Occupational Reallocation within and across Firms: Implications for Labor Market Polarization

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Abstract

This study analyzes how labor market frictions interact with firms' decisions to reallocate workers across different occupations during labor market polarization. We compare the patterns of occupational reallocation within and across firms in the US and Germany in recent years. We find within-firm reallocation contributes significantly to the decline in employment in routine occupations in Germany, but much less so in the US. We construct a general equilibrium model of firm dynamics and find the model with different firing taxes can replicate the difference in firm-level adjustment patterns across these countries. We conduct two counterfactual experiments for each country,

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highlighting the different roles played by the within-firm cost of reorganizing the occupational mix and across-firm frictions created by firing taxes. The results suggest the latter plays a more significant role in labor market polarization. Higher firing costs lead to greater and faster polarization in the US.

Keywords: Occupational Reallocation, Firing Costs, Labor Market Polarization
JEL Classifications: E24, J24, J62

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1. Introduction

In recent years, many advanced economies have experienced significant declines in employment in middle-skilled routine occupations. This phenomenon, often referred to as "labor market polarization," has received considerable attention in the macroeconomic and labor economics literature.[1] The polarization is often attributed to technological change, which allows firms to automate routine tasks by substituting workers with machines.

From a firm's perspective, automation requires occupational reallocation: reducing employment in occupations that are substituted with automation and increasing employment in occupations that complement automation. Given the heterogeneity in technology adoption and various (potentially time-varying) factors across firms, the transformation of the occupational mix likely accompanies reallocation of workers across firms.

How do firms reallocate workers across occupations under different labor market environments? In particular, do firms change their occupational mix by hiring and firing different workers or by changing workers' tasks within the firm? We ask this question with a particular focus on differences in labor market institutions. Several decades of research have shown the US economy and continental European economies have very different labor market institutions. One specific difference that has received extensive research attention is the ease of firing. In our context as well, across-firm occupational reallocation may be costlier in a labor market when firing is difficult.

Using micro-level panel datasets from the US and Germany, we develop

[1] See, for example, Autor et al. (2006) for the US, Goos and Manning (2007) for the UK, and Goos et al. (2009) for 16 European countries. Acemoglu and Autor (2011) survey the literature.

a novel decomposition method to compare the contributions of within-firm occupational reallocation with labor market polarization in both countries. We show within-firm reallocation contributes more to the decline of routine occupation employment in Germany than in the US.

Motivated by the empirical observations, we build a dynamic general equilibrium model with heterogeneous workers, extending the standard firm-dynamics framework by Hopenhayn (1992) and Hopenhayn and Rogerson (1993). Our framework departs from the standard model by considering three different occupations and firms' endogenous decisions regarding automation. When the firm decides to automate, it optimally adjusts the occupational mix, given the costs of adjustments within and across firms.

Our theoretical framework includes two distinct variables that determine the firm-level productivity. The first variable affects productivity in a Hicks-neutral manner. This variable is formulated as an exogenous idiosyncratic shock. This type of shock is commonly employed in the Hopenhayn (1992)-type standard firm-dynamics models. Essentially, this shock symmetrically affects the demand for all occupations. The second variable represents "automation productivity," which influences the marginal products of different tasks differently. Automation productivity is chosen by the firm: we formulate the improvement in automation productivity as the costly adoption of new technology.

We calibrate the model to the German economy. We also consider the US calibration and replicate the differences in the patterns of occupational reallocation between the US and Germany. We then conduct two counterfactual experiments for each country to assess how the frictions of occupational reallocation affect the degree and speed of labor market polarization. In the first experiment, we impose a firing tax at the German level on the US-calibrated economy. Next, we evaluate the impact of firms' reorganization cost, an adjustment cost for within-firm occupational reallocation in the US. Then, we move our focus to Germany. The third experiment examines the influence of the reorganization cost on the labor market outcome in the model economy calibrated to Germany. In the final experiment, we reduce the firing costs in the Germany-calibrated economy.

We find the within-firm reorganization cost has a small impact on the degree of polarization, whereas the firing cost has a significant impact on polarization patterns in the US. In particular, we find the firing tax makes the labor market *more* polarized in the US: the level of routine employment is higher without the firing taxes, whereas the level of cognitive employment is lower. Individual firms adjust the composition of occupational employment faster when the firing tax is larger. The reason for this seemingly counterintuitive result is that the firms are forward-looking. In the model, firms are constantly hit by idiosyncratic productivity shocks. When a firing tax is in place, firms that are likely to adopt automation technology in the near future reduce routine hires when they suffer a negative shock, seeing it as an opportunity to prepare for their future automation adoption. In contrast, without a firing tax, the firm is more likely to keep the routine workers because the firm can easily adjust the occupational composition in the future.

Our work is motivated by the recent empirical literature, which documents sizable within-firm occupational reallocation in several European countries during labor market polarization. Using French establishment data, Behaghel et al. (2012) find within-firm occupational reallocation following a firm's adoption of information and communication technologies (ICT). Battisti et al. (2023) and Dauth et al. (2021) report similar evidence using German establishment data after ICT or industrial robot-exposure shocks. Our empirical analysis finds patterns consistent with these studies.

Recent macroeconomic studies, such as Eden and Gaggl (2018), vom Lehn (2020), and Jaimovich et al. (2021), build general equilibrium models and quantitatively analyze the process of labor market polarization. With a representative-firm assumption, Eden and Gaggl (2018) and vom Lehn (2020) focus on accounting for the changes in occupational employment shares in the aggregate, whereas Jaimovich et al. (2021) analyze the adverse effects of automation on workers and labor market policies. By contrast, we study worker reallocation across occupations *and* firms, explicitly considering firm heterogeneity. We construct a novel theoretical framework, which is a natural extension of the standard heterogeneous-firm model à la Hopenhayn (1992) and Hopenhayn and Rogerson (1993).

In recent papers, Humlum (2021) and Rodrigo (2021) analyze the firm-level adjustment after adopting robots. These authors quantitatively analyze heterogeneous-firm models using micro-level datasets,[2] considering endogenous robot adoption and labor market responses. We conduct a cross-country comparison of the US and Germany and focus on the role of labor market adjustment costs. Neither of these studies considers across-firm labor adjustment costs (firing taxes), which is the main focus of our study.

[2] Humlum (2021) uses Danish data, and Rodrigo (2021) uses Brazilian data.

Finally, various studies have examined the interactions between institutions (policies) and shocks (technologies). Blanchard and Wolfers (2000) emphasize the interaction between shocks, such as the decline in productivity growth, and institutions, such as labor market policies, in explaining the increase in unemployment in Europe from the 1960s to the 1990s. Some studies explicitly consider the comparison between the US and Europe in the labor market institutions. Ljungqvist and Sargent (1998) argue that in European welfare states, characterized, for example, by more generous unemployment insurance, shocks to human-capital depreciation upon unemployment translate more strongly into a high unemployment rate. Mortensen and Pissarides (1999) analyze how skill-biased shocks, interacting with different policy regimes, explain the rise of unemployment in Europe. Using the quantitative general equilibrium model, Hornstein et al. (2007) demonstrate the labor market response to capital-embodied technological change can be different depending on the labor market institutions. Although our focus is on labor market polarization and occupational reallocation, the motivations are similar to those of these earlier studies: different labor market institutions can result in different responses to technology shocks.

The remainder of this article is organized as follows. Section 2 conducts the empirical analysis. Section 3 constructs a general equilibrium model of firm dynamics. Section 4 analyzes the model quantitatively and compares it with the data. Section 5 conducts counterfactual experiments using the calibrated model. Section 6 presents the conclusions of this study.

2. Empirical findings

Here, we document the patterns of occupational reallocation in the US and Germany. Both countries have experienced significant changes in the occupational composition of their labor markets in recent decades.[3] The patterns of reallocation, however, are markedly different across these two countries, as we show. We start by describing the data and then present the empirical results for the patterns of occupational reallocations.

