Technological Change and Unions
An Intergenerational Conflict with Aggregate Impact

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Abstract

Technological progress in the form of automation boosts productivity, but leads to adverse labor market outcomes for transitional generations. I study the role of unions in shaping employment and wages of workers exposed to labor replacement during the automation transition since 1980. Using variation across local labor markets in the U.S., I first document that unionization has shifted the incidence of wage and employment declines within routine-manual occupations from older, incumbent to young, incoming workers. Second, unions have accelerated the decline in overall employment within these occupations, measured as a greater decline early in the transition, and a subsequent catch-up in less unionized labor markets after 2000. I then build a quantitative model of technological change and unionization which jointly rationalizes the two empirical observations through the interaction of union-imposed firing costs and gradual automation adoption over time. Within automating occupations, unions reduce the welfare cost of automation to older workers along the transition by up to 4% of permanent consumption by lowering their layoff risk and wage decline. The impact is shifted to young workers, raising the welfare costs for cohorts entering the labor market during the transition by up to 2%. Incoming workers endogenously respond to automation by entering non-adopting occupations which limits the welfare impact on them. The impact of high unionization spills over into non-adopting occupations as the accelerated reallocation of labor suppresses wages there.

JEL Classications: E02, E24, J10, J24, J51, O33, O41

1 Introduction

The adoption of automation technologies, such as industrial robots, digital technologies and artificial intelligence, boosts productivity but temporarily disrupts labor markets for transitional generations through worker displacement and reduced earnings (Graetz and Michaels (2018), Humlum (2020), Acemoglu and Restrepo (2020)). Increased adoption of automation technologies, one prominent example being industrial robots, has spurred an active literature studying the impact on workers and discussing appropriate policy responses, most notably taxing automation (Beraja and Zorzi (2022), Costinot and Werning (2018)).

The existing literature on the labor market impact of automation assumes that firms can freely adjust their workforce, abstracting from labor adjustment frictions. Yet, the adoption of automation technology entails substantial labor adjustment, making frictions such as firing costs especially potent during technological transitions. Moreover, it is well documented that labor market institutions and employment protection laws that generate labor adjustment costs are empirically associated with reduced employment flows and increased capital deepening (Bassanini and Duval, 2006), as well as with raising unemployment particularly during times of economic turbulence (Ljungqvist and Sargent, 1998, 2008).

In this paper, I take labor adjustment costs during technological transitions seriously and study the role of unions in shaping the employment and wages of workers who are exposed to labor replacement during the automation transition. I start by providing empirical evidence, showing that the union effect can be decomposed into a distributional effect, shaping how the automation impact is allocated across different generations, and an aggregate effect, shaping the timing of overall employment decline within exposed occupations along the transition. To do so, I focus on the wages and employment of workers in routine-manual jobs, who have been particularly exposed to labor-replacing technologies since 1980 (Goos et al., 2014), and combine data from several sources to exploit variation in unionization and the evolution of employment in routine-manual occupations across local labor markets in the U.S. I find, first, that unionization is associated with a greater fall in routine-manual employment and wages among young workers entering the labor market, consistent with insider-outsider dynamics of unions.[1] Moving from a low-unionized labor market at 10th to a high-unionized labor market at the 90th percentile of routine-manual unionization means that the routine-manual employment share of young workers below the age of 30 falls by an additional 11% and their wages falls by an additional 9% relative

[1] See e.g. Carruth and Oswald (1987) who theoretically introduce insider-outsider dynamics into a standard union model.

to the average routine-manual wage during the first 10 years of the transition. As a result of the fall in employment of young workers, the routine-manual workforce in more unionized labor markets becomes older relative to less unionized labor markets, and I show that this relative aging persists throughout the transition. Second, unions accelerate the decline in overall routine-manual employment during the automation transition while leaving the long-run decline unchanged. In particular, I document a greater employment decline in high-unionized labor markets early in the transition, and a subsequent slow catch-up of employment decline in less unionized labor markets from 2000 onwards. By 2020, the gap has mostly closed.

I then develop a quantitative dynamic equilibrium model of endogenous technological change and unionization which demonstrates that the interaction of union-imposed firing costs and gradual technology adoption over time can jointly rationalize the documented distributional and aggregate employment effect of unions. Firing costs incentivize firms to replace their workforce through reduced hiring rather than through costly layoffs when adopting automation. Moreover, when firms anticipate more automation to come, they further shrink their workforce preemptively today in order to avoid firing costs in the future. This gives rise to an accelerated overall employment decline in routine occupations in high relative to low unionized labor markets. Similar to the extensive literature on labor market institutions and economic turbulence, the mechanism here builds on the interaction of adjustment costs and expectations about future technology adoption in driving current labor demand.[2]

To answer my research question, I use the model as a measurement device to quantify the impact of automation and unionization on labor market outcomes and life-cycle consumption paths of different cohorts of exposed workers during the automation transition. At its core, the model combines three building blocks that make it a suitable quantitative framework for that objective: 1) two occupations, with endogenous technology adoption in the routine sector; 2) overlapping generations of workers who make occupational choices; and 3) a labor union that represents incumbent routine workers by endogenously setting wage premia along the transition. The degree of unionization in the model is parameterized by the level of exogenous firing costs, which determine the union's ability to impose wage premia by reducing the elasticity of labor demand of firms. The two-sector setup with occupational choice endogenizes the supply of workers. This allows the model to decompose the documented overall employment decline in the routine occupations into a downward shift in demand driven by technology adoption and an endogenous supply response driven by incoming workers entering non-routine occupations instead in order

[2] Ljungqvist and Sargent (1998), Ljungqvist and Sargent (2008) and the literature thereafter.

to avoid the automation impact. The model therefore captures the life-cycle paths of a group of workers that is affected by unionization but that the data cannot directly speak to: Workers who would have entered routine occupations but, due to the combination of automation and unionization, enter non-routine occupations instead.

Firms trade off two opposing forces in their routine labor demand when deciding how to optimally adjust their workforce along the transition, which in turn determines the transitional dynamics of the model. First, firing costs incentivize adjustment through incoming workers as well as preemptively reducing the workforce in anticipation of automation adoption to avoid firing costs in the future. Moreover, firms internalize the path of wage premia for incumbent workers endogenously set by the union along the transition. Second, routine workers of different ages are imperfect substitutes in production because they are finitely lived and accumulate occupation-specific human capital on the job, allowing them to complete different tasks in production. Firms therefore prefer a balanced age composition of routine workers over time, which constrains the incentive to adjust through young, incoming workers only.

I calibrate the model to U.S. local labor market (MSA) data, targeting in particular life-cycle wage profiles, the routine employment share, and the aggregate labor share in 1980 and 2010. I model a technological transition through an unexpected fall in the path of automation prices from 1980 onward that matches the price path of capital goods in the U.S. The level of firing costs measures the degree of unionization in the model and is calibrated to match the relative decline in the routine employment share between 1980 and 1990 in high and low-unionized MSAs. Lastly, I connect the model with the empirical findings by validating that it matches the untargeted evolution of overall routine employment and the evolution of the age composition of routine workers along the transition.

Using the model as a measurement device, I first evaluate the impact of automation adoption on routine workers in a low-unionized labor market. Automation is most costly for incumbent routine workers who made their occupational choice without anticipating the upcoming transition. These workers are caught by surprise, facing the option to either stay in a declining sector or switch into non-routine occupations at the cost of losing their occupation-specific human capital. Especially routine workers who entered between 1970 and 1980 experience the full automation impact over their life-cycle, resulting in large permanent earnings losses. As a result, the welfare cost of automation to these workers rises up to 10% of permanent consumption in 2000, measured as the permanent percent decrease in consumption they would be willing to accept to avoid automation and go back to the 1980 steady state. Workers entering the labor market during the automation transition take the current and future impact of automation into account when making their occupational choice. As routine jobs become less desirable, only workers with a sufficiently large labor productivity in routine tasks relative to non-routine tasks still enter the routine occupations. As a result, average labor productivity, and in turn average life-cycle earnings and consumption paths, of incoming routine cohorts rise. This endogenous response to automation limits its impact on incoming cohorts. Nevertheless, entering routine workers would still pay up to 7% of permanent consumption to avoid automation.

I then study the automation impact in a high-unionized labor market to quantify to what extent unions reallocate the welfare cost of automation across generations. Unions protect incumbent routine workers by lowering layoff risk and limiting wage decline, which reduces the welfare cost of automation to incumbent cohorts by up to 4% of permanent consumption along the transition. The impact is shifted to incoming cohorts, increasing the welfare cost of automation to incoming routine workers by up to 2% of permanent consumption in high relative to low unionized labor markets, driven by falling routine entry wages. The difference in the welfare benefit to incumbent and the welfare cost to incoming cohorts reflects the ability of incoming workers to endogenously respond to automation by entering the non-routine occupation instead. Consistent with the empirical findings, high unionization causes a faster reallocation of employment from the routine to the non-routine occupation as firms in the high-unionized labor market preemptively replace workers in order to avoid future firing costs. The accelerated reallocation of labor means that non-routine wages fall relatively more in the high-unionized labor market early in the transition, resulting in a spillover of the union impact from routine to non-routine occupations.

Lastly, motivated by the model findings, I empirically evaluate the political implications of the intergenerational conflict unions generate. An emerging political economy literature connects adverse economic outcomes to ideological realignment as well as a shift in political preferences and voting behavior (**?**; Voorheis et al. (2015)). Autor et al. (2020) link trade-exposure to rising political support for strong-left and strong-right views as well as to pure rightward shifts across local labor markets in the U.S. My welfare analysis emphasizes that unionization has magnified the negative impact of automation on labor market experiences of less skilled cohorts of workers who entered routine and non-routine occupations since 1980. Cohorts of workers that have entered the labor market between 1980 and 2000 are in their 50s and 60s today, thus, the workers whose voting behavior has shifted. I test and find empirical support for the hypothesis that union-induced employment decline among young routine-manual workers in the 1980s across local labor markets is associated with a shift in voting from Democrats to Republicans in the 2016 and 2020 presidential elections relative to previous elections. This suggests that while unions protected incumbent workers from the adverse automation impact, it came at the cost of worsening labor market experiences for incoming workers, resulting in a shift in political preferences among these workers today. Consistent with the literature that highlights the role of economic outcomes in driving ideological realignment in the U.S., this finding emphasizes the political implication of shifting the negative impact of technology adoption on young, incoming workers.

Related Literature. This paper relates to several strands of the literature. First, it contributes to the extensive empirical and quantitative literature studying the labor market impact of automation and the corresponding decline in routine employment.[3] Several papers document reduced-form empirical evidence on the effect of industrial robots adoption on worker outcomes and productivity (Graetz and Michaels (2018), Acemoglu and Restrepo (2020), Humlum (2020), Koch et al. (2021) Bessen et al. (2023)), finding that robot adoption raises productivity, output and the wage bill of skilled workers while reducing the wages and employment share of for less skilled production workers. Similarly, across U.S. commuting zones, Acemoglu and Restrepo (2020) find negative effects on wages and employment that are more pronounced in routine-manual and blue-collar occupations. A large empirical body of work specifically documents the decline of routine employment since 1980 (see, for instance, Autor et al. (2003), Goos and Manning (2007), Cortes et al. (2020)). I complement this work in two ways. First, I empirically document the importance of unions in determining how the incidence of wage and employment decline in routine-manual occupations is distributed across workers, finding that unions shift the incidence from older, incumbent cohorts to young workers entering the labor market. Second, I focus not only on the overall extent but also the timing of employment decline in routine-manual occupations and document that unions accelerate the decline in routine-manual employment. Consistent with Acemoglu and Restrepo (2020) who document negative spillover effects of robot adoption on nontradable sectors such as construction and services, I show in the model that as unionization induces faster labor reallocation to non-adopting occupations, it also accelerates the negative spillover effects on wages in these occupations.

A growing body of work further analyzes the distributional consequences of automation and its policy implications in quantitative frameworks (Guerreiro et al. (2022), Costinot and Werning (2018), Beraja and Zorzi (2022)). These papers make the argument for taxing automation to alleviate welfare consequences and improve equity. By contrast, this paper does not focus on direct policy instruments such as taxation but on the role that unioniza-

[3] See, for example, Autor et al. (2003), Autor (2010); Acemoglu and Autor (2011) and the literature thereafter.

tion, and labor adjustment frictions more broadly, play in shaping the welfare consequences of technological transitions. In particular, I build a quantitative framework that allows me to quantify the union impact on how fast workers reallocate over time and on the welfare cost of automation across different cohorts of workers.

This paper further contributes to the literature on labor market institutions and economic turbulence. Since the 1980s, an active literature tried to reconcile the observation that unemployment during the 1950s and 1960s was lower in Europe than the U.S. but rose above the level of the U.S. in the 1980s and 1990s. In their seminal work Ljungqvist and Sargent (1998, 2008) argue that the interaction of economic turbulence and labor market institutions in Europe, particularly policies of employment protection that increase the cost of layoffs, can jointly explain both periods of the european unemployment experience. They argue that labor market institutions reduce employment flows when the economic environment is calm as in the 1950s and 1960s, thereby lowering frictional unemployment. However, in the context of economic turbulence as in the 1980s and 1990s, old human capital can become obsolete which hurts the reemployment options for laid off workers. As a result, labor market institutions increase unemployment by reducing the incentive of laid off workers to accept wage cuts in their new jobs. My paper is closely related, also emphasizing the interaction between labor market institutions, here in the form of labor unions, and economic change, here in the form of automation adoption. However, I focus on the impact on employed workers who are exposed to labor replacement and on the timing of aggregate labor reallocation rather than unemployed workers. I argue that firms respond to the combination of union-induced employment protection and technological change by adjusting their workforce to a larger extent through wages and employment of unprotected incoming workers to avoid firing costs. This in turn results in a faster overall reallocation of labor from automating routine to non-routine occupations.

In modeling union behavior, I draw from a long-standing empirical and theoretical literature on the effects and behavior of unions, building on the seminal strands of Dunlop (1944) and Ross (1948).[4]

The remainder of the paper is organized as follows: Section 2 describes the data and documents the empirical findings. Section 3 develops the model and discusses its element. Section 4 takes the model to the data by discussing the calibration strategy and validating the model output. Section 5 presents the main quantitative analysis. Section 6 briefly presents evidence on the political implications of the model findings and section 7 concludes.

[4]See Kaufman (2002) for an overview.

2 Empirical Analysis

This section documents the two main empirical findings on the effect of unions on the wages and employment of workers exposed to labor-replacing technologies. I start this section by describing the data sources and outlining the empirical approach.

Data. I exploit variation in unionization across local labor markets in the US. In the main analysis, local labor markets are defined as metropolitan statistical areas (MSAs).[5] I use public use micro data from the 1980, 1990, 2000, 2010, and 2019 American Community Survey (ACS) to construct population and employment data for each commuting zone at those four dates.[6] I further use the US Current Population Survey (CPS) to compute unionization by MSA. I construct population, employment and wage income measures at the MSA level, and at the industry and occupation level within MSAs. I restrict the analysis to workers in routine-manual (RM) occupations, and follow the recent literature (see, for instance, Cortes et al. (2020) for a classification) in the classification of occupations based on their routine- and manual-task content.[7] These occupations focus on tasks that follow a well-defined set of instructions and, as a result, can more readily be performed by automation technologies. Routine employment, classified as such, has fallen significantly since 1980, and progress in labor-replacing automation technology has been identified as a main driver (Autor et al. (2003), Goos et al. (2014)). I further use exposure to robots estimates from Acemoglu and Restrepo (2020), and long-run automation adoption measures from Leigh and Kraft (2018).

