

Document de travail (Docweb) n°2307

## **A Tale of Two Countries: Two Stories of Job Polarization**

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Septembre 2023

# L'histoire de deux pays : deux histoires de polarisation des emplois<sup>1</sup>

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**Résumé :** La polarisation de l'emploi aux États-Unis et en France semble similaire si l'on se fonde sur la répartition des emplois par tâche. Ce papier montre qu'ils sont différents lorsque l'emploi par tête et par tâche est utilisé pour identifier les sources de ces changements structurels. Nous construisons un modèle d'équilibre général multisectoriel avec des frictions de recherche, des licenciements endogènes et des choix de réallocations pour estimer l'impact du changement technologique biaisé et des changements dans les institutions du marché du travail. Notre analyse suggère que la polarisation des emplois est principalement due au changement technologique biaisé aux États-Unis, alors que les modifications des institutions du marché du travail entraînent la polarisation des emplois en France.

**Mots-clés :** polarisation des emplois, recherche d'emploi, institutions du marché du travail, changement technologique biaisé

## A Tale of Two Countries: Two Stories of Job Polarization

**Abstract :** The US and French job polarization appear similar based on employment shares by task. This study shows that they are different when per capita employment by task is used to identify the sources of these structural changes. We build a multi-sectorial general equilibrium model with search frictions, endogenous layoffs, and occupational choices to estimate the relative impact of TBTC (Task-Biased Technological Change) and LMI changes (Labor Market Institutions) on employment patterns. Our analysis suggests that job polarization is mainly driven by TBTC in the US, whereas LMI changes drive job polarization in France.

**Keywords :** job polarization, search and matching, labor market institutions, task-biased technological change

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<sup>1</sup>We thank the anonymous referees for helpful comments as well as Zsofia Barany, Andrea Bassanini, Aleksander Berentsen, Michael Burda, Federico Cingano, Alain Delacroix, Jean-Olivier Hairault, Grégory Jolivet, Etienne Lalé, Miguel Leon-Ledesma, Etienne Lehmann, Christian Merkl, Aysegul Sahin, Stephano Scarpetta, Christian Siegel, Hélène Turon and Bruno Van Der Linden, and participants to Aussois winter school, Bristol seminar, T2M conference, UQAM seminar, Société Canadienne de Sciences Economiques, Conference in honor of C. Pissarides at Science Po Paris, African Search And Matching Workshop, Istanbul Search And Matching Workshop, Louvain La Neuve Seminar, APET conference, FAU-IAB Seminar in Nuremberg, French Parliament, Kent University.

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## Abstract

The US and French job polarization appear similar based on employment shares by task. This study shows that they are different when per capita employment by task is used to identify the sources of these structural changes. We build a multi-sectorial general equilibrium model with search frictions, endogenous layoffs, and occupational choices to estimate the relative impact of TBTC (Task-Biased Technological Change) and LMI changes (Labor Market Institutions) on employment patterns. Our analysis suggests that job polarization is mainly driven by TBTC in the US, whereas LMI changes drive job polarization in France.

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**JEL Classification:** E24, J62, J64, O33

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# 1 Introduction

The digital revolution has often been proposed to explain the job polarization observed between the end of the 1970s and before the subprime crisis (see [Acemoglu & Autor \(2011\)](#) and [Autor & Dorn \(2013\)](#)), that is, the decline (increase) in the share of employment in occupations in the middle (the upper and lower) of the skill distribution.<sup>1</sup> As job polarization is a common feature of developed economies ([Goos et al. \(2009\)](#)), it may be tempting to hastily attribute the employment changes observed over these three decades solely to technological advancements. However, it is essential to recognize that during this same period, Labor Market Institutions (LMIs) evolved differently across countries ([Blanchard & Wolfers \(2001\)](#)), introducing an additional variable that could potentially bias assessments of the impact of technological change on the labor market.

The aim of this study is to assess the respective contributions of technology and changes in LMIs to job polarization. To achieve this, we investigate two countries, the United States and France, both of which have witnessed job polarization trends over the past three decades. These two countries have also progressively adopted technological advancements. However, their LMIs have followed contrasting trajectories. In the United States, minimum wage, replacement rates, workers' bargaining power, and labor taxes have declined, whereas, in France, they have increased.

Our analysis suggests that job polarization is mainly driven by changes in LMIs in France,, whereas technological change played a comparatively modest role in accounting for labor market dynamics. In contrast, in the US, LMI changes, moving in the opposite direction, eased the reallocations brought about by technological change. The originality of our contribution lies in using the evolution of employment *levels* by task (as opposed to changes in the task *shares* within total employment,) to identify the relative contributions of technological and LMI changes to job polarization. This approach enables us to distinguish between scenarios where job polarization occurs in an economy that generates new jobs (as seen in the US case) and situations where the overall employment level is diminishing (as observed in the French case). This finding underscores the significance of factoring in both LMI and technological changes when examining the labor market, especially in European countries where their substantial influence renders them highly constraining.