2.1. Data

For the US, we use the Survey of Income and Program Participation (SIPP), a household survey dataset that provides detailed information on

[3] See Acemoglu and Autor (2011) for the US and Böhm et al. (2024) for Germany.

individuals' labor market activities.[4] We use the following seven panels of the SIPP for our analysis: 1990, 1991, 1992, 1993, 1996, 2001, and 2004. These panels have a sample of 14,000–52,000 individuals. We select observations where an individual is between ages 23 and 55. We drop observations where an individual works in the public sector or is self-employed. Following Kambourov and Manovskii (2009), we also exclude managerial occupations from our analysis.[5] The details of the datasets and data-cleaning procedures are described in Appendix A.

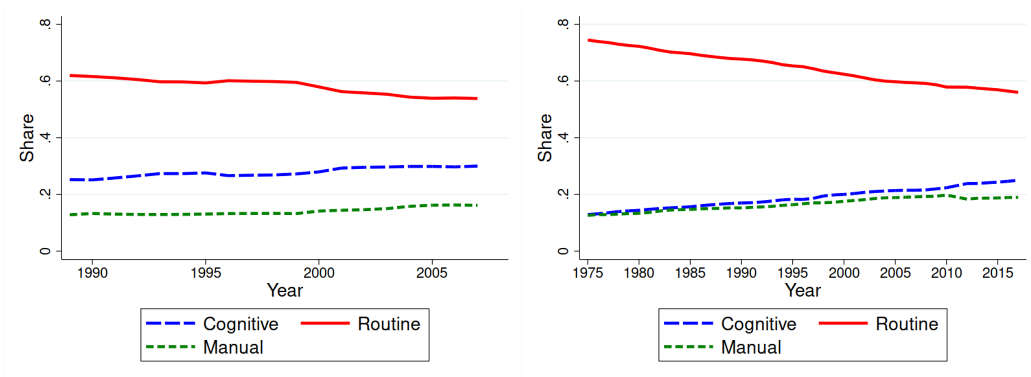
For Germany, we use the Sample of Integrated Labor Market Biographies (SIAB), an administrative dataset that contains employment records for a 2% sample of the German labor market for the period 1975–2017 (Antoni et al., 2019).[6] The dataset excludes the self-employed, civil servants, individuals performing military service, and those not in the labor force. Similar to SIPP, we select the sample of individuals between ages 23 and 55 and exclude managerial occupations.

For the US, we follow the literature of the task-based approach (Acemoglu and Autor, 2011) and identify occupational switches when a worker changes their occupations across three broad occupational groups, *Cognitive*, *Routine*, and *Manual*, based on the nature of tasks performed in an occupation. For Germany, we follow Böhm et al. (2024) to create task-based occupational

[4] An alternative dataset often used in the literature on occupational reallocation is the Current Population Survey (CPS). We use SIPP for our main analysis for two reasons. First, the 1994 redesign of the CPS and the associated introduction of dependent interviewing appears to have created a significant discrepancy between the periods before and after 1994, and thus, we cannot go back beyond 1994 for reliable data. Second, as discussed in Kambourov and Manovskii (2013), the CPS appears to have some data problems even after the introduction of its dependent interviewing after 1994. We limit the use of the CPS to the robustness check in Appendix C.1.

[5] This paper focuses on the effect of technological change on the horizontal reallocation of workers across occupations, not on career progression. Lee and Shin (2017) analyze the effect of technological changes on both workers (horizontal polarization) and managers (vertical polarization). Once the managerial occupation is included, the within-firm reallocation increases for both the US and German datasets.

[6] During the period, Germany experienced a series of labor market reforms (Hartz reforms). The most relevant one for our analysis is Hartz IV. Starting in January 2005, the Hartz IV reform restructured the unemployment benefit system by reducing the level of benefits and shortening the duration of benefit receipt. Although these changes can potentially affect the worker flows, we do not observe a large change in the patterns of internal-external reallocation before and after the reform.



(a) U.S. (b) Germany

Figure 1: Occupational Employment Shares in the US and Germany
Data Source: SIPP (US); SIAB (Germany).

groups comparable to those in Acemoglu and Autor (2011) and to identify occupational switches. These occupation groups are listed in Appendix A.4. Among the occupational switches, we further identify *within-firm occupational switches*, those that involve employer changes, and *across-firm occupational switches*, those that do not involve employer changes, by examining changes in job IDs in SIPP and in establishment IDs in SIAB.[7] We identify within-job and across-job occupational switches on an annual basis.

2.2. Time-series patterns of the occupational shares

Figure 1 plots the share of employment across occupations for the US from 1989 to 2007 and for Germany from 1975 to 2017. As is commonly observed in the literature (see Acemoglu and Autor, 2011), the share of routine-occupation employment has declined both in the US and Germany. By contrast, cognitive and manual occupations have gained employment shares. This phenomenon is often referred to as the labor market polarization.[8]

[7]The SIAB dataset includes only establishment IDs, allowing identification of establishment switches. If an occupational change within a firm is classified as an across-firm switch because the worker changes establishments but not employers, this could lead to an underestimation of within-firm occupational reallocation in Germany. Consequently, our findings regarding the US-German gap in within-firm occupational reallocation represent a lower bound.

[8]For the US, we confirm the same pattern with the CPS in Appendix C.1.

2.3. Decomposition of the occupational employment-share changes

Next, we investigate how firms reallocate workers behind the change in the stocks of occupational shares by analyzing the flows in and out of these stocks. To quantify the role of occupational switches within and across firms in the process of labor market polarization, we decompose the change in each occupational employment share into contributions of the net flows of the internal and external occupational changes. *Internal* occupational changes occur when a worker switches occupations but remains with the same employer. *External* occupational changes occur when a worker switches both the employers and occupations. Previous studies, such as Moscarini and Thomsson (2007), have documented the magnitude of internal occupation switches in the US. However, previous studies have not analyzed how the internal and external occupation changes separately contribute to the changes in occupation stocks.

Let ℓ_{it} be the stock of employment in occupation i at time t. The index i takes c, r, or m for cognitive, routine, and manual occupations, respectively. Further, let

$$E_t \equiv \sum_{i=c,r,m} \ell_{it}$$

be the total employment.

Now, we employ the following decomposition formula to quantify the contributions of different (net) flows to the change in the occupational stock. Let the employment share at time t for occupation i be ℓ_{it}/E_t. We decompose the change in the (log) employment share of occupation i from period t to period $t+T$:

$$\log\left(\underbrace{\frac{\ell_{i,t+T}/E_{t+T}}{\ell_{i,t}/E_t}}_{\Delta\text{Share}}\right) \approx \Bigg[\underbrace{\sum_{\tau=0}^{T-1}\sum_{j\neq i}\frac{f^{ji,s}_{t+\tau,t+\tau+1}-f^{ij,s}_{t+\tau,t+\tau+1}}{\ell_{i,t+\tau}}}_{\text{Internal Net Flow}} + \underbrace{\sum_{\tau=0}^{T-1}\sum_{j\neq i}\frac{f^{ji,d}_{t+\tau,t+\tau+1}-f^{ij,d}_{t+\tau,t+\tau+1}}{\ell_{i,t+\tau}}}_{\text{External } EE \text{ Net Flow}}$$
$$+ \underbrace{\sum_{\tau=0}^{T-1}\frac{f^{Ui}_{t+\tau,t+\tau+1}-f^{iU}_{t+\tau,t+\tau+1}}{\ell_{i,t+\tau}}}_{\text{External Net Flow from/to Unemployment and OLF}} - \underbrace{\sum_{\tau=0}^{T-1}\Delta^{E}_{t+\tau,t+\tau+1}}_{\text{Total Employment Effect}}\Bigg]. \tag{1}$$

The derivation of equation (1) is in Appendix B. The equation shows the cumulative change in employment share is decomposed into four components on the right-hand side. The first term (labeled as "Internal Net Flow") is the contribution of within-firm occupational switches. The notation $f^{ji,s}_{t+\tau,t+\tau+1}$ is the gross worker flow from occupation j to occupation i between time $t+\tau$ and $t+\tau+1$, conditional on staying with the same employer (s for "the same employer"). The term $f^{ij,s}_{t+\tau,t+\tau+1}$ is the worker flow in the opposite direction. Therefore, $\sum_{j\neq i} f^{ji,s}_{t+\tau,t+\tau+1} - \sum_{j\neq i} f^{ij,s}_{t+\tau,t+\tau+1}$ is the sum of the total inflow minus the sum of the total outflow for occupation i. Thus, this term is the net inflow due to the internal occupational switches. Similarly, the second term (labeled as "External EE Net Flow") is the contribution of across-firm occupational switches. $f^{ji,d}_{t+\tau,t+\tau+1}$ represents the gross worker flow from occupation j to occupation i between time $t+\tau$ and $t+\tau+1$, conditional on workers switching to different employers (d represents "different employers"). The third term (labeled "External Net from/to Unemployment and OLF," where OLF means "out of labor force") represents the net inflow from unemployment and out of the labor force, where $f^{Ui}_{t+\tau,t+\tau+1}$ is the flow from U to occupation i employment and $f^{iU}_{t+\tau,t+\tau+1}$ is the opposite flow. Finally, the fourth term (labeled as "Total Employment Effect") is the change in occupational employment share due to the change in total employment.