The empirical strategy is study if routine-manual workforces across MSAs, who differ in their rate of unionization but are similar otherwise, experience differential decline in their employment prospects and wages from 1980 onwards when automation technologies increasingly became available in all MSAs. Thus, I estimate to what extent differential decline in employment and wages among routine-manual workers across MSAs can be explained by variation in unionization among routine-manual workers, controling for the ex-ante exposure to labor replacement within MSAs. First, in order to account for the ex-ante exposure to automation, that is, the expected amount of automation which is unrelated but potentially correlated with unionization, I construct a rich set of controls at 1980, prior to the transition. In particular, I control for the industry composition within routine-manual occupations, the industry composition of the overall commuting zone, and the demographic composition of routine-manual workers in the commuting zone. Lastly,

[5] I provide additional evidence for robustness across states and across Consistent Public Use Microdata Areas (conspuma), which are finer than MSAs.

[6] See Ruggles et al. 2010.

[7] The literature goes back to Berman et al. (1994), Levy and Murnane (1996), Autor et al. (1998). See Katz and Autor (1999) for a summary of the early literature.

I add the exposure to automation measure by Acemoglu and Restrepo (2020), which is a commuting zone level measure that combines the industry composition of a commuting zone with industry-level adoption of industrial robots between 1993 and 2014 at the national level. I aggregate the measure to the MSA level using 1980 population weights. The identification assumption is that the remaining variation in unionization among routine-manual workers in exogenous to ex-ante exposure to technology adoption and changes in the ago composition of workers conditional on adoption.

I use different measures of changes in employment and wages in routine manual occupations since the start of the transition as outcome variables. In particular, for the change in variable y after t years of the transition, I estimate the following model across MSAs i

$$\Delta y_{i,1980+t} = \beta_0 + \beta_1 \text{Unionization}_i + \gamma X_{i,1980} + u_{i,t}, \tag{1}$$

where $\Delta y_{\mathrm{i},1980+t}$ is the realized change in y between in 1980 and $1980 + t$ (e.g. the decline in routine employment). The set of controls is constructed in 1980, prior to the transition, except for the exposure measure from Acemoglu and Restrepo (2020), which is based on adoption data between 1993 and 2014. I then run this model for different outcome variables y and at different stages of the transition, $t \in [10, 30, 40]$, to understand the effect of unionization on the level as well as timing of changes.

Lastly, I use data on the location and employment of robot integrators in 2016 from Leigh and Kraft (2018) to verify that the overall decline in routine employment across MSAs over the whole sample period (1980-2019) aligns with the number of robot integrators in 2016 across commuting zones.

2.1 The Aggregate Effect of Unionization

In order to understand the aggregate effect of unionization, that is, the effect on the MSA-level routine-manual employment share, I look at the timing and extent of overall employment decline. In particular, I regress the decline in the routine-manual employment share in a MSAs since 1980 on its routine-manual unionization rate and the set of controls. I do so for the decline until 1990, 2010 and 2019.

	Change in RM share		
	1990	2010	2019
	(1)	(2)	(3)
Unionization	-0.080^{***}	-0.040^{**}	-0.036^{*}
	(0.018)	(0.018)	(0.020)
Mean dependent	-0.062	-0.11	-0.11
Observations	147	147	147
R^2	0.712	0.629	0.554
Adjusted R^2	0.684	0.592	0.510
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table 1: Shows for regressing the change in the routine-manual employment share on routine-manual unionization and the set of controls.

Table 1 displays a negative effect of unionization on the change in routine-manual employment, meaning employment falls more in high-unionized labor markets. Importantly, the effect is large between 1980 and 1990, particularly relative to the 6.2% average routine-manual employment decline across MSA, and the effect then falls off from 2010 onwards. In order to understand the size of the effect, I plot the decline in routine-manual employment when going from the 10th to the 90th percentile of unionization across MSAs. Thus, the graph below plots the estimated coefficient of the union effect, scaled by the difference in routine-manual unionization between an MSA at the 90th and an MSA at the 10th percentile of unionization, which is 29% difference.

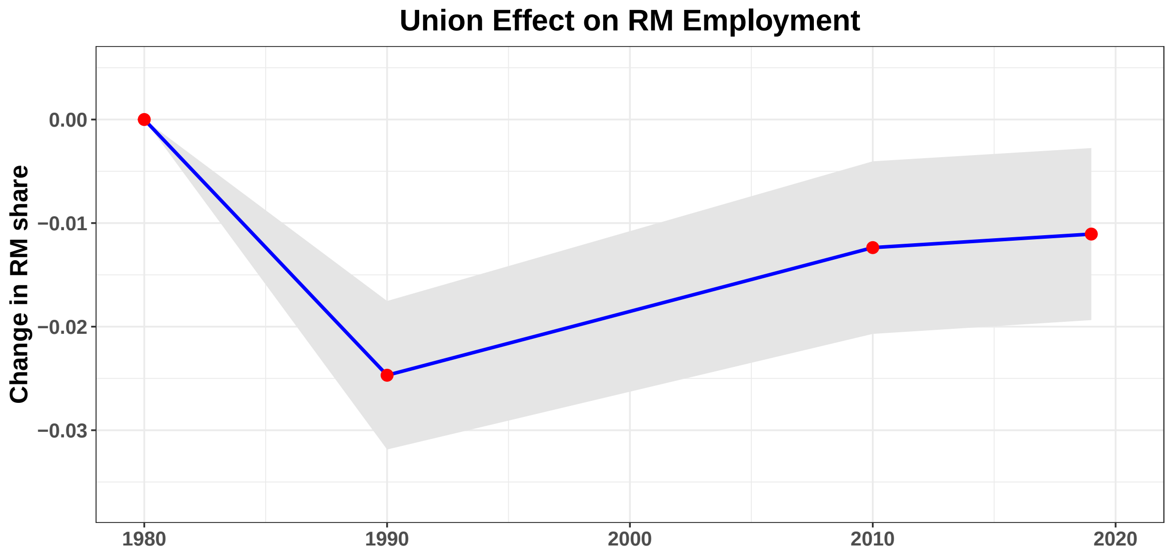

Figure 1: The graphs show the effect of going from the 10th to the 90th percentile of unionization on the RM employment share over time. The results hold for the 25th and the 75th percentile, see Appendix A.3.1 for details.

The graph shows that unionization is associated with an accelerated decline in the routine-manual employment share from 1980 onwards across MSAs. Going from the 10th to the 90th percentile in the rate of unionization leads to an additional decline of almost 3 percentage points in RM employment between 1980 and 1990. Throughout the transition, the decline in the routine-manual employment share then catches up in low-unionized places, and the union effect falls to 1 percentage point by 2019.

To get a sense of its magnitude, Figure 2 relates the union effect to the average decline in routine-manual employment across MSAs. It shows the above union effect divided by the average decline of the routine-manual employment share across all MSAs in the same time period.

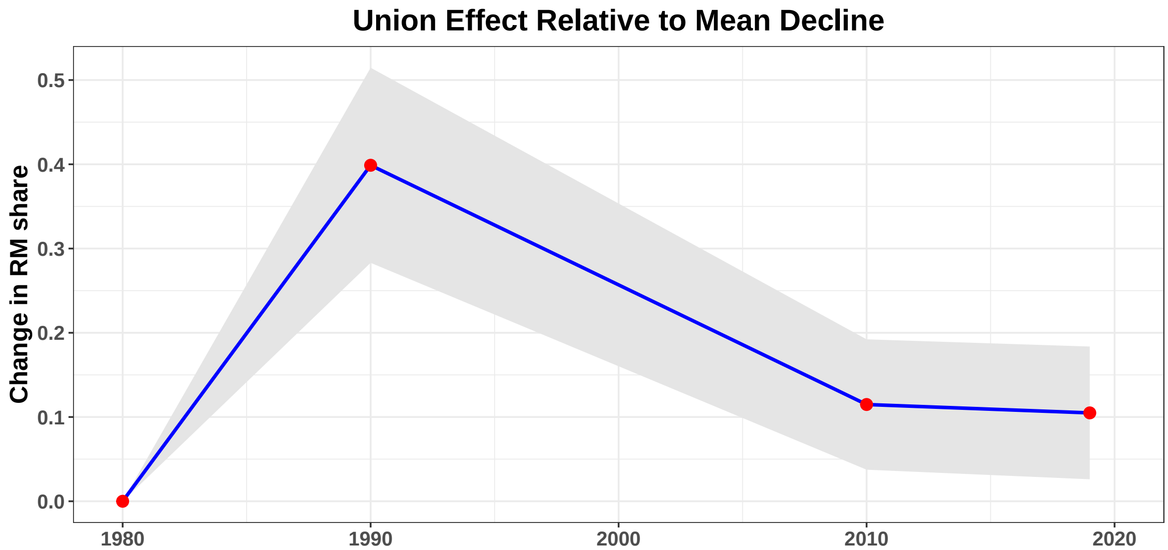

Figure 2: The graphs show the effect of going from the 10th to the 90th percentile of unionization on the RM employment share over time, relative to the mean decline in the RM employment share across all MSAs.

The union effect is large when relating it to the average decline across MSAs. In particular, the additional fall in the routine employment share during the first 10 years at the 90th percentile of unionization amounts to 40% of the average decline across MSAs. This effect again falls to roughly 10% of the average decline between 1980 and 2019 as the less unionized places catch up over time. Thus, unionization among exposed, routine-manual workers is associated with a substantial acceleration of employment decline early in the transition. By 2010 the less unionized places have caught up, but still exhibit a modestly smaller fall in their routine-manual employment share.

2.2 The Distributional Effect of Unionization

An extensive literature has documented the insider-outsider dynamics of employment regulation and organized labor, as model by Carruth and Oswald (1987) and the literature thereafter. In particular, employment protection is associated with greater job security for older, incumbent workers, and reduced the employment opportunities and wage prospects for younger workers (Bassanini and Duval (2006), Botero et al. (2004)). This section documents to what extent the insider-outsider dynamics were prevalent during the decline of routine employment since the 1980s. Insider-outsider dynamics predict that unionization induces a downward shift in the demand for young, incoming workers. In turn, the downward shift in demand then translates into a fall in the price and quantity of young workers in high relative to low-unionized places. Guided by this intuition, I test whether unionization among routine manual workers is associated with a larger decline in wages and employment among young relative to older routine manual workers since 1980.

Throughout the analysis, I control for the decline in the routine manual employment share in order to measure how the composition of routine manual workers changed conditional on a decline in employment.

2.2.1 Employment Effect for Young and Old Workers

To quantify to impact of unionization on the relative employment of young and old workers, I measure the union effect on the age composition of routine workers over the transition. How does the age composition of routine workers evolve over time if the fall in employment is to a larger extent driven by reduced inflow (hiring) of young workers rather than increased outflow (layoffs) across the age distribution? To build intuition and derive precise predictions to test in the data, imagine the following simple thought experiment that isolates the effect of the hiring and layoff margin.

There are two labor markets, A and B, which are initially in steady state with an identical and uniform age distribution of homogeneous workers aged 20 to 60. Each year the 60 year olds retire and are replaced by an inflow of 20 year olds. Labor market A is not unionized and firms face zero firing costs. By contrast, labor market B is unionized and firms face infinite firing costs. In 1980, an unexpected shock hits both labor markets which forces firms to reduce their workforce, firms in labor market A respond with uniform layoffs across the age distribution while firms in labor market B respond by lowering their hiring rate as firing is infinitely costly. Figure 3 shows the cdf of the age distribution of workers in both labor markets along the transition from a simple simulation.

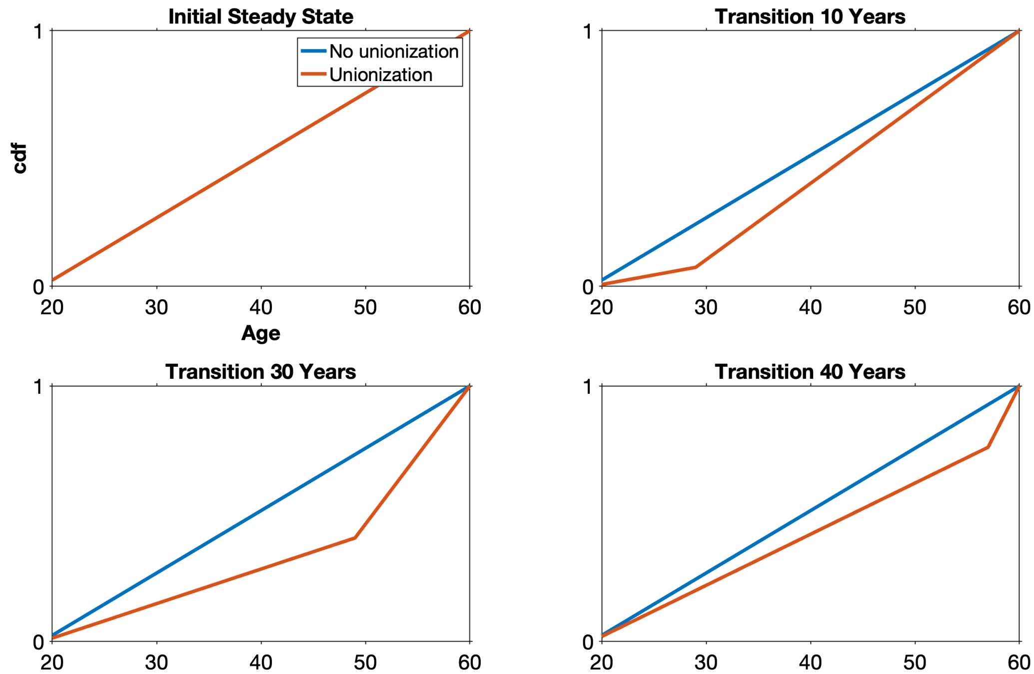

Figure 3: CDF of age distribution in high and low-unionized labor markets in simulated thought experiment.

While the age composition in labor market A never changes, the reduction in hiring in labor market B leads to a fall in the share of young workers and a slow transition as the age composition adjusts. The workforce in labor market B ages relative to A as more old workers remain, which results in a downward shift of its CDF compared to labor market A. 10 years into the transition, the downward shift is largest at age 30, which is the first cohort that experienced reduced hiring. All cohorts between the age of 20 and 30 experienced reduced hiring while all cohorts above the age of 30 did not, and thus the share of workers below age 30 has fallen most relative to the steady state. The downward shift then evolves along the transition. In particular, the largest downward shift moves up the age ladder with the first cohort to experience reduced hiring as it ages over the course of the transition. For example, 30 years into the transition the share of workers below the age of 50 has shifted down the most as all cohorts younger than age 50 have experienced reduced hiring. Thus, the simple thought experiment makes two detailed predictions about the effect of relative changes in hiring and layoffs to test in the data. First, the routine-manual workforce in more unionized MSAs becomes relatively older during the transition, measured as a relative downward shift in the CDF across all ages. Second, the downward shift is largest for the cohorts who entered around 1980 and moves up the age ladder with that cohort over time.