First, we look at US and French data. In line with the findings of [Goos et al. \(2009\)](#), we document that the changes in employment *shares* for abstract, routine, and manual jobs (the proportion of workers in each task relative to total employment) appear quite similar in both countries. Employment shares by task are widely used in the job polarization literature.<sup>2</sup>

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<sup>1</sup>We focus on this period to isolate the period of this structural change from strong business cycle movements that occurred during the financial crisis (2008-2011) and the Covid crisis (from 2020 to present). This allows us to work with raw data without any arbitrary filtering of the data.

<sup>2</sup>Based on mandatory annual reports filed by all French firms with employees (DADS data), [Harrigan](#)

However, this apparent similarity masks significant disparities in the dynamics of per-capita employment by task (referred to as employment *level* in the subsequent part of this paper). In the United States, routine per capita employment experienced an *increase* until the late 1980s, followed by a subsequent decline after 1990, thereby setting in motion the job polarization process in the United States. Conversely, the trajectory of French routine employment levels exhibited an opposite trend to that of the United States, decreasing until the mid-1990s before rebounding. This explains the contrasting patterns in aggregate employment levels before the year 2000, with employment increasing in the United States and declining in France. While the employment *shares* for different tasks in the United States and France may exhibit striking similarities, a narrative solely rooted in technological change seems to align well with occupational shifts in both countries. However, when scrutinizing the aggregate and occupational employment "levels," distinct patterns emerge. These disparities cast doubt on the relevance of a uniform job polarization explanation to both countries.<sup>3</sup>

We then propose a general equilibrium model in which technological and LMI changes can explain the evolution of both employment *shares* and employment *levels*. A "Task-Biased Technological change" (hereafter, TBTC) is introduced in our model as in [Autor & Dorn \(2013\)](#).<sup>4</sup> Technological changes encourage firms to replace routine tasks with computers, thereby triggering a large decline in occupations characterized by a high intensity of rule-based procedural activities (middle-skilled occupations). These technological improvements require more non-routine abstract tasks carried out by high-skill occupations to be fully efficient. Non-routine manual tasks involve service occupations that are performed by low-skill workers and cannot be replaced by machines. As in [Autor & Dorn \(2013\)](#), we model routine workers' endogenous mobility to manual jobs. We extend [Autor & Dorn \(2013\)](#) by looking at Search and Matching (SaM) frictions. SaM allows us to include in the model a wide range of LMIs, such as workers' bargaining power, minimum wage, unemployment benefits, and taxes on labor.<sup>5</sup> Although these LMIs affect all workers, the least productive ones are the most affected by LMI changes.<sup>6</sup> Given the observed differences in shifts in LMIs between

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et al. (2021) show that job polarization is at work in France over the period 1994-2007. They show that "techies" (workers in occupations related to developing, managing, installing, and maintaining technology) play a crucial role in adopting new technology.

<sup>3</sup>In this paper, we will look at employment by task. We do not study some additional aspects of job polarization, such as labor market participation and gender issues ([Cerina et al. \(2021\)](#)). While these issues are interesting, we want to establish the impact of TBTC and LMI changes on the polarization of aggregate employment in both genders without distinguishing between unemployed and non-employed workers. We leave labor market participation and gender issues to future research.

<sup>4</sup>We favor this view supported by empirical studies ([Michaels et al. \(2014\)](#), [Goos & Salomons \(2014\)](#)).

<sup>5</sup>We do not consider firing costs. Even if large differences in firing costs characterize France and the US, it has been rather constant over time (see [OECD indicators of employment protection](#)). As we are interested in contrasting the *dynamics* of employment over time, firing costs are not the key to this study.

<sup>6</sup>[Mortensen & Pissarides \(1999\)](#) have already shown that homogenous change in LMIs has heterogenous impacts across workers of different skills. [Bils et al. \(2012\)](#) have also shown that the labor market flows in the US have different elasticity across workers heterogenous per skill. These differences in worker flows per skill have also received support from [Elsby et al. \(2013b\)](#) based on OECD data.

the US and France, the model identifies the paths of TBTC and relative shares of skilled and unskilled labor supply<sup>7</sup> that allows it to match the observed dynamics of employment shares and levels across tasks for both countries. We find that these revealed paths of capital price (the exogenous source of the TBTC) and the shift in labor supply composition are close to their empirical counterparts, that is, the observed decline in investment good prices and labor supply composition. This encouraging result makes us confident in using the model for counterfactual simulations.

These simulations show that the rise in US routine employment can be primarily attributed to de-unionization that fostered routine jobs until the late 1980s in the US.<sup>8</sup> Since the early 1990s, TBTC has become the predominant driver of polarization in the context of increasing aggregate employment levels. Without TBTC, US employment gains would have been 40% lower. Therefore, the United States' narrative of job polarization revolves around the country reaping the benefits of technological advancements, resulting in job polarization when LMIs become more favorable to employment.

