (melt, vulcanize, grind, press, extract,
	distill, roll, form, surface treatment, temper)
	Weaving, spinning, knitting, cutting
	Packing, unpacking, prepare for shipping
	Quality control (check, measure, weight)

D Share measure and technological adoption

I use the BIBB data to test whether my measure of treatment intensity captures actual adoption of automatic machines. First I expand the BIBB sample to include the 1992 survey (BIBB and IAB, 1995). I then measure occupation level adoption of industrial robots in 1992.

In figure 14, I plot the relationship between occupation task composition and the adoption of industrial robots. We see that the share of routine manual tasks in an occupation in 1979 positively correlates with the adoption of industrial robots by 1992. At the same time, we see that occupations with a higher share of non-routine manual task had low adoption of industrial robots.

Figure 14: Industrial robot adoption and task intensity



(a) Routine Manual Tasks

(b) Non-Routine Manual Tasks

In the scatter plots, each dot represents an occupation. Figure (a) plots the correlation of routine manual task share in an occupation in 1979 and the share of workers using industrial robots at work in that occupation in 1992. Similarly, figure (b) plots the correlation of the non-routine manual task share in an occupation in 1979 and the share of workers using industrial robots in 1992. Source: BIBB.

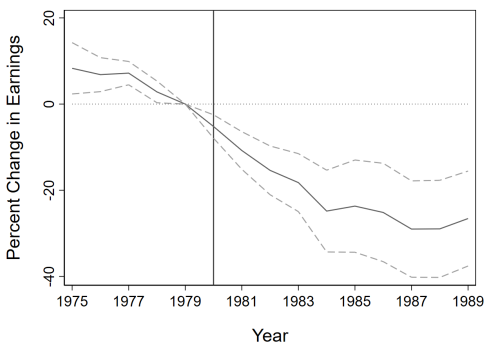
To test this relationship more rigorously, I follow the regression specification in Autor et al. (2003). I fit the following equations for occupations j with robust standard errors in parentheses:

$$\text{Robot Adoption}_{j,1992} = \underset{(.013)}{-.009} + \underset{(.06)}{.246} \text{ X } \text{Routine Manual Task Share}_{j,1979}$$

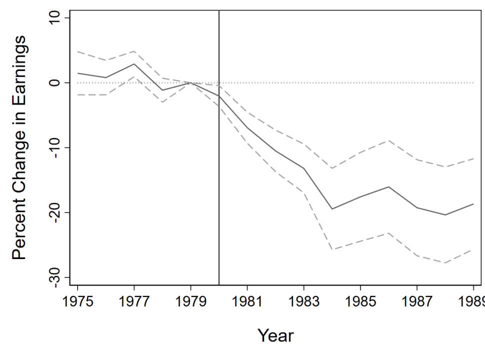
The results show how well these share measures from 1979 corresponds with the actual adoption of industrial robots by 1992. Two occupations that were 10 percentage points apart in routine manual skills would be 2.5 percentage points apart in the distribution of industrial robot adoption. In 1992, the median occupation had 2 percent of it's workers using industrial robots.

E Event study by cohort

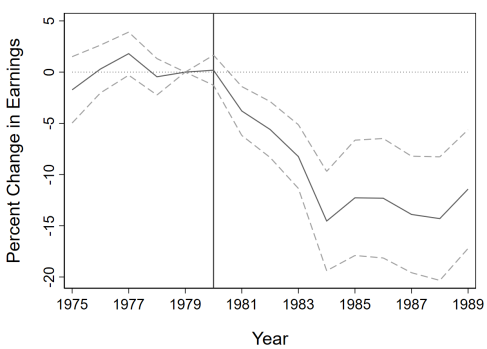
Figure 15: Parallel Trends with Routine Manual Treatment