We call the first term on the right-hand side *internal flow*, and the sum of the second to fourth terms *external flow*. We do not distinguish between the second to fourth terms, largely for the purpose of comparability.[9] In particular, making comparable distinctions between the third and fourth terms across the US (SIPP) and German (SIAB) datasets is difficult because survey data, such as SIPP, are often affected by sample attrition, which creates a spurious effect in the fourth term.[10] Given our focus is on the internal flow, the most important task is to distinguish the internal flow and other occupational switches.

Table 1 implements the decomposition equation (1) to SIPP for the US and SIAB for Germany from the periods 1989–2007 and 1975–2019, respectively. The frequency is annual.

We observe striking differences between the US and Germany. As Column (4) shows, internal switches play almost no role in explaining the increase in cognitive and the decrease in routine employment shares in the US. In

[9] Appendix C.2 provides further decomposition.

[10] To check how the sample attrition affects our results, we create and analyze the balanced panels of SIPP in Appendix C.4.

Table 1: Internal-External Decomposition of Occupational Employment Share Changes

	Occupational employment share			Decomposed contributions	
	(1)	(2)	(3)	(4)	(5)
US	1989	2007	log (ΔShare)	Internal	External
Cognitive	0.252	0.300	0.173	0.006	0.167
Routine	0.619	0.538	−0.140	0.001	−0.140
Manual	0.128	0.162	0.230	−0.013	0.243
Germany	1975	2017	log (ΔShare)	Internal	External
Cognitive	0.129	0.250	0.662	0.166	0.496
Routine	0.745	0.560	−0.285	−0.035	−0.250
Manual	0.126	0.190	0.408	−0.036	0.444

Data Source: SIPP (US); SIAB (Germany). *Note*: The numbers in the table are rounded.

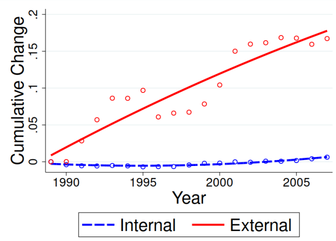
contrast, internal switches from routine and to cognitive occupations make non-negligible contributions to the changes in the occupational employment shares in Germany. In both countries, the contribution of internal switches moves in the opposite direction to the changes in the manual employment share. Given that the actual size of the effect of internal switches on manual employment share is relatively small compared to the other two in Germany, we focus primarily on the internal flows between routine and cognitive occupations later in our model.[11]

We plot the cumulative contributions of net flows to occupational employment changes over time in Figures 2. The figures show the dynamics that correspond to those in columns (4) and (5) in Table 1.

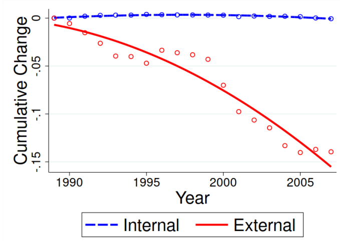
What is the cause of the different patterns between the US and Germany in Table 1? In the next two sections, we construct a model of heterogeneous firms to investigate the role of labor market policies in the process of labor market polarization.[12]

[11] The size of the effect of internal switches on manual employment share can be calculated by multiplying the initial manual employment share by the change brought by the internal switches as $0.126 \times (-0.036)$.

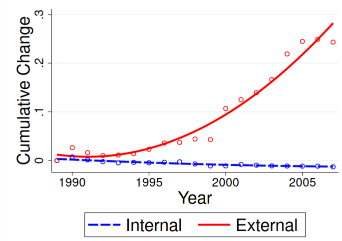
[12] Appendix C.3 explores alternative explanations, examining whether demographic composition plays any role in the difference between the US and Germany. We find that the educational composition has some explanatory power regarding the differences in internal flows to cognitive occupations, although it does not explain the entire difference between



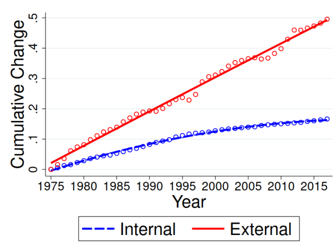
(a) US, Congnitive



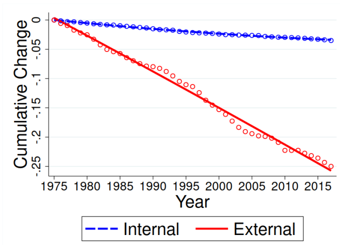
(b) US, Routine



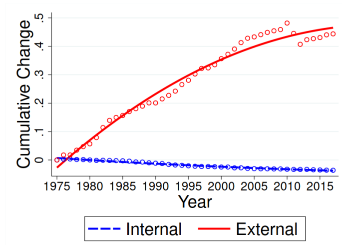
(c) US, Manual



(d) Germany, Congnitive



(e) Germany, Routine



(f) Germany, Manual

Figure 2: Cumulative Internal and External Changes in Occupational Employment Shares
Data Source: SIPP (US); SIAB (Germany). *Note:* The circular dots indicate results from the internal-external decomposition, and the lines indicate quadratic fits to them.

3. Model

This section constructs a dynamic model with heterogeneous firms to examine the interaction between labor market policies and the process of polarization. Our model builds on Hopenhayn (1992) and Hopenhayn and Rogerson (1993), and features a CES production structure with three broad types of occupations (cognitive, routine, and manual) and two firm-level productivity variables. As in Hopenhayn (1992) and Hopenhayn and Rogerson (1993), the first variable is an exogenous Hicks-neutral productivity shock. The second variable, which represents firm-level automation, is an endogenous choice variable for each firm. Automation affects different types of occupational labor demand differently. This differential labor demand drives the labor market polarization.[13]

the US and Germany.

[13] Although many causes of labor market polarization are possible (e.g., the effect of offshoring has often been pointed out), in this model, we focus on the effect of automation.

3.1. Setup

Time is discrete. We assume an infinitely-lived representative consumer exists. The consumer supplies labor and receives wage income. They also own the firms and receive the profit. The consumer is a price-taker and maximizes utility

$$\sum_{t=0}^{\infty} \beta^t U(C_t, N_t)$$

subject to

$$C_t = w_t N_t + \Pi_t + R_t.$$

Here, $\beta \in (0,1)$, $U(\cdot,\cdot)$ is the period utility function, C_t is consumption at period t, and N_t is the labor supply. On the income side, w_t is the wage rate and Π_t is the profit from production in the firm. Firms pay firing taxes to the government, which is rebated in a lump sum to the consumer as R_t. Below, we assume a quasi-linear period utility

$$U(C_t, N_t) = C_t - \xi \frac{N_t^{1+1/\eta}}{1+1/\eta},$$

where $\xi > 0$ and $\eta > 0$ are parameters. This specification implies the equilibrium return to saving has to be equal to $1/\beta - 1$. To simplify the notation below, we adopt the recursive formulation, where the next-period variable is denoted by prime ($'$).