To account for the fact that routine-manual workforces in all MSAs experience a mixture of reduced inflow and increased outflow in the data, I estimate the union effect on the downward shift in the CDF relative to 1980. Figure 4 shows the downward shift in the age distribution in each labor market relative to their initial steady state levels in the thought experiment.

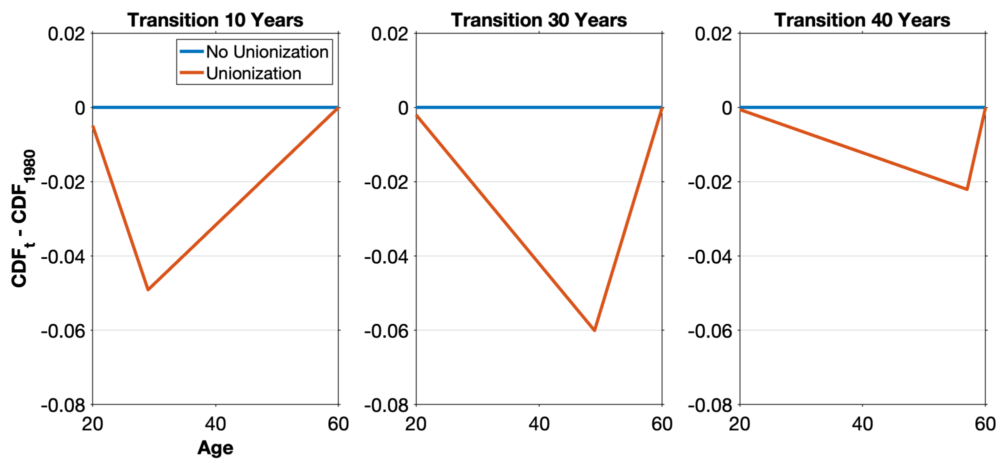

Figure 4: Change in CDF of age distributions relative to steady state in simulated thought experiment.

To test the predictions for the age composition of routine-manual workers, I estimate the gap between the orange and blue line with the following model:

$$\mathrm{CDF(a)}_{\mathrm{i},t} - \mathrm{CDF(a)}_{\mathrm{i},1980} = \Delta\mathrm{CDF(a)}_{i,t} = \beta_0 + \beta_1^{\mathrm{a},t} \cdot \mathrm{Unionization}_{\mathrm{i}} + \gamma X_{\mathrm{i},t} + u_{\mathrm{i},t}. \quad (2)$$

The coefficient $\beta_1^{\mathrm{a},t}$ estimates the gap between the orange and blue line t years into the transition at age a. To account for differences in the initial age distributions, I control for the 1980 age composition among routine-manual workers. Moreover, to isolate the insider-outsider dynamic from the aggregate effect, I further control for the decline in the routine-manual employment share between 1980 and t ($\Delta\mathrm{RM}_{i,t}$).

	Dependent variable: Change in CDF across Ages				
	Age 20	Age 30	Age 40	Age 50	Age 60
	(1)	(2)	(3)	(4)	(5)
CDF Change 1980-1990	-0.043^{***}	-0.126^{***}	-0.114^{***}	-0.062^{***}	-0.023^{**}
	(0.012)	(0.027)	(0.026)	(0.020)	(0.011)
CDF Change 1980-2010	-0.044^{***}	-0.106^{***}	-0.119^{***}	-0.142^{***}	-0.046^{***}
	(0.014)	(0.035)	(0.028)	(0.030)	(0.017)
CDF Change 1980-2019	-0.037^{**}	-0.026	-0.067^{**}	-0.087^{***}	-0.084^{***}
	(0.017)	(0.029)	(0.033)	(0.031)	(0.024)
Note:	*p<0.1; **p<0.05; ***p<0.01.				

Table 2: Table shows the effect of unionization on the change in the age distribution of routine-manual workers between 1980 and different stages of the transition (1990, 2010, 2019). See A.3.2 for the full regression tables.

Table 2 displays the coefficient $\beta_1^{a,t}$ measuring the union effect across the age distribution (columns) at different points in the transition (rows). First, the union effect is significant and negative throughout. Consistent with the first prediction, unionization is associated with a downward shift in the CDF of routine-manual workers relative to 1980 across all ages. That means, more unionized routine-manual workforces have become older relative to less unionized routine-manual workforces along the transition as the share of young workers has fallen and more older workers have remained. Second, between 1980 and 1990 the downward shift is largest at young ages and peaks at age 30. Over time, the downward shift moves up the age ladder with the cohorts who entered around 1980, consistent with the second prediction. Figure 5 constructs the graphs from the thought experiment from the regression estimates to directly compare the results with the prediction and to understand the magnitude of the effects. In particular, it plots the union effect on the downward shift for the average MSA at the 10th and 90th percentile of routine-manual unionization, which amounts to an increase of 29 percentage points in unionization.

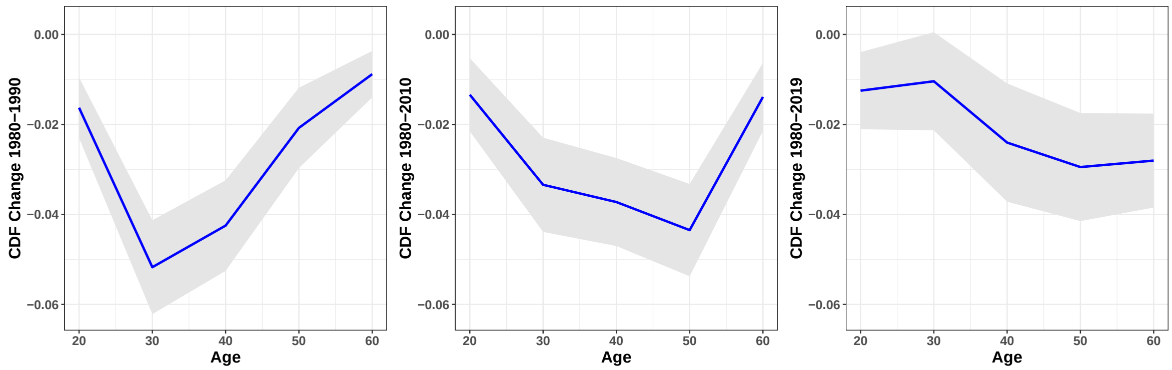

Figure 5: The plot shows the shift in the age distribution (CDF) relative to 1980 when going from the average MSA at the 10th percentile of routine manual unionization to the average MSA at the 90th percentile of routine-manual unionization. The difference in unionization is 29 percentage points.

The plot closely resembles the prediction from the thought experiment. To understand the magnitude, note that the share of routine manual workers below the age of 30 falls by roughly 5 percentage points in the high-unionized MSA relative to the low-unionized MSA during the first 10 years of the transition. This translates into an additional 11% decline relative the 1980 share of routine-manual workers below the age of 30.

Thus, conditional on reducing employment higher unionzation is associated with a larger reduction of employment of young workers and a smaller reduction of employment of old workers. This is consistent with insider-outsider dynamics due to union protection of incumbent workers, thereby incentivizing firms to adjust through young and incoming workers from 1980 onwards. The initial decline in the employment share of young workers in more unionized routine-manual workforces has then translated into persistent changes in the age composition over time as the middle and right panel show.

2.2.2 Wage Effect for Young and Old Workers

A downward shift in the demand for young workers driven by unionization should also lead to a fall in the price of young workers, that is, their wage. To quantify the differential effect of unions on wages of young, incoming and older, incumbent workers, I look at the changes in the wage ratio between young to old routine-manual workers. Table 3 displays the results of regressing a change in the wage ratio between 1980 and 1990 on unionzation as well as the set of controls. The wage ratio is measured as the average wage of routine-manual workers below the age of 30 divided by the average wage of routine-manual workers over the age of 30 in the first two columns, and divided by the average wage of workers over the age of 50 in the last two columns. The controls again additionally include the overall decline of routine employment between 1980 and 1990.

	Change in Wage Ratio 1980-1990			
	$\Delta\frac{\text{Wage age}\leq 30}{\text{Wage age}>30}$		$\Delta\frac{\text{Wage age}\leq 30}{\text{Wage age}>50}$	
	(1)	(2)	(3)	(4)
Unionization	-0.184^{***}	-0.175^{**}	-0.307^{***}	-0.289^{***}
	(0.069)	(0.069)	(0.096)	(0.096)
Change RM-share 1980s		0.250		0.525
		(0.290)		(0.374)
Mean dependent	0.032		0.024	
Observations	200	200	200	200
R^2	0.282	0.285	0.281	0.289
Adjusted R^2	0.244	0.243	0.243	0.247
Note:	*p<0.1; **p<0.05; ***p<0.01.			

Table 3: Table shows the effect of unionization on the change in the wage ratio between young and older routine-manual workers between 1980 and 1990. The first two columns define the wage ratio as the average wage of routine-manual workers below the age of 30 divided by the average wage of routine-manual workers over the age of 30. In the last two columns, the wage ratio is measured as the average wage of routine-manual workers below the age of 30 divided by the average wage of routine-manual workers over the age of 50.

Unionization is negatively correlated with a change in the wage ratio, that is, in more unionized routine-manual workforces the wages of young workers have declined by more relative to wages of older workers compared to less unionized routine-manual workforces. Looking at the first two columns, a 1 percentage point increase in unionzation is associated with a 0.18 percentage point decline in the wage ratio between workers below and above age 30. The effect rises to a roughly 0.3 percentage point decline for the wage ratio between workers below age 30 and above age 50, shown in the last two columns. To put this into perspective, going from the 10th to the 90th percentile of unionization is then associated an 6 and 9 percentage point decline in the wage ratio between 1980 and 1990 in the first and last two columns, respectively. This effect is quantitatively large as the average unconditional change in the wage ratio across local labor markets is even slightly positive with 0.032 and 0.024 percentage point increases, respectively. Thus, while the wage ratio between young and older routine-manual workers has been stable on average across

MSAs, wages of young workers have declined significantly more relative to wages of older workers in unionized local labor markets. Consistent with rising protection in tenure and age, the effect grows larger when conditioning the group of older workers to higher ages, shown by the last two columns relative to the first two columns.

To the extent that the effects measured above are driven by a union induced fall in the demand for less protected young workers during the transition, the relative decline in wages of young workers should be a temporary effect during the transition rather than a persistent change in the wage structure. Table 4 looks at the union effect on changes in the wage ratio between 1980 and 2010.

	Change in Wage Ratio 1980-2010			
	$\Delta\frac{\text{Wage age}\leq 30}{\text{Wage age}>30}$		$\Delta\frac{\text{Wage age}\leq 30}{\text{Wage age}>50}$	
	(1)	(2)	(3)	(4)
Unionization	−0.037	−0.029	0.030	0.035
	(0.096)	(0.094)	(0.117)	(0.116)
Change RM-share 1980-2010		0.837*		0.437
		(0.434)		(0.550)
Mean dependent	0.023		-0.062	
Observations	200	200	200	200
R^2	0.125	0.147	0.167	0.170
Adjusted R^2	0.069	0.088	0.114	0.112
Note:	*p<0.1; **p<0.05; ***p<0.01.			

Table 4: Table shows the effect of unionization on the change in the wage ratio between young and older routine-manual workers between 1980 and 2010. The first two columns define the wage ratio as the average wage of routine-manual workers below the age of 30 divided by the average wage of routine-manual workers over the age of 30. In the last two columns, the wage ratio is measured as the average wage of routine-manual workers below the age of 30 divided by the average wage of routine-manual workers over the age of 50.

Over a longer horizon of the transition, between 1980 and 2010, higher unionization is not associated with an additional decline in the wage ratio between young and old routine manual workers. To summarize, unionization is associated with a larger fall in employment and wages of young workers during the first decades of the transition. These effects are temporary and vanish by 2019, consistent with a fall in demand for young workers during the initial adjustment phase of the transition. Importantly, while employment of young workers in more unionized routine-manual labor markets recovers by 2019, the initial fall in their employment has a persistent effect on the age composition of routine manual workers.

3 The Model

Motivated by the empirical findings, I develop a quantitative dynamic equilibrium model that interprets the documented facts through the lens of union-imposed firing costs interacting with gradual technology adoption over time. After validating that the model can replicate the different transitions observed in high and low unionized labor markets, I will use the model as a measurement device to quantify the welfare cost of automation for routine workers and the intergenerational transfer that unions give rise to during technological transitions. I will first outline the model and provide a more detailed discussion of the model choices and properties in section 3.7.

3.1 Overview

Time is discrete and one period corresponds to 10 years. The model is a small open economy without aggregate uncertainty, combining three core elements. First, firms produce the final good by combining output from non-routine and routine occupations while endogenously and gradually adopting automation in routine production as capital prices fall. Second, overlapping generations of workers make an occupational choice between routine and non-routine occupations based on their anticipated life-cycle wage paths in each occupation. Third, a monopoly union represents incumbent routine workers by posting the wage schedule for routine workers of different ages each period, taking labor demand of firms into account. The level of firing costs parameterize the degree of unionization as the union derives its ability to impose wage premia from firing costs which limit how much firms can reduce labor in response.

3.2 Job levels

In this model, firms, the union, and workers interact through job levels in the routine occupations. In practice, job levels describe the specific task requirements of each job. An extensive literature on the internal labor markets (ILMs) and the production process of firms documents the importance of job levels in the design of production processes.[8] In

[8]See, for instance, **?**, Baker et al. (1994) Bayer and Kuhn (2023). **?** provide an overview of the early literature.

particular, job levels are a key input in production and progression across job level accounts for the majority of life-cycle wage growth of workers. Moreover, unions directly bargain for wages at different job levels. Following that literature, routine production in this economy is organized around job levels, and firms decide how many workers to employ at each job level. Young workers entering the routine occupation are hired at the lowest job level and progress in job levels by accumulating human capital on the job. Lastly, the union sets the job level wage profile in the routine occupations.

3.3 Production

Technology. There is a continuum of perfectly competitive firms that produce the final consumption good by combining the output y_t^i from two occupations i, the non-routine and the routine occupations, with a CES production technology G according to

$$y_t = G(y_t^R, y_t^N) = \left[\phi (y_t^R)^\nu + (1-\phi)(y_t^N)^\nu\right]^{\frac{\theta}{\nu}}, \tag{3}$$

where ϕ is the share of automatable routine occupations and $(1-\phi)$ is the share of non-automatable non-routine occupations in the economy. $\nu < 1$ is the elasticity of substitution between routine and non-routine occupations. To accommodate decreasing returns to scale with convex adjustment costs, I assume that firms need to use land as another input in production which is in fixed and limited supply L, as in Huo and Ríos-Rull (2020). Without loss of generality, I assume there is a total of one unit of land $L = 1$ and there is a firm operating each unit of land. $\theta < 1$ measures the returns to scale and the land is then priced by the value of the representative firm.