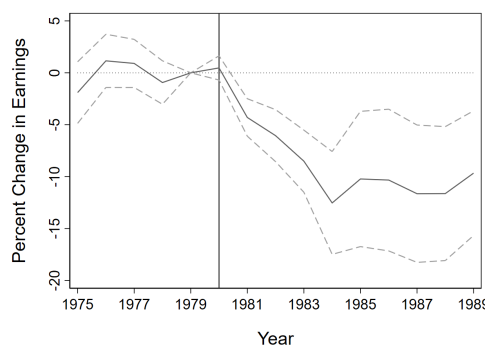
(a) 25-29



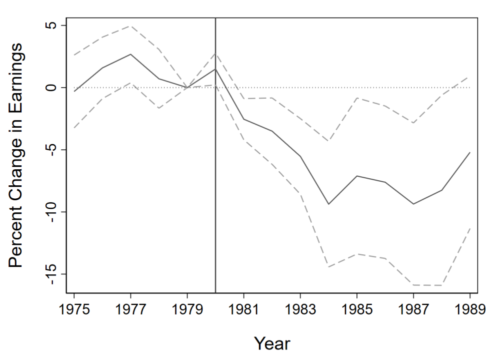
(b) 30-34



(c) 35-39



(d) 40-44



(e) 45-49

Panel (a) plots the coefficient β from the event study specification for log earnings for men aged 25-29 in 1979 with routine manual task shares as the measure of treatment intensity. Panel (b) plots the same for those aged 30-34, panel (c) for those aged 35-39, panel (d) for those aged 40-44, and panel (e) for the oldest cohort, those aged 45-49.

F Possible Mechanisms

Table 6: Treatment Intensity and Unions

Age	45-49	40-44	35-39	30-34	25-29
Treatment (RM share)	-0.0748*	-0.0998**	-0.107**	-0.166***	-0.267***
	(0.0275)	(0.0329)	(0.0318)	(0.0383)	(0.0551)
Treatment*High Union	0.0188	0.0642	0.0954	0.0870	0.0315
	(0.0504)	(0.0625)	(0.0738)	(0.0651)	(0.102)
High Union	-0.0255	-0.0391	-0.0431	-0.0454*	-0.0376
	(0.0163)	(0.0196)	(0.0226)	(0.0179)	(0.0263)

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table results the coefficients from the generalized difference-in-difference for treatment intensity interacted with union strength over different age cohorts with earnings as the outcome variable. Each coefficient represents the results of running the specification separately for each cohort. The specification controls for experience, experience squared, and education as well as occupation and year FE. Standard errors are clustered at the treatment occupation and year level.

Table 7: Attrition by cohort

Cohort (age in 1979)	Share of Workers Observed in 1989
25-29	0.81
30-34	0.81
35-39	0.82
40-44	0.82
45-49	0.72

Notes: This table reports the share of workers in each cohort who are observed in both 1979 and in 1989 at the end of the sample.

G Additional Analysis

G.1 Interaction of Nonroutine Cognitive and Routine Manual Tasks

While the main analysis shows that higher exposure leads to larger relative earnings losses, we know that automation also has the possibility of improving the productivity of certain workers. To test for this type of effect in my data, I examine the effect of automation on workers in nonroutine cognitive occupations. I categorize an occupation as nonroutine cognitive if the nonroutine cognitive share is larger than the shares of any other types of tasks. I then estimate the main specification for the sample of nonroutine cognitive workers. Appendix G reports the results. I see that, for nonroutine cognitive-dominant occupations, those with higher exposure to routine manual tasks saw larger earnings gains. This suggests that, in contrast to the more general result, the interaction of nonroutine cognitive tasks and routine manual tasks benefits those higher in the distribution. This make sense if we consider professionals in engineering, a nonroutine cognitive occupation where workers also perform more routine manual tasks, would have more to gain directly from the automation of manual tasks than academics.

Table 8: Interaction of Non-routine Cognitive and Routine Manual Tasks

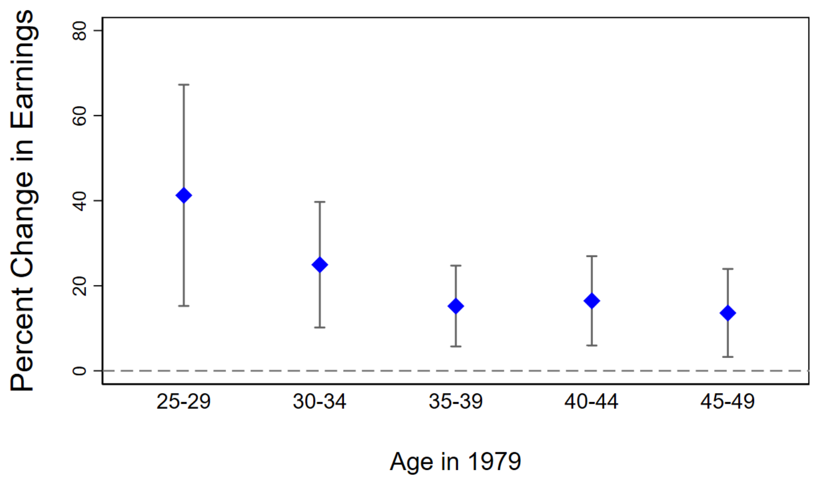
	(1)	(2)
Routine Manual Treatment	0.15	-0.11
	(.078)	(.030)
Observations (1979)	190,922	2,204,352

This table records the estimated coefficient β for men from the two-way fixed effect specification in equation (2) with log annual earnings as the outcome variable and standard errors in paraentheses. In column (1), the sample is restricted to workers in occupations that are dominated by non-routine cognitive tasks. Column (2) reports the results for the sample of workers excluding those in non-routine cognitive tasks.