A unit mass of firms exists, and we abstract from entry and exit for simplicity. Firms produce the consumption goods using labor. They act competitively in both the product and labor markets. The production process involves three different tasks (which correspond to three different occupations):

Many researchers find automation is linked to the occupational switching of workers. Rodrigo (2021) examines Brazilian data. His idea is that, in Brazil, robots are all imported, and from the customs data, one can tell the location where robots are sent. Through this information, we can identify the region where the robots are introduced. Comparing the regions with and without robot adoption, he finds the introduction of robots induces occupational switching (see Section 4 of that paper). Restrepo (2024) writes a survey paper that contains some recent empirical papers that relate automation to changes in occupational structure. The discussion of our paper, published in this volume, also points out another potential factor of polarization, that is, the change in the composition of the labor force. In the main text, we do not consider heterogeneous labor. In Appendix D, we construct a simple model with heterogeneous labor and show the model (qualitatively) behaves similarly to our baseline model as long as the margin of the ex-ante skill choice by workers is operative.

manual (m), cognitive (c), and routine (r). The production function also features two additional variables that affect worker productivity. The first is the standard Hicks-neutral total factor productivity (TFP) shock, denoted by s_h, which is exogenous and acts similarly to the standard firm-dynamics model by Hopenhayn (1992) and Hopenhayn and Rogerson (1993). The second, denoted by s_a, is a choice variable for the firm's automation productivity. It represents the degree of introduction of new technology (machines). A firm can choose the next period s_a, denoted by s'_a, subject to cost (denote it $\Gamma(s_a, s'_a)$). Here, we specify the $\Gamma(s_a, s'_a)$ function as follows. We assume each firm's s_a can take two possible values, $\underline{s}_a$ and $\overline{s}_a$, where $\underline{s}_a < \overline{s}_a$. The interpretation of $\underline{s}_a$ is "before automation" and $\overline{s}_a$ is "after automation." The transition between these two values is one direction: from $\underline{s}_a$ to $\overline{s}_a$. Therefore, $\overline{s}_a$ is the absorbing state. The cost of transition is assumed to be $\bar{c}_a$. The cost is zero when the value of s_a does not change. Because $\overline{s}_a$ provides a higher productivity than $\underline{s}_a$, when the additional (present) value surpasses $\bar{c}_a$, firms prefer to pay the cost and transition from $\underline{s}_a$ to $\overline{s}_a$. A firm with $s_a = \underline{s}_a$ has an opportunity to automate (by paying the cost $\bar{c}_a$) with i.i.d. probability p. The value of p governs the aggregate speed of automation.[14]

After observing the s_h shock, a firm makes hiring decisions (as well as the automation decision), where employment at task $i \in \{m, c, r\}$ is denoted as n_i. Note that, in the model, we build in a mechanism where the labor market polarization is driven by the firm's automation choice. Various existing studies have investigated the fundamental cause of labor market polarization and suggested several potential causes, including automation. Here, we focus solely on the effect of automation. In particular, what is important here (by calling s_a as "automation") is that a change in s_a causes differential responses to the demands for different tasks (occupations).

The production function is specified as

$$f(\mathbf{n}, \mathbf{s}) = s_h \mathbf{F}^{\alpha},$$

where $\alpha \in (0, 1)$ is the returns-to-scale parameter,

$$\mathbf{F}(n_m, \mathbf{G}) = \left(\mu_m n_m^{\frac{\sigma_m - 1}{\sigma_m}} + (1 - \mu_m) \mathbf{G}^{\frac{\sigma_m - 1}{\sigma_m}} \right)^{\frac{\sigma_m}{\sigma_m - 1}},$$

[14] Appendix E explores an alternative formulation of the automation cost. There, the automation opportunity is open to all firms, and the automation cost falls deterministically. The overall results are very similar to the specifications in the main text.

where $\sigma_m \geq 0$ is the elasticity of substitution parameter and n_m is the manual labor,

$$\mathbf{G}(n_c, \mathbf{M}) = \left(\mu_c n_c^{\frac{\sigma_c - 1}{\sigma_c}} + (1 - \mu_c)\mathbf{M}^{\frac{\sigma_c - 1}{\sigma_c}} \right)^{\frac{\sigma_c}{\sigma_c - 1}},$$

where $\sigma_c \geq 0$ is the elasticity of substitution parameter and n_m is the cognitive labor,

$$\mathbf{M}(n_r, s_a) = \left(\mu_r n_r^{\frac{\sigma_r - 1}{\sigma_r}} + (1 - \mu_r) s_a^{\frac{\sigma_r - 1}{\sigma_r}} \right)^{\frac{\sigma_r}{\sigma_r - 1}},$$

where $\sigma_r \geq 0$ is the elasticity of substitution parameter and n_r is the routine labor. One can interpret s_a as the (automation) capital stock. This specification of the production function is in line with the existing literature on labor market polarization. For example, $\sigma_r = \infty$ corresponds to Cortes et al. (2017) and the $\sigma_c = 1$ case corresponds to Autor and Dorn (2013). Using the same specification as above, vom Lehn (2020) estimates the values of σ_i and μ_i. For simplicity, we assume the workers are (ex-ante) homogeneous, and thus, each occupation pays an identical wage.[15]

Changing occupational employment from one period to the next may require the firm to pay certain costs for adjustment. To describe these costs, we first introduce new notations. Let us denote the current period's employment in occupation $i \in \{m, c, r\}$ as n'_i.[16] The previous period's employment in occupation i is denoted as n_i. Firms decide on the vector $\mathbf{n}' \equiv \{n'_m, n'_c, n'_r\}$ for given $\mathbf{s} = \{s_h, s_a\}$ and $\mathbf{n} \equiv \{n'_m, n'_c, n'_r\}$. That is, $\mathbf{s}$ and $\mathbf{n}$ are the state variables for the firm's employment decision $\mathbf{n}'$.

[15] In Appendix D, we formulate and solve a simple model where the worker skills are heterogeneous. There, we also assume the workers can make the skill decision ex-ante. We find qualitative results are essentially the same as in the baseline. The intuition is that, in the heterogeneous-skill labor market, the changing labor demand for different occupations translates into changing skill premium, and the skill premium influences the skill-acquisition decision of workers. Thus, the skill-decision margin can act as a channel to move the equilibrium occupational mix as automation occurs. The mechanism that firing taxes moves the composition of internal versus external adjustment is the same as in the baseline model. When firing taxes exist, the firm has an incentive to reassign (retrain) some workers internally instead of through firing and hiring. Therefore, the essential economic mechanism is the same in this heterogeneous-worker economy as in the baseline model.

[16] The convention of using $'$ for the current-period employment follows Hopenhayn and Rogerson (1993).

When the firm increases the number of occupational hires ($n_i' > n_i$), the firm has to bring in new workers into that occupation from inside or outside the firm. Define $\tilde{n}_i' \in [0, n_i']$ as the internal workers (from any occupation but from the same firm) who now work in occupation i this period. Then, $\tilde{n}_i' - n_i$ is the number of internally-moved workers and $n_i' - \tilde{n}_i'$ is the number of workers who are brought from outside. Furthermore, define $\hat{n}_i' \in [0, \min\{n_i, \tilde{n}_i'\}]$ as internal workers who stayed in the same occupation i (i.e., the same firm and occupation) from the previous period. Then, $\tilde{n}_i' - \hat{n}_i'$ is the number of workers who are internally brought into that occupation (from another occupation) within the firm.[17] Let $\tilde{\mathbf{n}}'$ be the vector of $\tilde{n}_i'$, and let $\hat{\mathbf{n}}'$ be the vector of $\hat{n}_i'$.

In summary, the firm makes three layers of employment decisions: (i) how many people to hire this period $\mathbf{n}'$; (ii) within $\mathbf{n}'$, how many people come from the same firm ($\tilde{\mathbf{n}}'$); and (iii) how many people in $\tilde{\mathbf{n}}'$ are the ones from the same occupation ($\hat{\mathbf{n}}$). Clearly, $\hat{n}_i$ cannot exceed n_i, and the sum of $\tilde{n}_i'$ must be less than the sum of n_i.