The non-routine occupations use homogenous labor input N_t to operate a constant returns to scale technology given by

$$y_t^N = N_t. \tag{4}$$

Routine Production. The routine occupations use automation α_t, and workers at $J = 5$ different job levels $l_t = (l_{t,1}, ..., l_{t,J})$ to produce routine output with a CES production technology F given by

$$y_t^R = F_t(l_{t,1}, ..., l_{t,J}, \alpha_t) = \left[\sum_{j=1}^{J} \eta_j l_{(t,j)}^{\varphi} + \eta_\alpha \alpha_t^{\varphi}\right]^{\frac{1}{\varphi}}, \tag{5}$$

where $\eta = (\eta_1, ..., \eta_J, \eta_\alpha)$ governs the share of automation and job level input, and $\varphi < 1$ is the elasticity of substitution between routine inputs.

Workers accumulate the necessary skills to produce the tasks required at higher job levels on the job. In particular, I assume the technology is such that it takes workers one period (10 years) to learn the skills to work the next job level. That is, a worker on job level j in period t can be promoted to job level $j+1$ in period $t+1$. I restrict attention to employment contracts between firms and routine entrants that commit the firm to compensate the rising human capital path of workers or otherwise terminate the contract at firing cost c_f. Thus, routine workers progress one job level per period consistent with their accumulated skill or are fired otherwise. As a result, age becomes a sufficient statistic for job level which makes the firm and worker problem tractable.

Optimization. Taking the path for the non-routine wage and the routine wages across job levels, $(w_t^N, \{w_{t,j}^R\}_j)_t$, as well as the price of automation $(p_t)_t$ as given, the firm chooses period t automation α_t and labor demands $(\{l_{t,j}\}_j, N_t)$ to maximize the discounted sum of future profits:

$$W_t(\{l_{t-1,j}\}_{j=1}^J) = \max_{\alpha_t, \{l_{t,j}\}_j, N_t} G(y_t^R, y_t^N) - \sum_{j=1}^J w_{t,j}^R l_{t,j} - p_t \alpha_t - w_t^N N_t - \sum_{j=1}^J c_f(f_{t,j}) + \frac{1}{1+r_t} W_{t+1}(\{l_{t,j}\}_j), \tag{6}$$

$$\text{s.t.} \quad f_{t,j} = l_{(t-1,j-1)} - l_{t,j} \quad \forall j \geq 2,$$
$$c_f(f_{(t,j)}) = c \cdot f_{(t,j)}^2,$$

where $f_{t,j} = l_{t-1,j-1} - l_{t,j}$ denotes fired workers at job level j. Firing costs are the same across job levels and parameterized by c. I assume firing works as a lottery, thus, which workers at job level j are fired is random, and workers cannot share the risk of being fired ex-ante.

3.4 Households

Agents and Preferences. The economy is populated by overlapping generations of households. Each period a measure one of young households is born who live for 5 periods, from age 20 to 60. Thus, in every period there is a total of 5 generations alive. Young workers choose which occupation to work in and spend resources on consumption and saving while supplying labor inelastically and accumulating human capital on the job. Workers born in period t maximize expected lifetime utility U_t given by

$$U_t = \sum_{a=1}^{5} \beta^{a-1} E\left[u(c_{t+a-1,a})\right], \tag{7}$$

where the period utility function $u(c)$ is at least twice continuously differentiable with $u'(c) > 0$ and $u''(c) < 0$, and satisfies the lower Inada condition, thus $\lim_{c\to 0} u'(c) = \infty$.

Human capital accumulation process. Workers enter the labor market with initial routine labor productivity z^R and non-routine labor productivity z_1^N. Initial non-routine labor productivity z_1^N is ex-ante identical across workers while routine labor productivity z^R differs across workers and is drawn from distribution f_z. Human capital is occupation-specific and deterministically accumulates on the job in both occupations.

Households working in non-routine occupations accumulate human capital each period in the form of labor productivity growth. They move up a discrete labor productivity grid $(z_1^N, z_2^N, z_3^N, z_4^N, z_5^N)$ which is calibrated to match average life-cycle wage paths of non-routine workers in the data.

Workers in the routine occupation accumulate human capital on the job through job level progression which drives their life-cycle wage growth. In particular, routine workers who are not laid off move up one job level per period as specified in their employment contract. Routine labor productivity z^R is a permanent type that applies to all job levels. As a result, human capital in the routine occupation follows a step function. Job level progression captures steps over the life-cycle which are common across workers and give rise to wage dispersion across age. z_R captures the overall level of the step function which differs across workers and gives rise to wage dispersion within age groups. Routine workers have perfect information about the endogenous probability of being laid off in the routine occupations.

Occupational Choice. At labor market entry, workers only differ in their permanent routine labor productivity z^R which determines their initial occupational choice. They take into account the expected life-cycle path of earnings in each occupation. There is no aggregate uncertainty, thus workers have full information about the life-cycle path of wages in each occupation $(\{w_{t,j}^R\}_j, w_t^N)$. They face individual uncertainty in the form of firing risk when working in the routine occupations. The probability of being fired at each job level is endogenously chosen by firms but is fully known by workers. In each consecutive period, workers choose whether to switch or stay in their current occupation. Routine workers who are laid off switch to the non-routine occupations and stay there for the remainder of their life. I assume they cannot reenter the routine occupations after being laid off.

Assets. Financial markets are incomplete, in particular routine workers cannot trade contingent assets against the risk of being laid off. Households have access to risk-free bonds at world interest rate R which is exogenous and constant. In the baseline model, the land is owned by risk-neutral capitalists who receive the firm dividends. In practice, equity participation is limited, especially for low and medium skilled workers (Mankiw and Zeldes, 1991) with limited asset holdings. Since the model captures precisely the impact of automation on the subset of less skilled workers who are most exposed to automation technology, I take as baseline an economy in which these workers are impacted through wages but not through profits. In appendix B.1, I show results for the case when workers hold fixed equity shares in the firms.

The Worker Problem. At the beginning of period t, the state of a worker is her age a, wealth b, labor productivities (z^R, z^N), and previous occupation, s. There is no incentive for a worker to initially enter the non-routine occupation and then switch to the routine occupation later. Thus, the problem of a worker previously employed in the non-routine occupation, $s = 1$, can be simplified and solved by imposing the occupational choice to stay in the non-routine occupation. I verify in equilibrium that non-routine workers do not want to switch. The problem then consists only of the consumption-savings decision for the remainder of her life given by

$$\begin{aligned} V_t^{hh}(k, z^R, z_i^N, a, s = 1) &= \max_{c,k'} u(c) + \beta V_{t+1}^{hh}(k', z^R, z_{i+1}^N, a+1, s' = 1), \\ \text{s.t.} \quad c + k' &= w_t^N z_i^N + (1 + r_t)k. \end{aligned} \tag{8}$$

The problem of worker previously employed in the routine occupation, $s = 0$, is more complicated as it involves the discrete choice about whether to stay a routine worker or switch into the non-routine occupation. It can be written as a two-stage problem. In the first stage, the household decides on the occupation s', in the second stage the household makes a consumption-savings decision conditional on the realization of the occupational choice. Since routine workers face an endogenous, possibly positive probability of being fired, a worker may decide to stay in the routine occupation but is fired and forced to switch occupations. Conditional on working in occupation s' after stage 1, the stage 2 problem of a worker previously employed in the routine occupation is then given by

$$\begin{aligned} v_t^{hh}(k, z^R, z^N, a, s = 0|s') &= \max_{c,k'} u(c) + \beta V_{t+1}^{hh}(k', z^R, z^N, a+1, s'), \\ \text{s.t.} \quad c + k' &= s' w_t^N z^N + (1 - s') w_{t,j(a)}^R z^R + (1 + r_t)k, \end{aligned} \tag{9}$$

where $w^R_{t,j(a)}$ is the routine wage at job level $j(a) = \frac{a}{10} - 1$ which maps the age of workers $a = (20, 30, 40, 50, 60)$ into their job level $j = (1, 2, 3, 4, 5)$.

For routine workers who either decide to switch into the non-routine occupation or who are fired, the above post-decision problem is the same as the beginning of period problem of workers who were previously employed in the non-routine occupation:

$$v^{hh}_t(k, z^R, z^N, a, s = 0|s' = 1) = V^{hh}_t(k, z^R, z^N, a, s = 1). \tag{10}$$

Given the value in stage 2, one can solve for the occupational choice in stage 1 of a routine worker. I assume workers face choice specific taste shocks to smooth the discrete occupation choice s, $\sigma_s \epsilon_t(s)$. The taste shocks are additively separable and follow an extreme value distribution, as in McFadden (1973) and the literature thereafter. Due to firing, the realized occupation s' can differ from the chosen occupation $\tilde{s}'$, which solves the stage 2 problem given by

$$\begin{aligned} V^{hh}_t(k, z^R, z^N, a, s = 0) = \max_{\tilde{s}'} \Bigg\{ & \tilde{s}' \Big(V^{hh}_t(k', z^{R\prime}, z^{N\prime}, a+1, s' = 1) + \sigma_s \epsilon_t(\tilde{s}' = 1) \Big) \\ & + (1 - \tilde{s}') \Big(\mu_{t,j(a)} V^{hh}_t(k', z^{R\prime}, z^{N\prime}, a+1, s' = 1) + \sigma_s \epsilon_t(\tilde{s}' = 1) \\ & \quad + (1 - \mu_{t,j(a)}) V^{hh}_t(k', z^{R\prime}, z^{N\prime}, a+1, s' = 0) + \sigma_s \epsilon_t(\tilde{s}' = 0) \Big) \Bigg\}, \end{aligned} \tag{11}$$

where $\mu_{t,j(a)}$ denotes the probability of being fired from the routine occupation as a worker at job level $j(a)$. The probability of deciding to stay a routine worker and the probability of ending up a routine worker differ due to endogenous firing. In particular, the discrete choice policy function, $\mathcal{P}_t(\tilde{s}'|k, z^R, z^N, a)$, is given by the standard logit choice probability with a extreme value distributed taste shock:

$$\mathcal{P}_t(\tilde{s}'|k, z^R, z^N, a) = \frac{\exp\left(V^{hh}_t(k', z^{R\prime}, z^{N\prime}, a+1, \tilde{s}')/\sigma_s\right)}{\exp\left(V^{hh}_t(k', z^{R\prime}, z^{N\prime}, a+1, = 0)/\sigma_s\right) + \exp\left(V^{hh}_t(k', z^{R\prime}, z^{N\prime}, a+1, 1)/\sigma_s\right)}. \tag{12}$$

Based on the discrete choice policy function, the probabilities for the realization of the occupational choice, $P_t(s' = 1|k, z^R, z^N, a)$, is then given by

$$P_t(s' = 1|k, z^R, z^N, a) = \mathcal{P}_t(\tilde{s}' = 1|k, z^R, z^N, a) + \mu_{t,j(a)} \mathcal{P}_t(\tilde{s}' = 0|k, z^R, z^N, a), \tag{13}$$

$$P_t(s' = 0|k, z^R, z^N, a) = (1 - \mu_{t,j(a)}) \mathcal{P}_t(\tilde{s}' = 0|k, z^R, z^N, a). \tag{14}$$

3.5 The Union

All incumbent workers in the routine occupations are represented by a labor union. I abstract from union formation and instead assume that all incumbent routine workers are represented. The union acts within a standard monopoly union framework by setting wages as a monopolist while firms choose labor demand in response.[9] However, I extend the basic monopoly union model by allowing the firm to set the full job level wage profil to account for the fact that workers at different job levels are imperfect substitutes in production and therefore can have different wages. The union then chooses wage growth across job levels by setting the full job level wage profile in the current period, and seeks to maximize the total wage bill paid to its current members:

$$\Theta_t = \max_{\{w^R_{t,j}\}_j} \sum_{j=2}^{J} w^R_{t,j} l_{t,j}. \tag{15}$$

Thus, the union is constrained by the employment response of firms $\{l_{t,j}\}_j$ which is endogenous to the wage schedule, $\{w^R_{t,j}\}_j$, posted by the union.

The degree of unionization in the model is measured by the level of firing costs c. The union's ability to extract rents from firms by raising wage premia is determined by the elasticity of labor demand of firms. If the elasticity is high, firms respond to wage premia by reducing their labor input which drives down the wage bill. Firing costs reduce the demand elasticity and thereby increase the ability of the union to increase the wage bill through wage premia, thus, providing a measure of the degree of unionization in the model. Consistent with that, unions empirically obtain higher firing costs for members (Parsons (2005a,b,c), Millward et al., 1992, Colonna, 2008a,b).

3.6 Competitive Equilibrium and Transitional Dynamics

I focus on perfect foresight equilibria in which there is no aggregate uncertainty.

Definition 1 (Competitive Equilibrium). Given a path for automation prices p_t and interest rates r_t, and an initial worker distribution Φ_0, a competitive equilibrium consists of paths for non-routine wages w^N_t, routine wages $(w^R_{t,1}, ..., w^R_{t,J})$, firm policies $(l_{t,1}, ..., f_{t,J}, \alpha_t, N_t)$, worker policies $V_t, c_t, k_{t+1}, \mathcal{P}_t$, and the worker distribution Φ_t that satisfy for all $t \geq 0$:

1. Given the paths for prices $\{r_t, w^N_t, (w^R_{t,1}, ..., w^R_{t,J})\}_{t\geq 0}$, and the firm implied firing probabilities $\{(\mu_{t,1}, ..., \mu_{t,J})\}_{t\geq 0}$, $V_{t\geq 0}$ solves the optimization problem of workers and $\{c_t, k_{t+1}, \mathcal{P}_t\}_{t\geq 0}$ are the corresponding decision rules.

[9] The basic monopoly union framework goes back to Fellner 1949; Cartter 1959.

2. Given the paths for prices $\{Q_t, w_t^N, (w_{t,1}^R, ..., w_{t,J}^R)\}_{t\geq 0}$, $W_{t\geq 0}$ solves the optimization problem of the firm and $\{l_{t,1}, ..., f_{t,J}, \alpha_t, N_t\}_{t\geq 0}$ are the corresponding policies.

3. The aggregate resource constraint holds:

$$G(y_t^R, y_t^N) = \int c(k, z^R, z^N, a, s)\mathrm{d}\Phi_t. \tag{16}$$

4. The non-routine wage clears the labor market for non-routine workers:

$$\begin{aligned} N_t = &\int z^N \mathrm{d}\Phi_t(k, z^R, z^N, a, s=1) + \\ &\int z^N \mathrm{d}\Phi_t(k, z^R, z^N, a, s=0) P_t(s'=1|k, z^R, z^N, a, s=0). \end{aligned} \tag{17}$$

5. The labor markets for incoming routine workers clears:

$$l_{t,1} = \int z^R \mathrm{d}\Phi_t(k, z^R, z^N, a=1, s) P_t(s'=0|k, z^R, z^N, a=1, s). \tag{18}$$

6. The law of motion of the worker distribution is induced by the optimal decisions of the firm and workers

3.7 Discussion

This section discusses the two key model elements, the job-level based routine production process and the union model.