G.2 Skill-Biased Technological Change

Finally, I use the same methods to examine other types of technological change. While automation in the 1980s certainly had an effect on workers performing routine manual tasks, advances in computers have also been documented to enhance the productivity of high-skilled workers. This process is often referred to as skill-biased technological change. To examine how this might have affected workers across age groups, I examine how exposure to nonroutine cognitive tasks, which tend to complement computer technologies, varies by age. Estimates of the TWFE specification for men by age are presented in Appendix G. The estimated average causal response for men is positive for all cohorts. Again, we see trends across cohorts. A one-standard-deviation higher exposure to nonroutine cognitive tasks leads to a 1.6-percent earnings gains for the oldest cohort and a 4.6-percent increase for the youngest cohort.

Figure 16: Estimated Average Causal Response across Age for Men



This figures plots the estimated coefficient β for men from the two-way fixed effect specification in equation (2) with log annual earnings as the outcome variable and non-routine cognitive task shares as the measure of treatment intensity. The lines represent the 95 percent confidence intervals.

H Model Supplement

H.0.1 Entrants Problem

Entrants enter the labor market with general human capital $h_0 > 0$. Entrants occupation choices are similar to those of incumbents, but they do not start associated with a given occupation. Entrants draw a vector of labor market opportunities $\epsilon_0 = [\epsilon_0^1, ..., \epsilon_0^J] \in \mathbb{R}_+^J$ where each draw represents the workers the opportunities that can be realized if the worker chooses a given occupation in the first period. Labor market opportunities ϵ_0^j in each occupation j are iid Frèchet with scale parameter λ and shape parameter α. The $1 \times J$ *human capital* *transferability* vector τ^0. In τ^0, each element τ^0 is positive and again determines the amount of human capital a worker can take with her into a given occupation j.

The vector $h_0\tau^0 \circ \epsilon_0 \in \mathbb{R}_+^J$ describes how much effective human capital the worker can supply to each occupation she is choosing over. Here $\circ$ denotes element-by-element multiplication. Once the choice of an occupation is made, the available human capital for the first period is:

$$h_1 = h_0 \tau_{j_1}^0 \epsilon_0^{j_1} \tag{18}$$

where j_1 denotes the occupation that the worker choose for the first period.

Similarly, elements of the $1 \times J$ *amenity value* vector χ^0, with positive elements denoted by χ_j^0 represent the non-pecuniary value of choosing occupation j. The Bellman equation for entrants is:

$$V_0(h) = \beta \mathbb{E}_{h'} \max_j \left\{ \chi_j^0 \big[V_1(j', h') \big] \right\} \tag{19}$$

where the expectation is over the the worker's idiosyncratic labor market opportunities ϵ and the human capital low of motion is defined as in equation (18). Note that non-pecuniary values χ^0 affect occupations choices, but do not affect the evolution of human capital.

H.0.2 Firm Problem Derivations

To characterize optimal choices, I set up an equivalent profit maximization using the production expression from equation (5). Let:

$$\hat{Y}_j = \left[\int_0^{I_j} (\kappa(i)k(i))^{\frac{\rho-1}{\rho}} + \int_{I_j}^1 \ell^M(i)^{\frac{\rho-1}{\rho}} di \right]^{\frac{\rho}{\rho-1}(\eta_j)} (L^N)^{1-\eta_j} \tag{20}$$

then define the profit maximization problem:

$$\Pi_j = \max_{k_j, \ell_j^M, \ell_j^N} \left[P_j \hat{Y}_j - w_j \big(\int_{I_j}^1 \ell_j^M(i) di + L_j^N \big) - p_k \int_0^{I_j} k_j(i) di \right] \tag{21}$$