We assume two types of costs for employment adjustment. The first is the *firing taxes* imposed by the government. We denote it as $g(\mathbf{n}, \tilde{\mathbf{n}}')$ and assume it takes the form

$$g(\mathbf{n}, \tilde{\mathbf{n}}') = \tau \left(\sum_{i=m,c,r} n_i - \sum_{i=m,c,r} \tilde{n}_i' \right),$$

where $\tau \geq 0$ is the tax rate. We also assume a firm has to incur a *reorganization cost*, $h(\tilde{\mathbf{n}}', \hat{\mathbf{n}}')$, which takes the form

$$h(\tilde{\mathbf{n}}', \hat{\mathbf{n}}') = \sum_{i=m,c,r} H_i(\tilde{n}_i' - \hat{n}_i'),$$

where $H_i(\cdot)$ is an increasing function. In the quantitative analysis below, we consider a quadratic form of H_i function:

$$h(\tilde{\mathbf{n}}', \hat{\mathbf{n}}') = \sum_{i=0}^{k} \kappa_i (\max\{\tilde{n}_i' - \hat{n}_i', 0\})^2,$$

where $\kappa_i \geq 0$.

[17]Note we implicitly assume the firm keeps the workers in the firm and in the same occupation whenever possible. This assumption can be justified by, for example, having an infinitesimally small cost of moving workers across firms and occupations.

Formally, the firm's problem is

$$V(\mathbf{n}, \mathbf{s}; t) = \max_{\mathbf{n}', \tilde{\mathbf{n}}', \hat{\mathbf{n}}', s_a'} f(\mathbf{n}', \mathbf{s}) - w\mathbf{1} \cdot \mathbf{n} - g(\mathbf{n}, \tilde{\mathbf{n}}') - h(\tilde{\mathbf{n}}', \hat{\mathbf{n}}')$$
$$+ \beta E_{s_h'}[p\{V(\mathbf{n}', s_h', s_a'; t+1) - \Gamma(s_a, s_a')\} + (1-p)V(\mathbf{n}', s_h', s_a; t+1)],$$

subject to

$$\sum_{i=m,c,r} \tilde{n}_i' \leq \sum_{i=m,c,r} n_i,$$

where

$$g(\mathbf{n}, \tilde{\mathbf{n}}') = \tau \left(\sum_{i=m,c,r} n_i - \sum_{i=m,c,r} \tilde{n}_i' \right),$$

and

$$h(\tilde{\mathbf{n}}', \hat{\mathbf{n}}') = \sum_{i=m,c,r} H_i(\tilde{n}_i' - \hat{n}_i').$$

Here, we use the fact that the quasi-linear utility of consumers implies the firm's discount factor to be β.

In the competitive equilibrium of this economy, the wage w_t is determined by the labor market clearing condition. Next, we examine the transitional dynamics of the aggregate economy from one steady state to another.

4. Quantitative analysis

The empirical analysis in Section 2 highlights a significant difference in how firms react to the labor market polarization process. Motivated by this outcome, we quantitatively assess how labor market institutions affect the reallocation of workers across occupations and firms during the transition dynamics.

4.1. The transition economy

We consider the transition process of automation. The economy starts from the steady state where all firms have $s_a = \underline{s}_a$. In each period, some firms (who have an opportunity) choose to transition into $s_a = \overline{s}_a$ and the economy eventually converges to the new steady state where $s_a = \overline{s}_a$ for all firms. This process leads to gradual changes in the demand for each occupation. Therefore, the transition process entails labor market polarization.

Below, we further impose a restriction that the *within-firm* occupation reallocation occurs only from the routine occupation to the cognitive occupation. This simplification is motivated by the analysis of the German data in Section 2, where the within-firm reallocation contributes to the polarization mainly through the transition from routine to cognitive occupation.

With this assumption, $\hat{n}'_m = \tilde{n}'_m = \min\{n_m, n'_m\}$ holds because no internal movements of workers occur for manual occupation. For routine workers, suppose $x' \geq 0$ workers move to the cognitive occupation. If $n'_r > n_r - x'$, $\hat{n}_r = \tilde{n}_r = n_r - x'$ and the remaining workers $(n'_r - (n_r - x'))$ must be brought in from outside the firm. If $n_r - x' \geq n'_r$, $\hat{n}_r = \tilde{n}_r = n'_r$ and the excess workers $((n_r - x') - n'_r = n_r - (n'_r + x'))$ must be fired. For cognitive workers, $n'_c - x'$ workers have to come from either previously cognitive workers or outside the firm. If $n'_c - x' > n_c$, $\hat{n}_c = n_c$, $\tilde{n}_c = n_c + x'$, and $(n'_c - x') - n_c$ workers must be brought in from outside. If $n_c \geq n'_c - x'$, $\hat{n}_c = n'_c - x'$, $\tilde{n}_c = n'_c$, and the excess workers $(n_c - (n'_c - x'))$ must be fired. In short, the firm chooses four numbers (n'_m, n'_r, n'_c, x'), the firing tax is $\tau(\max\{n_m - n'_m, 0\} + \max\{n_c - (n'_c - x'), 0\} + \max\{n_r - (n'_r + x'), 0\})$, and the reorganization cost is $\kappa x'^2$. The computational details are described in Appendix F.

4.2. Calibration

The calibration of parameters is summarized in Table 2. The main calibration target is set in Germany to determine a coherent set of parameters, including those governing frictions. First, τ^{DE} is based on the reference formula for the severance payment in the German Protection against Dismissal Act (Kündigungsschutzgesetz), which is $0.5 \times$ monthly wage $\times$ years of employment, and the average tenure of 10 years in Germany.[18] Therefore, the ratio of average severance payment to annual wage is calculated as $\tau^{DE} = 0.5 \times (1/12) \times 10$. Note that, here, we measure the firing tax as a severance payment, which does not necessarily have the same effects depending on the model structure. Here, we are implicitly disallowing the contract that can "undo" the severance payment by lowering wages.[19] Next, the disutility for work ξ is set to clear the labor market at the initial steady state with $\tau = \tau^{DE}$ and $w = 1$. The Frisch elasticity η is in the range of standard values to calibrate macroeconomic models. The return-to-scale parameter α^{DE} is

[18] See Goerkea and Pannenberg (2010).

[19] See Garibaldi and Violante (2005) for the detailed analysis in the context of the model environment where these two have different effects.

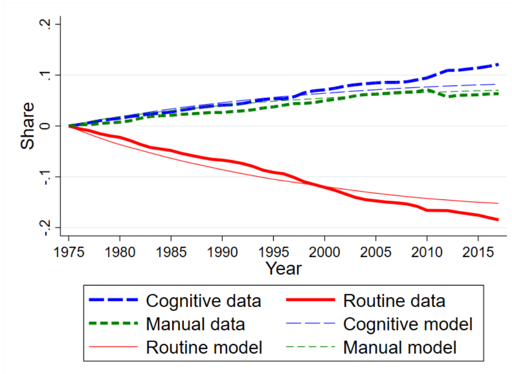
Table 2: Calibrated Parameters

Parameter	Value	Description
τ^{DE}	0.417	Based on German Protection against Dismissal Act
ξ	4.077	To match $w = 1$ at the steady state with $s_a = \underline{s}_a$ and $\tau = 0$
η	2	Standard value
α^{DE}	0.764	Bachmann and Bayer (2013)
$\underline{s}_a$	1	Normalized to 1
$\overline{s}_a$	2.566	
μ_m	0.094	
μ_c	1.518×10^{-9}	Jointly determined to target the shares of tasks and labor share of Germany
μ_r	0.972	
σ_c	0.106	
σ_m	1	Normalization
σ_r	∞	Cortes et al. (2017)
β	0.962	Annual safe interest rate of 4%
ρ_h^{DE}	0.950	Bachmann and Bayer (2013)
σ_h^{DE}	0.0905	Bachmann and Bayer (2013)
$\bar{c}_a$	0.880	Highest value with which the conversion immediately starts at $t = 0$
p	0.05	To hit the change in the share of tasks in Germany
κ	580	To match the internal reallocation from the routine occupation in Germany
τ^{US}	0	Frictionless
α^{US}	0.830	Veracierto (2001), Bachmann and Bayer (2013)
ρ_h^{US}	0.969	Lee and Mukoyama (2015)
σ_h^{US}	0.282	Lee and Mukoyama (2015)