Job Levels. Routine production in this model is organized around job levels. In practice, job levels categorize jobs by explicitly describing specific task requirements of jobs along the dimensions of responsibilities, complexity, and autonomy. This builds on an extensive literature that studies internal labor markets (ILMs) and career dynamics and emphasizes the role of the organizational structure of firms, and, in particular, the importance of job levels in the design of the production process.[10] One of the main insights going back to Doeringer and Piore (1985) and confirmed by the subsequent literature is that "in many jobs in the economy, wages are not attached to workers, but to jobs." (Doeringer and Piore (1985, p. 77)). Based on that idea, the literature documents two findings with respect to the determinants of wages and wage growth that make job levels a suitable modeling choice in this context. First, life-cycle wage growth is largely driven by job level progression over

[10] See the seminal works of Doeringer and Piore (1985) and Baker et al. (1994), as well as the literature thereafter.

time (Baker et al. (1994), Dohmen et al. (2004), Bayer and Kuhn (2023)). Second, unions bargain for wages and benefits at the level of job levels Bayer and Kuhn (2023).

In the model, routine workers accumulate skill on the job and, as a result, move up in job levels. Thus, this yields a standard process of human capital accumulation as wages rise in response to skill accumulation. Consistent with the empirical evidence on how unions operate, the union sets wages at the level of job levels in the model, taking into account labor demand. As a result, the job level model yields life-cycle wage growth that reflects a standard human capital accumulation process as well as an endogenous union wage premium.

From the firm's perspective, the job level model allows for workers with different experience levels to be imperfect substitutes in production. As a result, the firm optimally produces with a range of workers of different experience levels, and it allows for wages to differ across job levels. I restrict the analysis to employment contracts with full utilization of human capital, meaning the firm commits to progressing workers to the next job level each period as their experience accumulates. This allows the model to be tractable as age becomes a sufficient statistic for job levels, and to abstract from the managerial decision about which workers to promote and when to promote. In practice, unions similarly bargain for wage growth in employment contracts, and, thus, for contractual commitments by the firm to compensate rising human capital over time or terminate the contract otherwise.

The Union. The model of the labor union here follows the literature initiated by Dunlop (1944) whose starting point is the microeconomic theory of firms. The labor union is modeled as an economic entity that maximizes an economic objective, such as the wage bill, while facing constraints, in particular the labor demand of the firm. The literature thereafter largely uses two frameworks. First, monopoly union models in which the union acts as a monopolist and imposes its wage policy while the firm chooses employment in response. Second, since the 1980s game-theoretic bargaining frameworks were developed. These frameworks were developed with the intend to properly model the sources of bargaining power, such as strikes, and the bargaining process. In both cases, the union generally imposes a wage premium, resulting in an inefficient outcome in which the wage is above and employment is below their market clearing levels. While in the bargaining framework variation in the bargaining power offers a direct model analog to the empirically observed variation in the degree of unionization, the difficulty of introducing bargaining here stems from the fact that it requires specifying the value of the disagreement outcome. In this model, this would require specifying the outside value for the union and the firm that materializes if no agreement regarding an employment contract is found and, thus, no workers are hired. How to sensibly define the outside values is not obvious here since the union represents all employed heterogenous routine workers, and the firm is an aggregate firm who is the only producer in the economy. Therefore, I abstract from the bargaining process and model the union within a monopoly union framework. Importantly, the solution to bargaining frameworks in which the firm and union bargain over wages coincides with the monopoly union model when the union has all the bargaining power. I then use the size of firing costs as a measure of unionization instead of an explicit bargaining power. Empirically, unions obtain higher firing costs for members (Parsons (2005a,b,c), Millward et al., 1992, Colonna, 2008a,b), through bargaining for higher severance pay and the ability to impose strike costs. In the model, the union maximizes the wage bill of its members by extracting rents from the firm. Since the union acts as a monopolist, its ability to extract rents from the firm is driven by the elasticity of demand from the firm. Firing costs reduce the demand elasticity and, thus, increase the ability of the union to increase the wage bill. Thus, firing costs drive the power of the union and thereby provide a measure of the degree of unionization in the model.

4 Quantitative Evaluation

In this section, I outline the calibrate strategy before evaluating the quantitative behavior of the model. I then connect the model back to the empirical findings by validating that the untargeted distributional and aggregate union effects along the transition match the data moments.

4.1 Calibration

I calibrate the initial steady state of the model to MSA-level data in the U.S. in 1980. I then explore the response of the economy to an unexpected fall in the path of automation prices from 1980 to 2010 that matches the decline in capital prices observed in the U.S., as measured by Hubmer (2023). In particular, agents in the economy learn in 1980 about the complete future path of automation prices, thus, there is no aggregate uncertainty. The timing is motivated by the fact that existing measures of capital prices show a more rapid decline from the 1980s onward (Hubmer (2023)), and the adoption of industrial robots has picked up from 1990 onwards (Acemoglu and Restrepo (2020)). This is also consistent with the observed fall in the routine employment share and the manufacturing labor share from 1980 onwards (Hubmer (2023), Cortes et al. (2020)).

I take the low-unionized labor market as an economy that is characterized by low firing costs, and calibrated that economy to the average MSA at the 10th percentile of unionization. The high-unionized labor market corresponds to a MSA at the 90th percentile of unionization with high firing costs. I calibrate the common parameters in the low-unionized economy which is the baseline. A subset of parameters is calibrated exogenously, either following direct empirical observation or the existing literature. The remaining parameters are estimated in the model using the method of simulated moments. Since the objective is to use the model as a measurement device to quantify the impact of automation and unionization on the consumption paths of different workers, the calibration aims in particular at matching two sets of targets: First, the 1980 and 2010 routine-manual employment share and aggregate labor share to capture the amount of exposed workers and their employment loss. Second, life-cycle wage profiles of workers in both occupations.

Data. I estimate the targeted data moments using the same data as in the empirical section. Thus, I construct MSA-level estimates by combining public use micro data the American Community Survey (ACS), and the Current Population Survey (CPS).[1] I take the remaining targets from the existing literature and indicate when I do so.

Share paramaters in the production technology. The share parameters in the production function are calibrated to match the employment and labor shares. In particular, I calibrate the share parameter ϕ for routine output to match an initial routine manual employment share in 1980 of 27%. The share parameter of automation in the routine technology, η_α, is calibrated to match an initial aggregate labor share in 1980 of 64%, which I take from the U.S. Bureau of Labor Statistics (BLS). Lastly the share parameters of job level inputs in the routine technology, $(\eta_1, ..., \eta_5)$, are calibrate to match life-cycle wage profiles in 1980, see section 4.1 below for the estimation of life-cycle wage profiles.

Substitution elasticities in the production technology. The substitution elasticities are calibrated to match the change in the routine employment and aggregate labor share between 1980 and 2010. In particular, I calibrate the substitution elasticity across the two occupations, ν, to match the routine manual employment share in 2010 of 16%. The substitution elasticity across routine inputs, φ, is calibrated to match an aggregate labor share in 2010 of 56% (BLS).

Firing costs. The firing cost schedule is pinned down by one parameter c. Recall that the low-unionized economy is characterized by a low level of firing costs, c_l, which I calibrate to match the change in the age composition of routine-manual workers in MSAs at the 10th percentile of unionization in the data. The level of firing costs in the high-unionized economy, c_h, is then calibrated to match the documented union effect on the decline in the routine manual employment share between 1980 and 1990. That is, I target that the routine

[1]See Ruggles et al. 2010

employment share in the high-unionized economy declines by 2.5 percentage points more between 1980 and 1990 than in the low-unionized economy.

Human capital accumulation. Using repeated cross-sectional data from the CPS, I estimate life-cycle wage profiles by decomposing earnings growth into cohort, experience and time effects for cohorts born between 1940 and 1980, following Heckman et al. (1998), and more recently Lagakos et al. (2018) and Fang and Qiu (2021). The estimated experience effects capture the component of life-cycle wage growth that is driven by human capital accumulation. I then estimate experience effects separately for routine manual and non-routine occupations to calibrate life-cycle wage paths in both sectors in the model.[11] Workers in the non-routine occupation all enter with the same labor productivity z_1^N, and accumulate labor productivity every period on the job. I calibrate the life-cycle path of non-routine labor productivity, $z^N = (z_1^N, z_2^N, z_3^N, z_4^N, z_5^N)$, to match the estimated experience effect, and normalize mean labor productivity, $\bar{z}^N = 1$. Note, the estimated experience effect implies $z_5^N = z_4^N$ as human capital stops growing at age 50, after 30 years of experience.

Remaining parameters. The world interest rate is set to 3% annually, taken from estimates of the natural rate of interest for the U.S. from Davis et al. (2023). I abstract from the fact that real rates started to decline particularly from 2000 onward and keep the interest rate constant over the transition. Note that saving plays a minor role in this model as households have rising life-cycle wage paths, do not face retirement, and face permanent income risk in the form of a small layoff probability in the routine occupation. The initial automation price $p_{1980} = 0.2$ is fixed in a first-stage calibration. The automation share η_α is then calibrated conditional on $p_{1980} = 0.2$ as the two are not separately identified.

[11]See appendix A.1 for details on the estimation.

Parameter	Description	Value	Target
		Preferences	
$1/\sigma$	IES	0.5	Standard
β	Discount factor	0.75	$\beta_{\text{annualized}} = 0.97$
σ_s	Taste shocks	0.05	Small - smooth occ choice
		Human capital	
z^N	Non-routine labor productivity		Life-cycle wage profile
$\bar{z}^N$	Mean labor productivity	1	Normalization
		Small open economy	
r	Rate of return	0.34	3% annual Davis et al. (2023)
p_{1980}	Automation price 1980	0.12	Normalization
g_p	Growth rate of price	-0.06	Hubmer (2023)

Table 5: Externally calibrated parameters.

Parameter	Description	Value	Target
		Production and technology	
f_z	Routine labor productivity	$\mathcal{U}(0.2, 1.8)$	Routine Wage Dispersion
ϕ	Share of automatable occupations	0.75	1980 RM employment share
θ	Returns to scale	0.8	Land-output ratio
η_l	Job level shares		Life-cycle wage profile
η_α	Automation share	0.3	1980 labor share
ν	Substitution elasticity: sectors	0.75	2010 RM employment share
φ	Substitution elasticity: routine inputs	0.85	2010 labor share
		Union	
(c_l, c_h)	Firing costs	$(0.01, 0.05)$	Total union effect 1980-1990

Table 6: Internally calibrated parameters.

4.2 Model Mechanism

Figure 6 shows the shows the fall in capital prices which induces the firm to gradually adopt automation over time and thereby triggers the transitional dynamics.

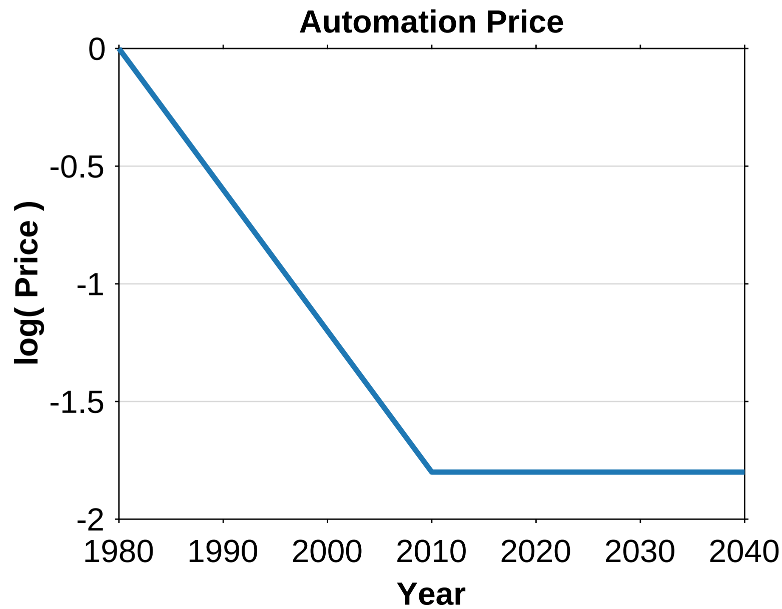

Figure 6: Price of automation along the transition matches measured capital prices in the U.S. between 1980 and 2010 from Hubmer (2023).

In 1980, the economy is in steady state. In 1990, agents in the economy wake up and learn about the new path of automation prices. Thus, they learn that the automation price has already fallen in 1990 and will further decline until 2010. The price decline matches the price decline of capital goods in the U.S. since 1980. The fall in automation prices triggers a fall in routine employment in both labor markets as routine workers are imperfectly substitutable with automation. However, higher firing cost in the unionized labor market increase the cost of layoffs and incentive the firm to adjust through the hiring margin. As a result, demand for young workers entering the routine sector falls relatively more in the high-unionized labor market. Figure 7 shows hiring of young workers in the routine occupations relative to the 1980 steady state in both labor markets.

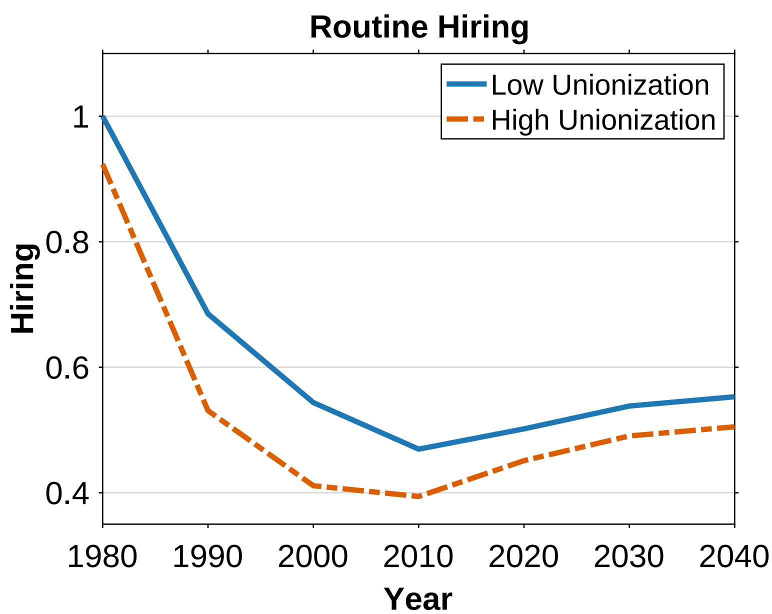

Figure 7: Hiring and entry wages fall by more in the high-unionized labor market as firing cost generate insider-outsider dynamics.

In the initial steady state, hiring of routine workers is 8% lower in the high-unionized labor market since wage premia imposed by the union increase wages but reduce the level of routine employment across all age groups. After automation becomes available, routine hiring falls in both labor markets, however, it falls substantially more in the high-unionized labor market early in the transition. The greater fall in hiring in the high-unionized labor market in 1990 is driven by larger adjustment through incoming workers in response to current automation adoption as well as by a further preemptive reduction in hiring in anticipation of future adoption to avoid firing costs along the transition.

Figure 8 shows the union effect on wages and paints a similar picture. Early in the transition, unionization reduces entry wages in the routine occupation further by lowering demand for incoming workers. In particular, routine entry wages decline 3.5% more until 1990 and 5% more until 2000 in the high-unionized relative to the low-unionized labor market.