Note that since units of labor are homogeneous, the law of one price for skill applies. The price for a unit of labor to perform any tasks is the same for all i and both routine manual and other tasks. Then, we can characterize optimal choices:

$$w_j = \frac{(1-\eta_j) P_j \hat{Y}_j}{L_j^N} \tag{22}$$

$$w_j = \eta_j P_j \hat{Y}_j \frac{\ell_j^M(i)^{\frac{-1}{\rho}}}{\int_0^{I_j}(\kappa(s)k_j(s))^{\frac{\rho-1}{\rho}}ds + \int_{I_j}^1(\ell_j^M(s))^{\frac{\rho-1}{\rho}}ds} \tag{23}$$

$$p_k = \frac{\eta_j P_j \hat{Y}_j}{k_j(i)} \frac{(\kappa(i)k_j(i))^{\frac{\rho-1}{\rho}}}{\int_0^{I_j}(\kappa(s)k_j(s))^{\frac{\rho-1}{\rho}}ds + \int_{I_j}^1(\ell_j^M(s))^{\frac{\rho-1}{\rho}}ds} \tag{24}$$

Then after re-arranging the FOCs:

$$k_j = \left(\frac{\eta_j P_j \hat{Y}_j}{w_j[\int_0^{I_j}(\kappa(s)k_j(s))^{\frac{\rho-1}{\rho}}ds + \int_{I_j}^1(\ell_j^M(s))^{\frac{\rho-1}{\rho}}]}\right)^{\rho} \kappa(i)^{\rho-1} \tag{25}$$

$$\ell_j^M = \left(\frac{\eta_j P_j \hat{Y}_j}{w_j[\int_0^{I_j}(\kappa(s)k_j(s))^{\frac{\rho-1}{\rho}}ds + \int_{I_j}^1(\ell_j^M(s))^{\frac{\rho-1}{\rho}}]}\right)^{\rho} \tag{26}$$

Then define $K_j = \int_0^{I_j} k_j(i)di$ and $L_j^M = \int_{I_j}^1 \ell_j^M(i)di$. Then, take the integral of the above two equation to derive K_j and L_j^M;

$$K_j = \left(\frac{\eta_j P_j \hat{Y}_j}{w_j[\int_0^{I_j}(\kappa(s)k_j(s))^{\frac{\rho-1}{\rho}}ds + \int_{I_j}^1(\ell_j^M(s))^{\frac{\rho-1}{\rho}}]}\right)^{\rho} \int_0^{I_j} \kappa(s)^{\rho-1}ds \tag{27}$$

$$L_j^M = \left(\frac{\eta_j P_j \hat{Y}_j}{w_j[\int_0^{I_j}(\kappa(s)k_j(s))^{\frac{\rho-1}{\rho}}ds + \int_{I_j}^1(\ell_j^M(s))^{\frac{\rho-1}{\rho}}]}\right)^{\rho} (1-I_j) \tag{28}$$

Note that these equations imply:

$$k_j(i) = \frac{\kappa(i)^{\rho-1}}{\int_0^{I_j}\kappa(s)^{\rho-1}ds} K_j, i \in [0, I_j) \qquad \ell_j^M(i) = (1-I_j)^{-1} L_j^M, i \in [I_j, 1] \tag{29}$$

We then substitute these expressions into the production function in equation (20) to get the occupation production function in terms of factors levels aggregated at the occupation level.

$$\hat{Y}_j = \left[(\int_0^{I_j} \kappa(i)^{\rho-1}di)^{\frac{1}{\rho}} K_j^{\frac{\rho-1}{\rho}} + (1-I_j)^{\frac{1}{\rho}} L_j^{M\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}(\eta_j)} (L_j^N)^{(1-\eta_j)} \tag{30}$$

where $K_j = \int_0^{I_j} k_j(i)di$ and $L_j^M = \int_{I_j}^1 \ell_j^M(i)di$. This form is helpful for characterizing production numerically.

FOCs for the final good problem follows the standard CES optimization form. First, we set-up the Lagrangian:

$$\mathcal{L} = [\sum_{j=1}^{J} \pi_j Y_j^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma}{\sigma-1}} + \lambda(I - \sum_{i}^{J} P_j Y_j) \tag{31}$$

Then we take FOCs which holds for all j:

$$Y^{1/\sigma} \pi_j^{\frac{1}{\sigma}} Y_j^{-1/\sigma} = \lambda P_j \tag{32}$$

And we can write demand for occupation j as:

$$Y_j = \frac{\pi_j}{\pi_i} \left(\frac{P_j}{P_i} \right)^{-\sigma} Y_i \tag{33}$$