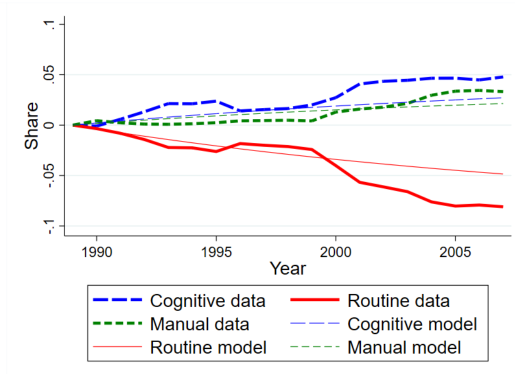
based on Bachmann and Bayer (2013). The initial level of s_a, $\underline{s}_a$, is set to unity. Meanwhile, the final level of s_a, $\overline{s}_a$, is calibrated jointly with the parameters of the production function except σ_m and σ_r. Those parameters are determined so that the initial steady-state values of shares of tasks and the labor share under τ^{DE} for firms hit their counterparts of Germany in 1975, and the final steady-state values of shares of tasks hit their counterparts in Germany in 2017. Then, σ_m is set to unity to reduce it to Cobb-Douglas. The remaining parameter of production function σ_r is assumed to make the automation capital stock a perfect substitute for the routine task. This assumption is also employed in Cortes et al. (2017). The discount factor β is set to be consistent with the annual safe interest rate of 4%. Regarding the idiosyncratic TFP shock s_h, we assume that $\log(s_h)$ follows an AR(1) process

$$\log(s_h') = \rho_h \log(s_h) + \epsilon_h, \text{ where } \epsilon_h \sim N(0, \sigma_h^2),$$

and the parameter values for ρ_h^{DE} and σ_h^{DE} in Germany are taken from Bachmann and Bayer (2013). The value for the cost of transition $\bar{c}_a$ is set to the highest value with which the conversion immediately starts at $t = 0$ with



(a) Germany



(b) US

Figure 3: Occupation Shares in Data versus Model: Germany and the US

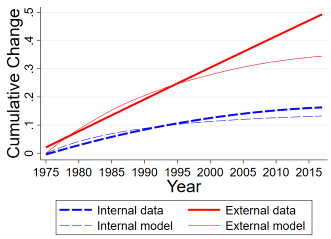
$\tau = \tau^{DE}$. The probability p that a firm can make a transition decision is set so that the changes in shares of tasks in the transition match the changes in the counterparts of Germany. Finally, the reorganization cost κ is set to match the internal reallocation flow from the routine occupation in Germany.

We consider the US to be the case where $\tau = 0$, the value of α^{US} is taken from Veracierto (2001), and the values of ρ_h^{US} and σ_h^{US} are taken from Lee and Mukoyama (2015).

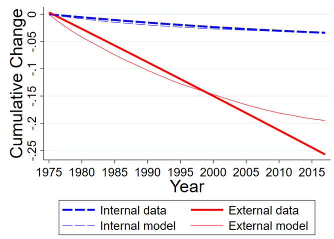
4.3. Model fit

We simulate the model's general equilibrium separately for Germany and the US. Note in the US case, x' is always 0 because adjusting the occupational composition through hiring and firing rather than internal reallocation is always cheaper when $\tau = 0$.

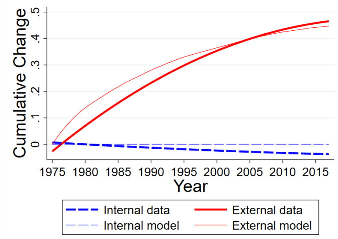
Figure 3a plots the German data (SIAB), presented in Section 2.2, and the model simulation, normalizing the levels of shares at the first year to zero. The model captures the main features of the data pattern very well: the routine share falls over time, whereas the manual and cognitive shares increase. This pattern of labor market polarization is driven by the endogenous automation (s_a moving from $\underline{s}_a$ to $\overline{s}_a$) of individual firms. Existing macroeconomic studies, such as Eden and Gaggl (2018) and vom Lehn (2020), generate similar patterns in the representative-firm framework. In our model, heterogeneous firms make the automation decision at different timings from each other. Figure 3b plots the corresponding figures for the US. Note we do not target any moments of the US data. The model also does well in capturing



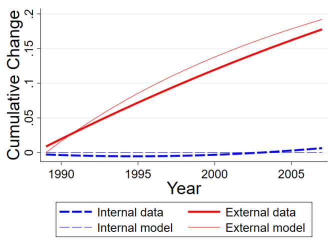
(a) Germany, Congnitive



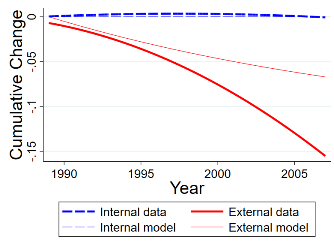
(b) Germany, Routine



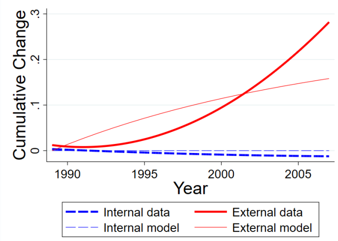
(c) Germany, Manual



(d) US, Congnitive



(e) US, Routine



(f) US, Manual

Figure 4: Cumulative Share Changes in Data versus Model: Germany and the U.S

the data patterns, although the share levels shown in Table 3 differ from those in Table 1.

Now, we move to the net flows. The model is targeted to match the cumulative change in the share of routine occupation via internal reallocation in Germany. Figures 4a through 4f compare the actual (presented in Section 2.3) and model-simulated data in terms of the cumulative change in the share of occupations. Again, the model does well in recovering the features of the data for other non-targeted components. Table 3 also summarizes the model results regarding net flows.

5. Counterfactual experiments

Here, we investigate the effects of these two parameters τ and κ by conducting counterfactual experiments. In the experiments, the parameter τ (and/or κ) is set at a different value, and the economy starts from the steady state with these counterfactual parameter values. These parameter values are kept constant over time.

We present four experiments. In the first experiment, we introduce the firing tax τ in the US-calibrated economy. Next, we evaluate whether chang-

Table 3: Summary of the Calibrated Model's Results for Germany and the US

	Occupational employment share			Decomposed contributions	
Germany: Model	1975	2017	$\log(\Delta\text{Share})$	Internal	External
Cognitive	0.135	0.217	0.476	0.132	0.343
Routine	0.740	0.588	-0.230	-0.033	-0.197
Manual	0.125	0.195	0.446	0.000	0.446
US: Model	1989	2007	$\log(\Delta\text{Share})$	Internal	External
Cognitive	0.129	0.156	0.191	0.000	0.191
Routine	0.746	0.698	-0.067	0.000	-0.067
Manual	0.125	0.147	0.158	0.000	0.158

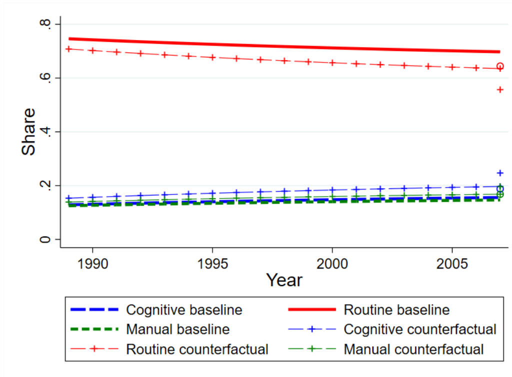
Note: The numbers in the table are rounded.

ing κ has an impact on the results of the first experiment. In the third experiment, we reduce the value of κ to half in Germany to see if the results differ from the previous experiment. In the final experiment, we reduce the value of the firing tax τ to half in Germany. For all experiments, we highlight outcomes from two separate questions: How is the speed of labor market polarization affected by the change in these parameters? How is the margin of adjustments, internal or external, affected by these parameters?