Unionization spills over into the non-routine occupation, resulting an additional 0.3% decline in non-routine wages until 2000 in the high-unionized labor market. The spillover is driven by the accelerated routine employment decline in the high-unionized labor market, which in turn accelerates the reallocation of workers to the non-routine occupations and suppresses wages there.

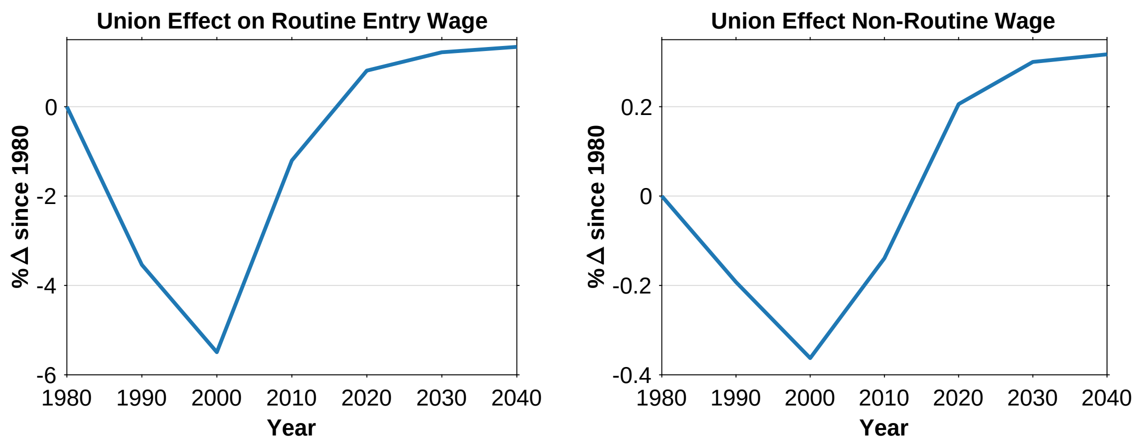

Figure 8: Hiring and entry wages fall by more in the high-unionized labor market as firing cost generate insider-outsider dynamics.

4.3 Model Validation

The evolution of aggregate routine employment and the evolution of the age distribution of routine workers along the transition are not targeted by the calibration. To validate the model and connect it with the empirical findings, I test whether it matches the evolution of routine employment and the age composition, and thus, whether it matches the aggregate and distributional union effect documented in the data.

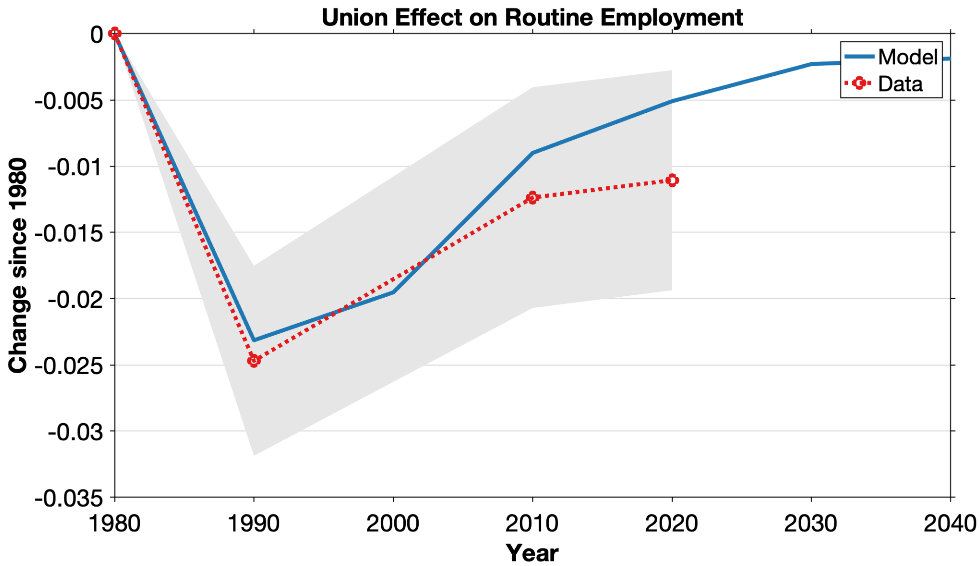

Figure 9: The graphs show the effect of unionization on routine employment over time. The red line shows data estimates for going from the 10th to the 90th percentile of unionization. The blue line shows the model output.

How does unionization shape the timing and extent of the overall routine employment decline in the model? Figure 9 displays the union effect on the routine employment share as documented in the data as well as in the model. In particular, for the model it shows the difference between the change in the routine employment share in the low and high-unionized economy. Recall, the firing costs are calibrated to match the 1990 data point and, thus, the match between data and model in 1990 is no surprise. Without being targeted, the model matches well that from 2010 onwards the routine employment decline in the low-unionized economy catches up. By 2020, routine employment in the high unionized economy has declined by roughly 3.5% more, consistent with the data. The model can speak to the dynamics between 1990 and 2000 for which no data is available. In the model, the acceleration in routine employment decline driven by unionization continues into the 2000s, driven by a continued reduction in hiring in anticipation of upcoming adoption. I now turn to the underlying distributional effect to see if the model can match how unions shape the distribution of transitional costs between young and old.

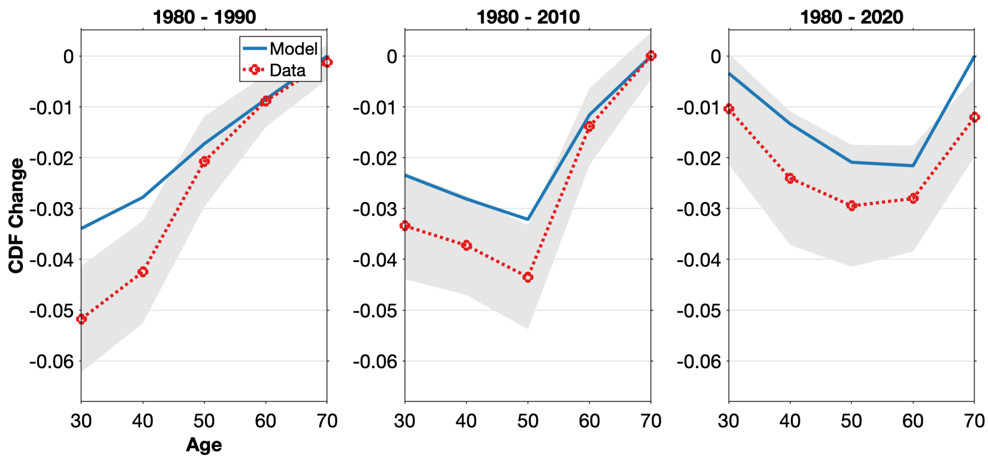

Figure 10: The graphs show the effect of unionization on routine employment over time. The red line shows data estimates for going from the 10th to the 90th percentile of unionization. The blue line shows the model output.

The model matches well the downward shift in the cdf of the age distribution of routine workers, though the shift is even larger in the data. Consistent with the data, unionization results in a downward shift in the cdf that is driven by a fall in the share of young workers. By 1990, the share of incoming workers below the age of 30 declines by 4 percentage points more in the high-union economy. This initial reduction in new hires then moves up the age ladder over time as the 1980 cohort ages. As a result, differences between the age composition of routine workers in the low and high-unionized economy persist throughout the transition. In particular, unionization results in an older routine workforce throughout the transition.

5 The Welfare Cost of Automation

5.1 Measurement of the Welfare Cost of Automation

To measure the individual-specific welfare impact of automation, I calculate the permanent percent decrease in consumption a worker would be willing to accept to go back to the 1980 steady state and avoid automation. I then compute this consumption equivalent variation at different times during the transition to show the evolution of the automation impact over time. Let $x_t(s, k, z^R, z^N, a)$ be the required compensation in consumption to be indifferent to automation for a worker with individual state (s, k, z^R, z^N, a) in period t. It is given by

$$x_t(s, k, z^R, z^N, a) = \left(\frac{V_{1980}(s, k, z^R, z^N, a)}{V_t(s, k, z^R, z^N, a)} \right)^{\frac{1}{1-\sigma}}.$$

My primary interest is in understanding to what extent welfare costs differ across routine workers of different cohorts and how unionization impacts these welfare costs. In particular, I focus on the difference between workers who entered the routine occupation before the automation shock hit and are caught by surprise, and workers who entered during the transition and therefore anticipate the current and future impact of automation when making their occupational choice.

5.2 The Welfare Cost of Automation for Routine Workers

Before studying how unionization affects the welfare cost of automaion, I start by looking at the the welfare cost of automation for routine workers in the low-unionized labor market to understand how automation shapes life-cycle wage paths of routine workers from 1980 onwards.

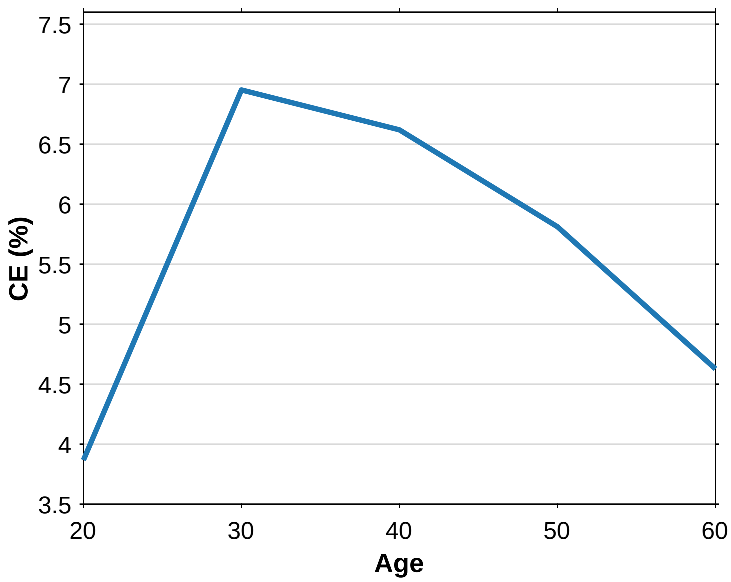

Figure 11: The graph shows the welfare cost of automation for routine workers in 1990 in the low-unionized labor market.

Figure 11 displays the welfare impact of automation for routine workers of different ages, averaged across all routine workers in that age group, in the low unionized labor market in 1990. In particular, I here focus on workers who are routine workers are layoff decisions and occupational choices have been made. The welfare costs are postitive for all age groups, meaning automation in 1990 is costly for all existing routine workers. For routine workers, automation is costly for two reasons: Displacement risk in the form of layoff risk, and permanent earnings losses as current and future routine wages fall. The welfare costs are large quantitatively and range from 4% of permanent consumption for the incoming workers to 7% for workers aged 30.

What drives the inverted u-shape of the welfare costs by age in 1990 and 2000? As the shock hits in 1990, incoming workers anticipate the full negative impact of current and future automation on their life-cycle wage path and expected layoff risk in the routine occupation. The routine occupation becomes less desirable and the required routine labor productivity z^R that justifies entering the routine occupation rises. As a result, the average labor productivity of the incoming routine cohort in 1990 is higher than for the older, incumbent cohorts. More productive workers have a higher life-cycle wage and consumption path which limits the welfare impact of automation for them. By contrast, incumbent routine workers are less productive on average as they made their occupational choice prior to the automation shock. Their consumption paths on average are lower which increases the welfare impact of automation. The costs are particularly driven by the subset of workers who would not have entered the routine occupation if they had anticipated the automation transition, but are now stuck as switching occupations comes at the cost of losing their accumulated occupation-specific human capital. Among incumbent cohorts, the welfare costs are highest for the youngest workers aged 30 as they still have 40 years of routine work ahead of them and will experience the full automation impact over time. The horizon of older, incumbent routine workers is shorter which limits the welfare impact of automation on them.

Figure 12 displays the welfare cost to routine workers along the transition.

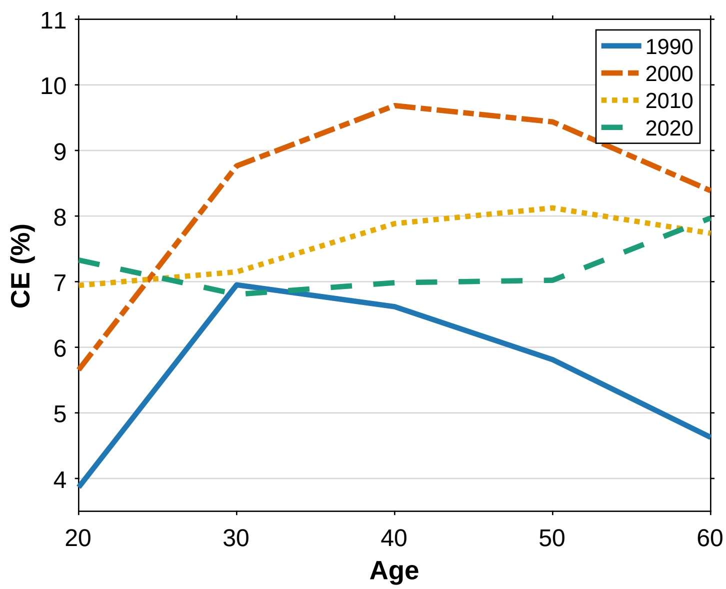

Figure 12: The graph shows the welfare cost of automation for routine workers along the transition in the low-unionized labor market.

As capital prices keep falling, firms increase automation adoption in 2000 which raises the level of welfare cost relative to 1990. Note that the routine workers aged 40 in 2000 are, abstracting from layoffs, the same workers who were 30 years old in 1990. Along the transition, the welfare cost is highest for the cohort of workers that entered the routine occupations between 1970 and 1980, right before the automation shock. These workers experience large permanent earnings losses over their full life-cycle, and would be willing to give up almost 10% of permanent consumption in 2000 to avoid automation. Automation prices fall until 2010 and cohorts entering from 2010 onward enter either at the end or after the transition. As a result, the welfare costs in 2010 and 2020 are driven by the long-term impact of automation on routine workers which is similar across cohorts, leading to a flattening of the curve.

5.3 The Union Induced Transfer of Automation Costs

How does unionization shape the welfare cost of automation for routine workers along the transition? To answer this question, I compare the welfare cost of automation as computed above in the low and high unionized labor market.

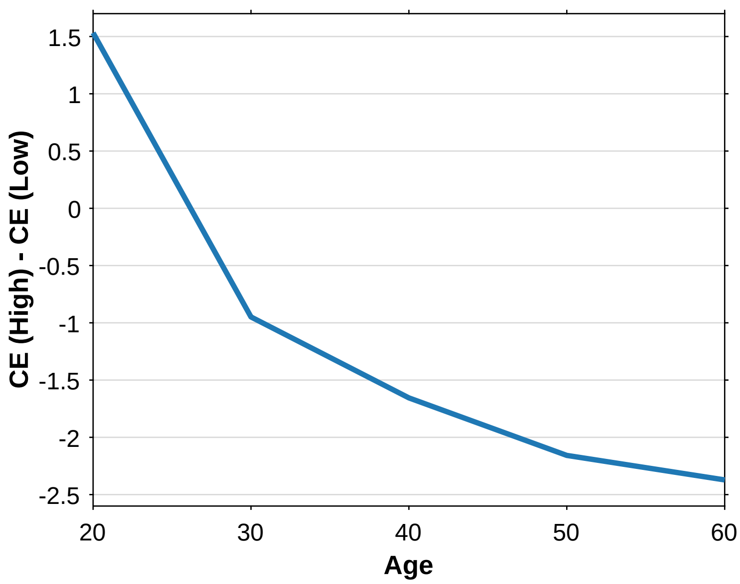

Figure 13: The graph shows the union effect on the welfare cost of automation in 1990.