With the CES form, we can also derive an exact price index for an unit increase in Y, where P is the expenditure needed to buy one unit of the final good Y:

$$P = \left(\sum_{j}^{J} \pi_j P_j^{1-\sigma} \right)^{\frac{1}{1-\eta}} \tag{34}$$

I Simulation

In order to simulate individual labor market histories, we need to characterize policy decisions for individuals given their draw of ϵ. Starting with the generalized Bellman equation, equation (7), Dvorkin and Monge-Naranjo (2019) show that given the linearity of the human capital law of motion and utility, the Bellman equation can be factorized and becomes:

$$v(j, \epsilon) h^{1-\gamma} = \left(\frac{(w_j)^{1-\gamma}}{1-\gamma} + \beta \max_{j'} \{ \chi_{j,j'} (\tau_{jj'}^t \epsilon^{j'})^{1-\gamma} E_{\epsilon'}[v_{t+1}(\text{j}', \epsilon')] \} \right) h^{1-\gamma} \tag{35}$$

simplifying

$$v(j, \epsilon) = \left(\frac{(w_j)^{1-\gamma}}{1-\gamma} + \beta \max_{j'} \{ \chi_{j,j'} (\tau_{jj'}^t \epsilon^{j'})^{1-\gamma} E_{\epsilon'}[v_{t+1}(\text{j}', \epsilon')] \} \right) \tag{36}$$

define $v_t^j \equiv E_{\epsilon'}[v_{t+1}(\text{j}', \epsilon')]$, which we've characterized as in equation (12). So we can rewrite the worker's problem equation:

$$v(j, \epsilon) = \left(\frac{(w_j)^{1-\gamma}}{1-\gamma} + \beta \max_{j'} \{ \chi_{j,j'} (\tau_{jj'}^t \epsilon^{j'})^{1-\gamma} v_{t+1}^{j'} \} \right) \tag{37}$$

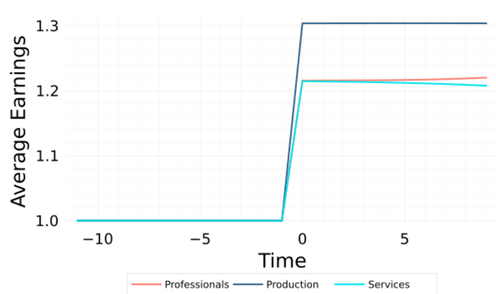
Simulation Algorithm:

1. Solve for wages in equilibrium
2. Given wages, solve for v_t, equation (12), by backward induction
3. Given v_t, characterize individual policy choices using (37)
4. Use individual policy choices to simulate worker panel

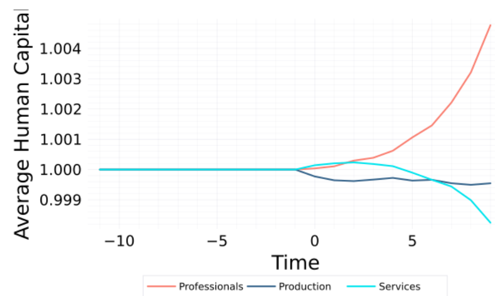
When simulating the model earnings profiles and running the DID specification, there are pre-trends, due to difference in the human capital paths across workers, that make it difficult to estimate the causal effect on the raw data. I thus run an alternative simulation where agents outcomes are as if the automation shock never occurred. I normalize earnings and human capital by dividing simulated earnings by a worker's earnings in the no shock alternative simulation. This means, allows me to remove the pre-trend and isolate differences in earnings and human capital stemming from the shock.