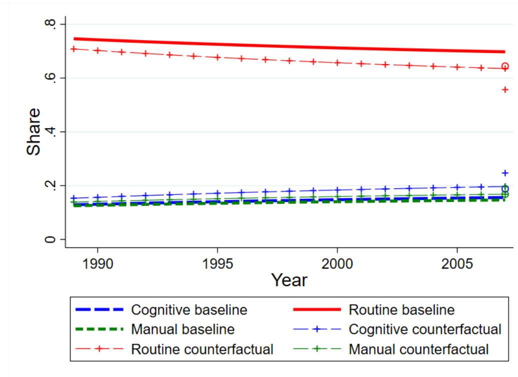
5.1. Introducing $\tau > 0$ in the US-calibrated economy

Our first experiment imposes a Germany-level firing tax ($\tau = 0.417$) on the US-calibrated economy. The reorganization cost κ is set at the same level as Germany. Figure 5a shows the path of stocks. The thick lines are the baseline US case, and the thin lines are from the counterfactual economy with $\tau = 0.417$. The figures of the counterfactual results hereafter mark the final steady-state values on the right end. Circles correspond to baseline, whereas plus signs correspond to counterfactual. (In the figures, the rightmost circle and plus indicate the point the paths eventually reach.) The result indicates the firing tax makes the labor market more polarized: the level of routine employment is higher without the firing taxes, whereas the level of cognitive employment is lower. The speed of polarization during the transition (indicated by the absolute value of the slopes for cognitive and routine occupations) is also *faster*.

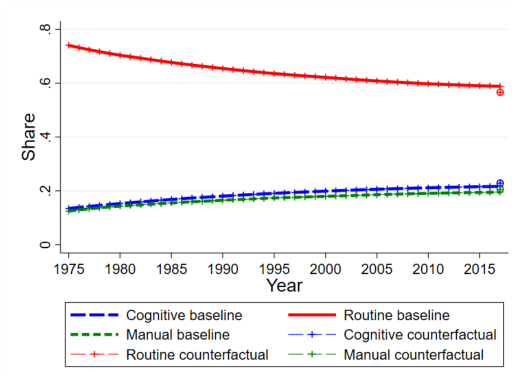
This result may sound counterintuitive, given that a larger τ implies greater frictions. The intuition here is that the firms are forward-looking. In a more frictional economy, firms adjust their occupational composition *before*



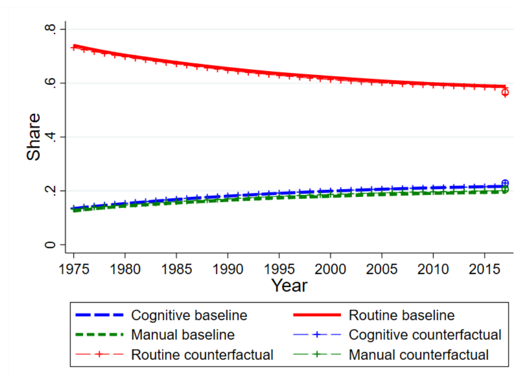
(a) Introducing $\tau > 0$ in the US



(b) Reducing κ by Half with $\tau > 0$ in the US



(c) Reducing κ by Half in Germany



(d) Reducing τ by Half in Germany

Figure 5: Counterfactual Occupational Employment Shares

they change s_a. Firms are constantly hit by the s_h shocks and adjust employment in each occupation in response to these shocks. The timing when a positive shock to s_h hits the firm is an opportunity to expand cognitive employment. When a negative shock to s_h hits the firm, the firm has to reduce its employment (by firing taxes). It uses this occasion as an opportunity to readjust the occupational composition. A firm that is likely to adopt automation technology reduces routine employment at that time, even though s_a is not yet upgraded.

We find that, although the polarization speed changes with τ, the speed of automation is almost identical between $\tau = 0.417$ and $\tau = 0$. On the one hand, the firing tax makes the reward of automation smaller and thus slows down the speed of automation. On the other hand, facing a higher firing

Table 4: Counterfactual Aggregate Variables

Variable	(1) US Introducing $\tau > 0$	(2) Germany Reducing τ by Half
Aggregate consumption	0.761	1.002
Aggregate output	0.761	1.002
Aggregate labor	0.608	1.001
Labor productivity	1.252	1.001

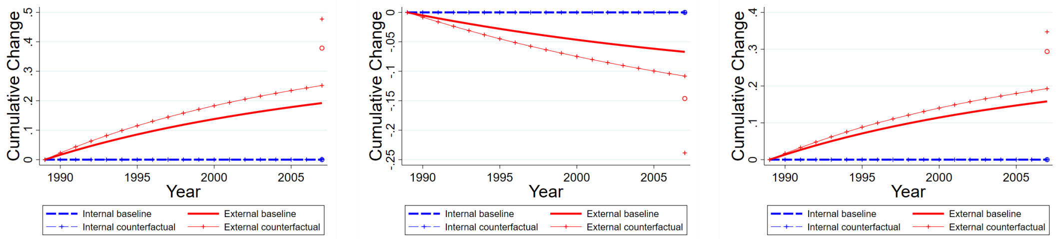
cost, a large and unproductive firm has a large incentive to automate so that it can utilize a large employment.[20] These two forces almost exactly offset each other. Therefore, the difference in the polarization speed in Figure 5a is almost entirely due to the firm's forward-looking adjustment of labor.

Figures 6a, 6b, and 6c show the impact on the flow dimension. With the German level of τ and κ, the external adjustment increases. Note that with $\tau > 0$, some adjustment is done internally. It is not visible in the graph because the magnitude is still small.

Column (1) in Table 4 presents the impacts of introducing τ on the US aggregate variables. We compare the four variables—aggregate consumption, aggregate output, aggregate labor, and labor productivity (output divided by labor)—in the end period of the above graph. The baseline US results are normalized to 1. As in Hopenhayn and Rogerson (1993), whether the aggregate labor input increases or decreases when τ changes is a quantitative question. Two counteracting forces exist: on the one hand, the firing tax discourages firing and thus increases employment. On the other hand, the firms are forward-looking, and the future possibility of firing tax payments makes firms reluctant to hire. In our model, similarly to Hopenhayn and Rogerson (1993), the latter effect is stronger in the US and the aggregate labor input is larger with a lower firing tax.

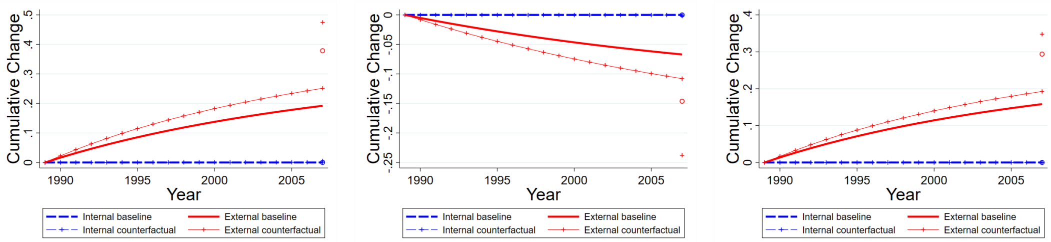
In contrast to Hopenhayn and Rogerson (1993), here, the labor productivity increases with the firing tax, although a lower τ should reduce across-firm misallocation. Several factors contribute to this result. One obvious factor is the decreasing returns to scale. We have a fixed number of firms with

[20] A similar intuition appear in Mukoyama and Osotimehin (2019) in a model of innovation and growth.



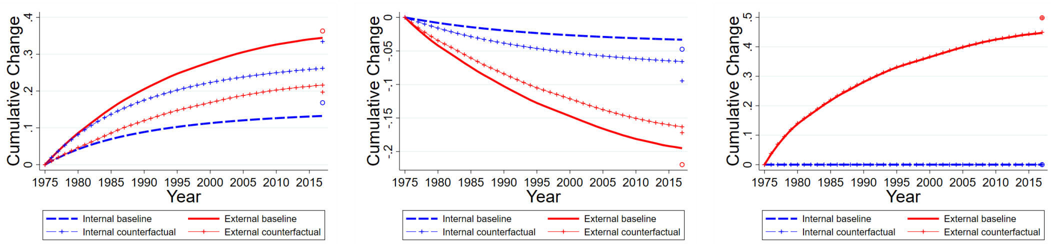
(a) US, Cognitive (b) US, Routine (c) US, Manual

Experiment: Introducing $\tau > 0$ in the US-calibrated economy.