Figure 13 shows the difference in the welfare impact of automation between the high and low unionized labor market in 1990. Unionization shifts the welfare costs from incumbent workers to young, incoming workers who enter the routine occupation. Consistent with the union effect on entry wages shown in figure 8, the cost of automation increases by 1.5% of permanent consumption for incoming routine workers as unionization lowers their entry wages. By contrast, unions protects incumbent routine workers by stabilizing their current wages and reducing their layoff risk, reducing the cost of automation to them by up to 2.5% of permanent consumption.

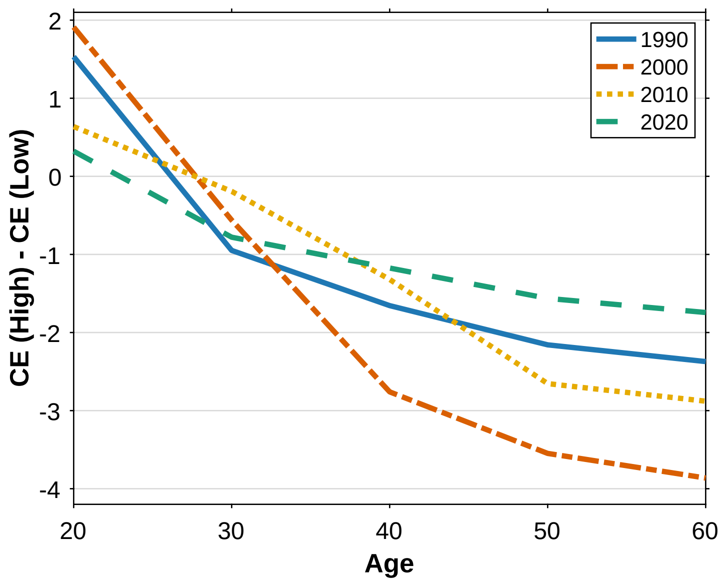

Figure 14: The graph shows the union effect on the welfare cost of automation along the transition.

Figure 14 shows the union effect along the transition. As automation adoption increases in 2000, the productivity of routine workers falls which puts downward pressure on wages and increases the incentive of firms to lay off workers. As a result, the union protection becomes more valuable for incumbent routine workers. Especially for 60 year old routine workers layoffs would result in large earnings losses, therefore, unionization reduces the welfare cost of automation for them by close to 4% of permanent consumption. Importantly, while the positive union impact on older, incumbent workers increases substantially between 1990 and 2000, the negative impact on incoming workers rises only slightly, reaching close to 2% of permanent consumption. This reflects the fact that incoming workers in 2000 endogenously respond to the impact of automation on their expected life-cycle earnings path in the routine occupation by not entering the routine occupation unless their routine labor productivity is sufficiently. By contrast, incumbent routine workers are surprised by the automation shock after their occupational choice. They are now stuck in a declining sector, facing increased layoff risk while switching occupations comes at the cost of losing their occupation-specific human capital. From 2010 onward the economy transitions to its new long-run steady state and the union effect flattens and declines in magnitude.

The welfare analysis emphasizes two things: First, among exposed routine workers who are substitutable with technology, automation is particularly costly for workers who made their occupational choice prior to the transition. These workers are caught by surprise and are stuck in a declining sector. While automation also comes at substantial cost for workers who still enter the exposed occupations during the transition by reducing their expected life-cycle earnings path, these workers are on average more productive as they incorporate the current and future consequences of automation into their occupational choice which limits the welfare impact. Second, unionization shifts the welfare cost from incumbent cohorts to incoming routine workers. Workers who still enter the routine occupations during the transition experience declining entry wages due to unionization, and less productive young workers who would have entered the routine sector in the past now instead enter the non-routine occupation.

6 Political Implications of the Conflict

An emerging political economy literature connects adverse economic shocks and outcomes to ideological realignment which induces shifts in political preferences and economic policy. In particular, ideological polarization by race and education have widened among voters, most notably seen in a shift of less-educated Whites to the GOP (Pew Research Center (2014, 2017). Mian et al. (2014) document a temporary increase in polarization in congressional voting outcomes following financial crises. Several studies document that the widening ideological polarization in Congress correlates with rising U.S. income inequality (McCarty et al. (2016), Voorheis et al. (2015)). Autor et al. (2020) find support for an ideological realignment in trade-exposed local labor markets in the form of rising support for strong-left and strong-right views, as well as pure rightward shifts. However, the causal relation between economic outcomes and shifts in voting behavior remains poorly understood.

How can the findings of this paper speak to and inform the narrative that puts economic factors at the center of political polarization? The model emphasizes that while unionization protects incumbent routine workers in response to an automation shock, it does so by shifting the cost of automation to young cohorts entering the labor market. In particular, unionization thereby causes a greater decline in routine entry wages for the subset of workers that still enter the routine occupation, as well as a larger reallocation of young workers to non-routine jobs. As a result, unionization has intensified the deterioration of labor market experiences of less skilled incoming cohorts in routine and non-routine occupations since 1980. Cohorts of workers that have entered the labor market between 1980 and 2000 are in their 50s and 60s today, and precisely the workers whose voting behavior has shifted. In order to test the importance of economic hardship as a driver of the shift in voting behavior, I test the hypothesis that union-induced employment decline among young routine-manual workers in the 1980s across local labor markets is associated with a larger shift of voting to republicans in the 2016 and 2020 presidential election.

I use data on county-level returns for presidential elections from 2000 to 2020 from the MIT Election Data and Science Lab (2017) and aggregate that data to the MSA level. Note, the data shows democratic and republican voter shares at the overall MSA level, not for the subset of routine-manual workers. The dependent variable is the change in the republican voter share in a MSA in the 2020 elections relative to the four previous elections in 2004, 2008, 2012 and 2016. I then regress the change in the voter share on the change the share of routine manual workers that is below the age of 40 between 1980 and 1990, the unionization rate among routine manual workers, the interaction between unionization and the age shift, as well as controls. The interaction term is the coefficient of interest. As before, a greater fall in the share of young workers below the age of 40, that is, an aging of the workforce, indicates less employment prospects for young routine-manual workers. The interaction with unionization then measures the additional fall in the share of young routine-manual workers that is driven by unionization which is the variation of interest.

	Dependent variable: Change in Republican Voter Share			
	2020-2004	2020-2008	2020-2012	2020-2016
	(1)	(2)	(3)	(4)
1980s CDF Change Age 40	0.129	0.370^{***}	0.348^{***}	0.077
	(0.131)	(0.127)	(0.120)	(0.095)
Unionization	0.038	0.034	0.082^{**}	-0.021
	(0.051)	(0.042)	(0.041)	(0.026)
Interaction	-1.241	-1.620^{***}	-1.504^{***}	-0.440
	(0.611)	(0.587)	(0.535)	(0.378)
Mean dependent	-0.025	0.026	0.0071	0.0059
Observations	167	167	167	167
R^2	0.495	0.540	0.491	0.285
Adjusted R^2	0.433	0.484	0.429	0.198
Note:	*p<0.1; **p<0.05; ***p<0.01.			

Table 7: The table shows the results from the regressing changes in the republican voter share over time on the change in the share of young routine-manual workers between 1980 and 1990, unionization and their interaction at the MSA level.

Table 7 shows the regression results. The interaction terms are negative for all four models. Across MSAs, high unionization among routine-manual workers combined with a greater fall in the share of young routine-manual workers between 1980 and 1990 is associated with an increase in the republican voter share in the 2020 presidential election relative to previous elections. The effect is particular pronounced relative to the 2004, 2008 and 2012 election. In particular, comparing a MSA at the 10th to a MSA at the 90th percentile in both independent variables, routine-manual unionization and the fall in the share of young routine-manual workers during the 1980s, is associated with a 3.9% and 3.6% additional increase in the republican voter share in the 2020 relative the 2008 and 2012 presidential elections, respectively. The effect is weaker relative to the 2016 election consistent with the 2016 presidential election already being polarized.

7 Conclusion

This paper documents that unions have shifted the incidence of wage and employment declines of routine-manual workers from older, incumbent to incoming cohorts since 1980. Moreover, unions have accelerated the decline in overall employment within routine-manual occupations, resulting in a greater fall in employment in high-unionized labor markets between 1980 and 2000, and subsequently catch-up of employment decline in less unionized labor markets.

I build a quantitative model of endogenous technological change and unionization which demonstrates that the combination of gradual automation adoption over time and firing costs imposed by unions can jointly rationalize the two empirical observations. Firing costs incentivize firms to replace their workforce through reduced hiring rather than through costly layoffs in response to automation adoption. Moreover, when firms anticipate more automation to come in the future, they additionally shrink their workforce already today in order to avoid firing costs in the future. This anticipatory adjustment channel is strong in the model and gives rise to an accelerated overall employment decline in routine occupations in high-unionized labor markets.

I use the model to quantify the effect of automation and unionization on the life-cycle consumption paths of routine workers across cohorts. The automation impact is most pronounced for incumbent routine workers who made their occupational choice prior to the transition, the welfare cost of automation to these workers reaches 10% of permanent consumption in 2000 in a low-unionized labor market. Workers entering the labor market during the transition endogenously adjust their occupational choice, and particularly less productive workers select into the non-routine occupations. Nevertheless, entering routine workers would still pay up to 7% of permanent consumption to avoid automation. In a high-unionized labor market, unions protect incumbent routine workers by lowering their layoff risk and wage decline which reduces the welfare cost of automation to these workers along the transition by up to 4% of permanent consumption. However, the cost is shifted to incoming cohorts. Routine entry wages and hiring falls relatively more in high-unionized labor markets, increasing the welfare cost of automation to incoming routine workers by up to 2% of permanent consumption along the transition. The difference in the welfare benefit to incumbent workers and welfare cost to incoming workers reflects the endogenous response of incoming workers to the automation shock. While older, incumbent workers are stuck in a declining sector, having made their occupational choice not anticipating automation, incoming workers take the automation transition into account, resulting in less productive potential routine workers to enter non-routine occupations instead.

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A Further Empirical Evidence

A.1 Cohort Effects Across US States

Measuring cohort effects of low-skilled and routine workers over time across US states allows to test whether unionization affects the price of incoming workers. Following Heckman et al. (1998), and more recently Lagakos et al. (2018) and Fang and Qiu (2021), I decompose earnings growth into cohort, experience and time effects for cohorts born between 1940 and 1980 at the state and education (and occupation) level. Experience effects measure human capital growth over the life cycle, cohort effects measure the relative human capital level of a cohort at labor market entry, and time effects capture growth of the price of human capital over time. Thus, cohort effects essentially measure the value of human capital of each cohort at lab or market entry in units of wages. Therefore, comparing the cohort component of earnings growth across states with high and low unionization in routine occupations quantifies by how much more the value, or the marginal product of labor, of incoming routine workers, measured in units of entry wages, has declined in states with high routine unionization relative to states with low routine unionization. It is well known that experience, cohort, and time effects cannot be separately identified without further assumptions due to perfect collinearity. In order to solve the identification issue I closely follow the literature, and in particular Fang and Qiu (2021), by adopting the standard identification strategy first used by Heckman et al. (1998). The identifying assumption is that there is no experience growth in final years of a worker's career which is based on theories of life cycle wage growth (human capital investment, search, learning (Rubinstein and Weiss (2006)). To see this, denote log wage $w_{i,c,t}$ of individual i from cohort c at time t as

$$w_{i,c,t} = p_t + h_{c,t} + \epsilon_{i,c,t}, \qquad \text{where } E_i[\epsilon_{i,c,t}] = 0.$$

Further decompose the cohort component into entry level human capital $s_c = h_{c,c}$ and return to e years of experience $r_{c,e} = r_e$ according to

$$w_{c,t} = p_t + s_c + r_e,$$

where p_t reflect time effects, s_c reflect cohort effects, and r_e reflect experience effects. It is straight forward to see that perfect collinearity $e = t - c$ now results in non-identification

$$w_{c,t+\tau} - w_{c,t} = p_{t+\tau} - p_t + s_c - s_c + r_{e+\tau} - r_e.$$

However, with the identifying assumption that there is no experience growth in final years of a worker's career, $r_e = 0$ for cohorts with $e \geq \bar{e}$, the above equation reduces to the following for workers of cohorts with $e \geq \bar{e}$:

$$w_{c,t+\tau} - w_{c,t} = p_{t+\tau} - p_t.$$

Thus, the assumption allows to identify common time effects through older cohorts. Since those time effects by definition are common across cohorts, this then allows for the identification of experience and cohort effects for all other cohorts. I apply the above estimation to decompose repeated cross-sectional annual earnings (total income) profiles from CPS non-parametrically into experience, cohort, and time effects at the state level.

Figure 15 displays the average cohort effects for highschool dropouts for states in the bottom and top quartile of unionization. In particular, the x-axis shows cohorts by birth year, the y-axis shows the cohort component of entry wages for each cohort relative to the cohort born in 1940. For the top row of plots states are weighted equally when ranked by percentile of unionization while the bottom row shows results when weighing states by their overall routine employment decline. Moreover, in the left column of plots unionization percentiles are computed based on routine unionization in 1987 while routine employment in 2003 is used in the right column.