J Shock Simulation

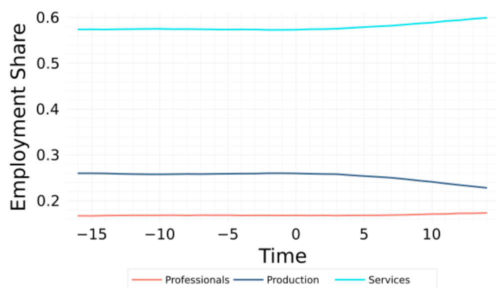
Figure 17: Simulation



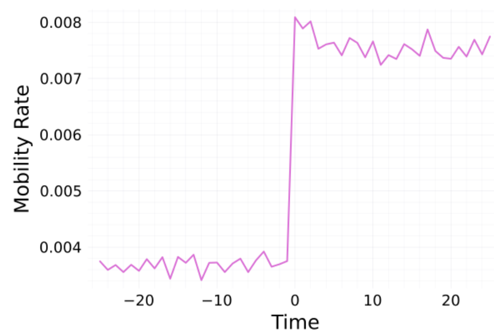
(a) Earnings



(b) Human Capital



(c) Employment

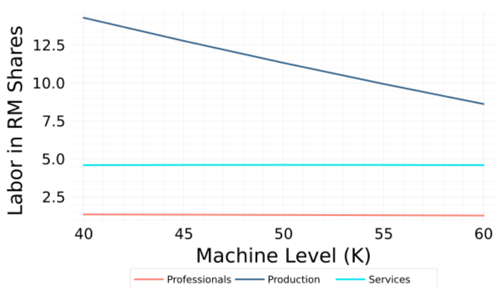


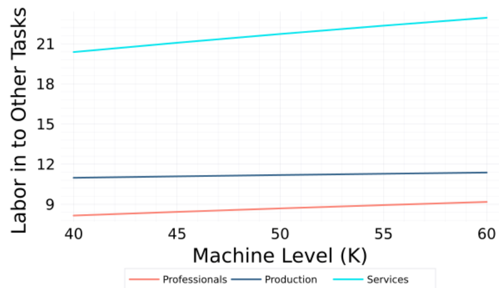
(d) Mobility

These figures plot the different outcomes pre- and post-automation using the full simulated panel. Panels (a) plots the path of average earnings in each occupation. Normalized by earnings if there was no shock. Panel (b) plots average human capital, normalized by human capital if there was no shock. Panel (c) plots employment shares Panel (d) plots the average mobility rate.

K Model Comparative Statics

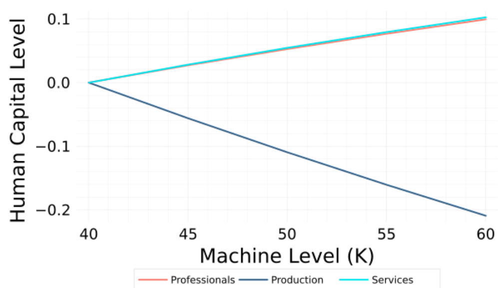
Figure 18: Steady State Comparisons





(a) Routine Manual Labor

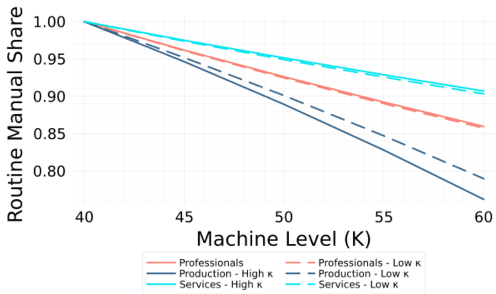
(b) Other Task Labor

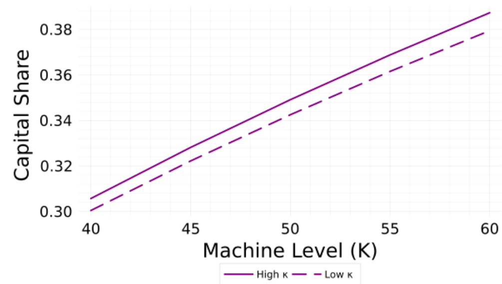


(c) Share of Aggregate Human Capital

The figures plot the comparative statics for different outcome variables for different levels of automatic machines. Panels (a) plots variation in the level of human capital employed in routine manual tasks by occupation. Panel (b) plots variation in the level of human capital employed in other tasks by occupation. Panel (c) plots changes in the level of human capital in each occupation.

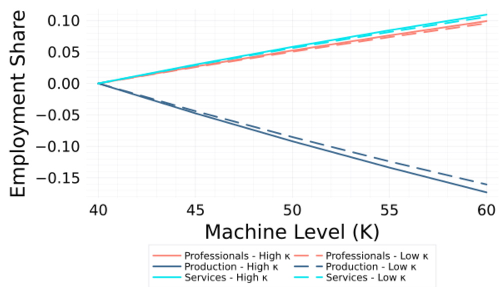
Figure 19: Steady State Comparisons





(a) Routine Manual Shares

(b) Capital Shares



(c) Employment Changes

These figures plot the comparative statics for different outcome variables for different levels of automatic machines and compares the result for high and low slope parameters. Panels (a) plots variation in routine manual shares across occupation. Panel (b) plots employment shares across occupations. Panel (c) plots the change in relative wages, where wages are relative to wages in professional occupations and panel (d) plots changes in employment.