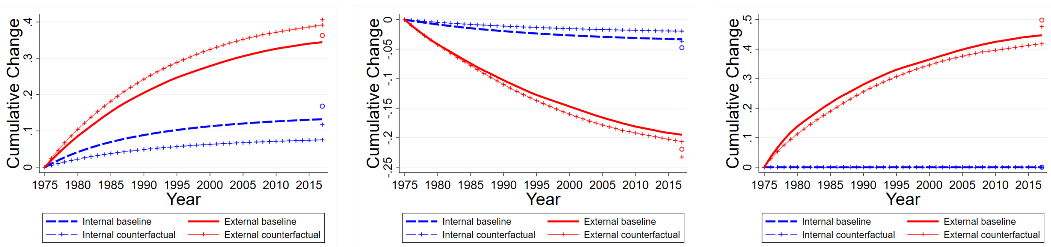
(d) US, Cognitive (e) US, Routine (f) US Manual

Experiment: Reducing κ by half in the US-calibrated economy.



(g) Germany, Cognitive: (h) Germany, Routine: (i) Germany, Manual:

Experiment: Reducing κ by half in the Germany-calibrated economy.



(j) Germany, Cognitive (k) Germany, Routine (l) Germany, Manual

Experiment: Reducing τ by half in the Germany-calibrated economy.

Figure 6: Counterfactual Internal and External Flows of Workers

decreasing returns to scale, and a larger labor input implies lower average productivity. Second, in this economy, the marginal product of labor is not infinity for a near zero-value of labor input, given the existence of s_a, and thus, sometimes allocating any labor to low-s_h firms is not worthwhile. In the simulation, we observe that the high-τ economy effectively shuts down many low-s_h firms and concentrates more resources on high-productivity firms.

5.2. Reducing κ in the US-calibrated economy with $\tau > 0$

The second experiment starts from the first experiment (i.e., set $\tau = 0.417$) and reduces the reorganization cost parameter κ by half ($\kappa = 290$). Figure 5b shows the time series of stocks. The figure is almost identical to Figure 5a—the change in reorganization cost κ has little impact on the path of stocks. This result implies that the timing of adjustment in individual firms is not significantly affected by the value of κ in the US.

Figures 6d, 6e, and 6f show the effect on the margins of adjustment. Again, the thick lines are the baseline US case and thin lines represent the counterfactual economy where $\kappa = 290$. The results are almost identical to the first experiment. Even with reduced κ, the firms are almost solely dependent on external reallocation. Because the occupational stock and the timing of automation are nearly identical in the first and second experiments, aggregate variables such as aggregate consumption, aggregate output, aggregate labor input, and labor productivity are also nearly identical in both experiments, and we do not report them here.

5.3. Reducing κ in the Germany-calibrated economy

The third and fourth experiments work with the Germany-calibrated baseline. Here, we start from the German baseline and reduce the reorganization cost parameter κ by half ($\kappa = 290$). Figure 5c shows the time series of stocks. As in the second experiment for the US, the reorganization cost has little impact on the path of stocks. The thick (baseline) and thin lines (counterfactual) overlap and are not visible separately. This result implies the timing of adjustment in individual firms is not significantly affected by the value of κ in the Germany-calibrated model.

The results regarding flows are very different in this experiment. Figures 6g, 6h, and 6i show the effect on the margins of adjustment. The thick lines are the baseline case, and the thin lines represent the counterfactual economy where $\kappa = 290$. In contrast to the US case, the effect of κ on the internal and external adjustment is both large and visible. When κ is small, the firm can shift a substantial part of the adjustment to internal worker movement. Therefore, this experiment reveals that the cost of internal adjustment plays an important role in *how* the labor market adjusts to the process of labor market polarization in the Germany-calibrated economy.

Because the occupational stock and the timing of automation are nearly identical in the baseline and the counterfactual, aggregate variables such as aggregate consumption, aggregate output, aggregate labor input, and labor productivity are also nearly identical, and we do not report them here.

5.4. Reducing τ in the Germany-calibrated economy

The final experiment reduces the firing tax parameter τ by half ($\tau = 0.208$), keeping κ as in the baseline. Figure 5d shows the path of stocks. The thick lines are the baseline German case, and the thin lines are from the counterfactual economy with $\tau = 0.208$. In contrast to the US case, the firing tax does not have substantial impacts on the path of stock (the lines are not separately visible). Recall that the difference between the US-calibrated economy and the Germany-calibrated economy (other than the values of τ) comes from the process of s_h shock. In the German case, the s_h shock is less volatile than in the US case, and hence, the firm's adjustment of occupational composition with the s_h shock, which was the driving force of the different speed of polarization in the first experiment, is smaller in the current experiment.

Figures 6j, 6k, and 6l show the impact on the flows. In contrast to the first experiment, the change in internal adjustment is now visibly large in terms of cognitive and routine. The increase in the external adjustment, due to lower τ, is offset by the decrease in the internal adjustment.

Column (2) in Table 4 presents the impacts of reducing τ on aggregate consumption, aggregate output, aggregate labor, and labor productivity (output divided by labor), in the final period of the above graph. The baseline German results are normalized to 1. It is noticeable that the magnitudes are considerably smaller here than in the first experiment, although the results are closer to those of Hopenhayn and Rogerson (1993). This difference arises because, in the German case, the volatility of the s_h shock is lower than in the US case, dampening the force that a high-τ economy shuts down low-s_h firms, thereby reducing misallocation when τ is lowered.

6. Conclusion

This paper analyzes how labor market frictions interact with firms' decisions to reallocate workers across occupations when the economy faces labor market polarization. Using datasets from the US and Germany, we document that the pattern of occupational adjustments differs between these two countries. US firms adjust the occupational mix almost entirely through firing and hiring. In Germany, within-firm reallocation plays non-negligible roles in the decline in routine occupations and the increase in cognitive occupations.

We then build a model of firm dynamics with occupational mobility and labor market frictions. Our model extends the standard firm-dynamics model in the tradition of Hopenhayn (1992) and Hopenhayn and Rogerson (1993) to multiple occupations and automation decisions. We calibrate the model to the German economy, and the model can replicate the different patterns of labor market adjustments during the labor market polarization across the US and Germany.

Using the calibrated model, we conduct two counterfactual experiments for each country. We find that within-firm reorganization costs have a small impact on the degree of polarization, whereas firing costs have a significant impact on polarization in the US. In particular, we find the firing tax makes the labor market *more* polarized in the US-calibrated economy: the level of routine employment is higher without the firing taxes, whereas the level of cognitive employment is lower. Individual firms adjust the composition of occupational employment faster when the firing tax is larger. In the model, firms are constantly hit by idiosyncratic productivity shocks. Thus, when a firing tax is in place, firms that are likely to adopt automation technology will reduce routine hires when they suffer a negative shock, seeing it as an opportunity to prepare for the future technology adoption event. Without a firing tax, the firm is more likely to keep the routine workers because the firm can easily adjust the occupational composition in the future.

Several issues are important to investigate along the lines of our research. First, our model does not feature the entry and exit of firms. How firm entry/exit interacts with worker mobility is an interesting and important question, especially when new technology (e.g., automation) is embodied in new firms. Second, researchers often argue an illiquid labor market may have the benefit of encouraging firm-specific human capital accumulation. Labor economics has long debated how important firm-specific human capital is, and investigating such claims requires further examination of the nature of human capital. Finally, the distinction of within- and across-firm reallocation also matters in the context of aggregate unemployment. One may easily imagine that one of the social costs of across-firm labor adjustments could be the unemployment of routine workers. Our model framework does not feature unemployment, although the model can be extended by adding friction to hiring workers. We leave these topics to future research.

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