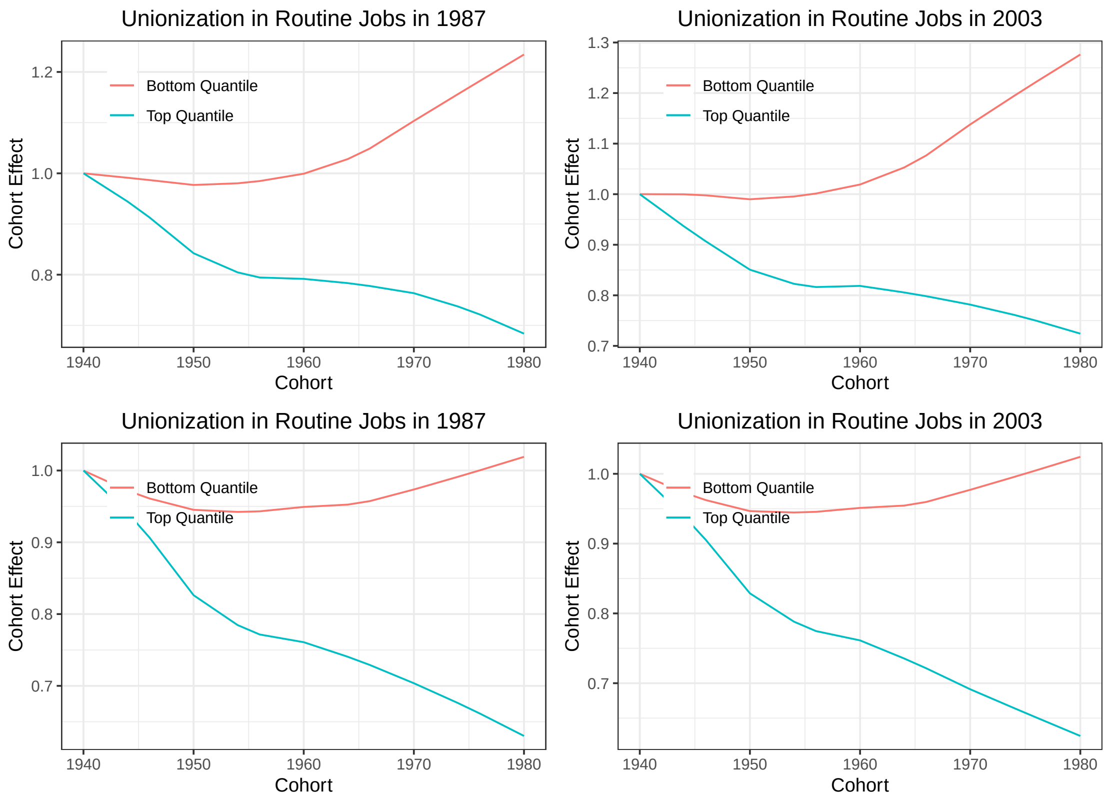

Figure 15

Focusing on the top right plot, it shows that entry wages in states with high routine unionization decline relative to states with low routine unionization from 1940 onwards. However, entry wages diverge more strongly from 1960 onward, that is, for cohorts that entered the labor market from around 1980 onwards. Thus, labor market entry conditions for highschool dropouts have deteriorated particularly from 1980 onwards in states with high routine unionization. Moreover, the results are very similar when using the 2003 routine unionization. This is an important robustness test as it bolsters the commuting zone level analysis which uses routine unionization between 1996 and 2005 as explanatory variable since CPS coverage at the commuting zones level is not sufficient before 1996.

A.2 Inflow-Outflow Decomposition

Following Cortes et al. (2020), I use monthly individual-level matched CPS data, and classify every individual observation into 9 mutually exclusive employment states: Non-routine cognitive (NRC), routine cognitive (RC), routine manual (RM), non-routine manual (NRM) (employed or unemployed), and not in the labor force (NLF). I then compute monthly labor market flows between 1986 to 2012 for each US states between these employment states, thus, transition rates between employment states over time. In order to quantify how much the outflow rate from routine employment (ERM) out of the labor force contributed to the reduction in overall routine employment (ERM), I construct counterfactual routine employment paths as Cortes et al. (2020) in the following way:

1. Fix the outflow rate from ERM to NLF at 1986 level:

$$\hat{\mu}_t(NLF, ERM) = \mu_{1986}(NLF, ERM) \; \forall t.$$

2. Leave other transition rates as in data, only rescale such that transition rates add up to 1 ($\sum_j \mu_t(NLF, i) = 1$).

3. Construct counterfactual employment shares over time:

$$S_{t+1} = \hat{\mu}_t S_t.$$

4. Compare the counterfactual decline in ERM to the realized one:

$$F(\text{ERM} \rightarrow \text{NLF}) \equiv 1 - \frac{\Delta E\hat{R}M_{cf}}{\Delta ERM}.$$

$F(\text{ERM} \rightarrow \text{NLF})$ measures how much decline in ERM would have been avoided if the transition rate from ERM to NLF stayed at its 1986 level $\mu_{1986}(NLF, ERM)$.

I then regress $F(\text{ERM} \rightarrow \text{NLF})$ on unionization in routine manual and a set of controls including the 1980 industry composition and demographics. In particular, I run the following model across US states s:

$$F(\text{ERM} \rightarrow \text{NLF}) = \beta_0 + \beta_1 U_s + \gamma X_s + u_s.$$

Table 8 shows the results for three regressions using as independent variable the percentile of unionization for each state. The first column uses a dummy variable that measures whether a states is above or below the median of unionization, columns 2 and 3 use categorial variables that measure the quartile and quintile of a state's unionization.

	Dependent variable: $F(ERM \to NLF)$		
	Union Coverage Q2	Union Coverage Q4	Union Coverage Q5
	(1)	(2)	(3)
	-0.064^{*}	-0.038^{**}	-0.031^{***}
	(0.038)	(0.018)	(0.012)
Observations	51	51	51
R^2	0.103	0.157	0.169

Table 8

The results shows that the statistical contributions of outflow rates to the overall decline in routine employment is negatively correlated with routine unionization. As expected, the coefficient falls in magnitude from the left to the right when going to smaller percentiles while becoming better identified. This is because the change in unionization between two quintiles in column 3 is smaller than between the bottom and top half of unionization in column 1. Moreover, the estimates are economically meaningful. Going from the 1st (lowest) to the 5th (highest) quintile of unionization is associated with a 15pp increase in the share of routine employment decline accounted for by outflow from routine employment out of the labor force.

A.3 Additional Material for Empirical Analysis

A.3.1 Additional Robustness: Effect on RM Employment Decline

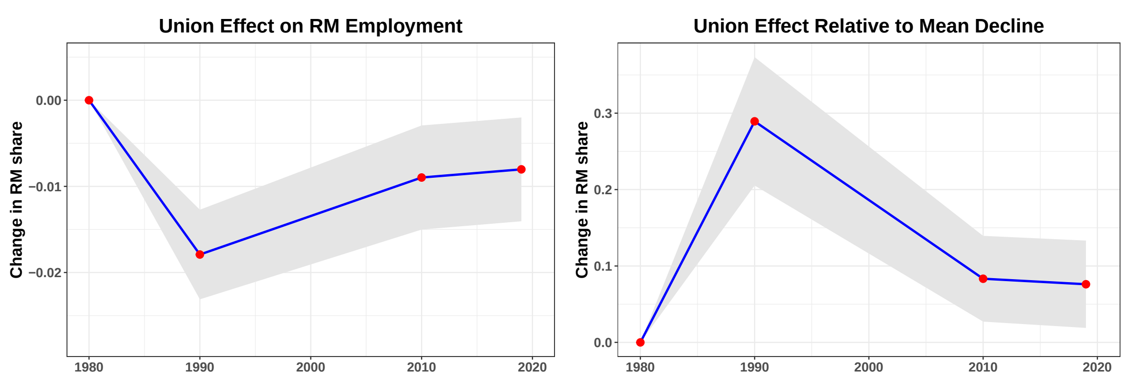

Figure 16: The graphs show the effect of going from the 25th to the 75th percentile of unionization on the RM employment share over time.

Figure 16 repeats the main exercise of regressing the change in the routine-manual employment share on routine-manual unionization and the set of controls, and it plots the coefficient for a MSA at the 25th percentile and an MSA at the 75th percentile of unionization. As expected, the magnitude of the effect falls relative to the main result that compares the 10th to the 90th percentile of unionization. However, the union effect remains significant and large. The routine-manual employment share falls significantly more in high-unionized MSAs between 1980 and 1990, after which employment decline in low-unionized MSAs starts to catch up. The union effect is large, reaching almost 30% of the mean routine-manual employment decline across MSAs between 1980 and 1990.

A.3.2 Main Results: Union Effect on Age Composition

	Dependent variable: Change in CDF across Ages				
	Age 20	Age 30	Age 40	Age 50	Age 60
	(1)	(2)	(3)	(4)	(5)
Unionization	-0.043^{***}	-0.126^{***}	-0.114^{***}	-0.062^{***}	-0.023^{**}
	(0.012)	(0.027)	(0.026)	(0.020)	(0.011)
Change RM 1980-1990	0.165^{***}	0.687^{***}	0.405^{***}	0.111	0.088^{*}
	(0.059)	(0.156)	(0.141)	(0.091)	(0.052)
Mean dependent	-0.072	-0.099	-0.017	0.026	0.012
Observations	200	200	200	200	200
R^2	0.314	0.474	0.367	0.261	0.260
Adjusted R^2	0.262	0.434	0.319	0.205	0.204
Note:	*p<0.1; **p<0.05; ***p<0.01				

Table 9: Effect of unionization on the change in the age distribution of routine-manual workers between 1980 and 1990.

	Dependent variable: Change in CDF Gap across Ages				
	Age 20	Age 30	Age 40	Age 50	Age 60
	(1)	(2)	(3)	(4)	(5)
Unionization	-0.044^{***}	-0.106^{***}	-0.119^{***}	-0.142^{***}	-0.046^{***}
	(0.014)	(0.035)	(0.028)	(0.030)	(0.017)
Change RM 1980-2010	0.051	0.580^{***}	0.551^{***}	0.272	0.055
	(0.065)	(0.189)	(0.155)	(0.175)	(0.094)
Mean dependent	-0.1	-0.2	-0.18	-0.083	-0.0063
Observations	200	200	200	200	200
R^2	0.260	0.334	0.331	0.364	0.256
Adjusted R^2	0.204	0.284	0.280	0.316	0.199
Note:	*p<0.1; **p<0.05; ***p<0.01				

Table 10: Effect of unionization on the change in the age distribution of routine-manual workers between 1980 and 2010.

	Dependent variable: Change in CDF Gap across Ages				
	Age 20	Age 30	Age 40	Age 50	Age 60
	(1)	(2)	(3)	(4)	(5)
Unionization	-0.037^{**}	-0.026	-0.067^{**}	-0.087^{***}	-0.084^{***}
	(0.017)	(0.029)	(0.033)	(0.031)	(0.024)
Change RM 1980-2019	0.115	0.226^{*}	0.349^{**}	0.302^{**}	0.237^{***}
	(0.078)	(0.135)	(0.153)	(0.143)	(0.086)
Mean dependent	-0.094	-0.17	-0.16	-0.11	-0.051
Observations	147	147	147	147	147
R^2	0.253	0.327	0.379	0.287	0.291
Adjusted R^2	0.174	0.256	0.313	0.211	0.216
Note:	*p<0.1; **p<0.05; ***p<0.01				

Table 11: Effect of unionization on the change in the age distribution of routine-manual workers between 1980 and 2019.

A.3.3 Additional Robustness: Union Effect on Age Composition

	Dependent variable: Change in CDF across Ages				
	Age 20	Age 30	Age 40	Age 50	Age 60
	(1)	(2)	(3)	(4)	(5)
CDF Change 1980-1990	-0.042^{***}	-0.121^{***}	-0.110^{***}	-0.060^{***}	-0.023^{*}
	(0.012)	(0.028)	(0.027)	(0.021)	(0.012)
CDF Change 1980-2010	-0.043^{***}	-0.104^{***}	-0.113^{***}	-0.138^{***}	-0.042^{**}
	(0.014)	(0.034)	(0.029)	(0.031)	(0.018)
CDF Change 1980-2019	-0.036^{**}	-0.022	-0.063^{*}	-0.080^{**}	-0.079^{***}
	(0.017)	(0.029)	(0.034)	(0.032)	(0.025)

Table 12: Robustness: Effect of unionization on the change in the age distribution of routine-manual workers between 1980 and different stages of the transition (1990, 2010, 2019). Regression uses routine-manual employment share in 1980 for each MSA as weights.

Table 12 reports the results when estimating the effect of unionization on the change in the age distribution of routine-manual workers between 1980 and different stages of the transition using the routine-manual employment share in 1980 for each MSA as regression weights. The results are robust to reweighting.

B Model Appendix

B.1 Workers hold fixed equity shares

Figure 17 displays the welfare cost to routine workers along the transition in the low-unionized labor market if workers hold fixed and equal equity shares in the firms. While the overall distribution and evolution of welfare costs to routine workers is similar to the baseline economy in which workers do not own equity, the level of welfare costs is lower. If workers hold equity, they benefit from automation due increased profits, which partially offsets the earnings losses they incur.

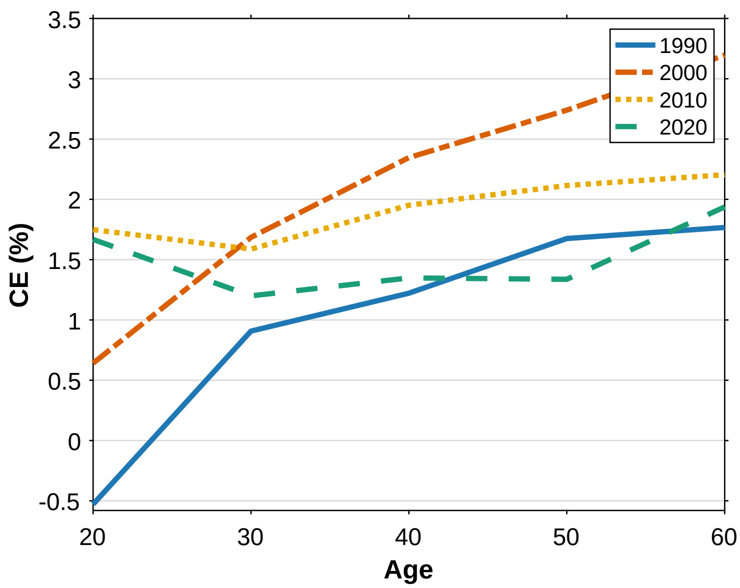

Figure 17: The graph shows the welfare cost of automation for routine workers along the transition in the low-unionized labor market when workers hold fixed and equal equity shares.

Figure 18 displays the union effect on welfare cost to routine workers along the transition in the low-unionized labor market for the fixed equity case. Again, the shape is similar to the baseline economy, unions shift the cost from older, incumbent cohorts to young workers. However, the union effect falls as wage income becomes a smaller component of workers' income, which in turn reduces the importance of lower layoff risk and limited earnings losses due to high unionization.

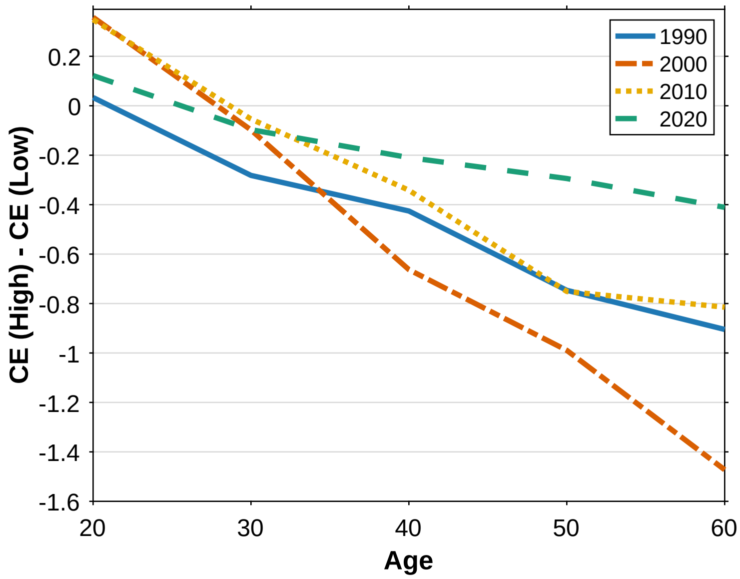

Figure 18: The graph shows the union effect on the welfare cost of automation along the transition.