In France, changes in LMIs appear to be the primary driver for job polarization: increases in minimum wage, replacement rate, and workers' bargaining power have spurred the destruction of low-paid routine jobs, resulting in a fall in routine employment levels, in the context of declining aggregate employment. This trend reversed when the impact of the minimum wage hike was alleviated by a subsidy policy aimed at low-wage workers in the late 1990s. While TBTC did influence the French employment level, changes in LMIs ultimately overcame its effects.

Beyond the analysis of aggregate employment dynamics, we demonstrate that these two narratives can have distinct implications for workers. In the United States, TBTC alters the labor market equilibrium by generating voluntary employment reallocation in an economy that generates new jobs. In contrast, job polarization in France is driven by numerous involuntary reallocations stemming from layoffs and firings.

Our contribution to the existing literature lies in our analysis of how TBTC and LMI changes jointly affect job polarization. While previous studies have examined these factors in isolation, our approach investigates the scenarios in which TBTC alone or LMI changes alone can generate job polarization. Given that the pace and extent of job polarization hinge on the race between TBTC changes and LMI adjustments, we focus on the transitional dynamics, departing from the steady-state analysis prevalent in the literature.

Our study bridges the gap between the two strands of the literature. The first strand of literature, building on the seminal works of Mortensen-Pissarides, seeks to elucidate the reasons behind the disparity in employment levels between Europe and the United States

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<sup>7</sup>During this period where educational attainment has risen in both countries, the model must include this shift in order to avoid any bias in the evaluation of TBTC and LMI contributions to job polarization.

<sup>8</sup>[Dinardo et al. \(1996\)](#) have underlined the impact on bargaining power in the US labor market.

(Ljungqvist & Sargent (1998, 2008)). Since the empirical works of Blanchard & Wolfers (2001), this literature has emphasized the role of LMIs (in interaction with aggregate shocks) in shaping transatlantic differences in employment rates.<sup>9</sup> We revisit the role of LMIs within the context of job polarization, shedding new light on their interplay with TBTC.

The second strand of literature (Autor & Dorn (2013), Barany & Siegel (2017)) delves into the employment structure and wage dynamics across skill groups as outcomes influenced by task-biased technological progress. In contrast to Autor & Dorn (2013), we propose a model with labor market frictions, in which there is no full employment in the unskilled and skilled labor markets. While the impact of biased technological changes has been explored in the Search and Matching (SaM) literature (Mortensen & Pissarides (1998); Hornstein et al. (2007)), we expand upon these investigations by placing a greater emphasis on transitional dynamics, as opposed to the standard steady-state analysis.

Our focus on transition dynamics within a non-stationary environment presents calibration challenges, as we cannot employ the conventional approach prevalent in the literature, which relies on steady-state empirical targets. Furthermore, along this transitional trajectory, we investigate the interplay between technological change, labor market institutions, and occupational choices. We find that transitional dynamics are characterized by voluntary occupational shifts in the United States, while France experiences layoffs and scrapping times. These distinctive experiences from the workers' perspective narrate divergent stories of job polarization. Occupational choices have also been studied in the SaM literature, as seen in Alvarez & Shimer (2011) and Carrillo-Tudela & Visschers (2021). Our work extends theirs by considering occupational changes in the context of structural change rather than from a business cycle perspective, fundamentally altering the analysis due to the non-stationary environment in which occupational decisions are made.

Finally, in both strands of the literature, the supply of skilled labor is usually fixed. We relax this assumption and explore the implications of the observed increase in the skilled labor supply.<sup>10,11</sup>

The remainder of this paper is organized as follows. We present our data in section 2, the

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<sup>9</sup>Using a general equilibrium matching model, Langot & Pizzo (2019) show that the changes in LMI have a large impact on employment rates and hours worked per employee in Europe and the United States. See Auray & Danthine (2010) for a larger set of countries but with fixed capital.

<sup>10</sup>In our model, the increase in educational attainment is exogenous, the endogenous response of educational attainment being left for future research. Barany (2016) studies the endogenous response of skill choices and technological changes to the fall in the US minimum wage. With respect to Barany (2016), we study the impact of LMI beyond the minimum wage. Here, we uncover the leading role of de-unionization in the US polarization process. We also consider the SaM model, whereas Barany (2016) discards matching frictions.

<sup>11</sup>Our model does not encompass certain elements such as savings, inactivity, mobility between routine and abstract workers, or educational choices. Furthermore, we do not wage inequalities or skill premiums, as our macroeconomic approach neglects essential aspects of wage inequalities, such as disparities within occupational groups. These extensions remain subjects for future research.

model in section 3, and the calibration strategy in section 4. Section 5 presents the evolution of aggregate employment and employment shares over the past decades, whereas sections 6 describe the job polarization process from workers' viewpoints. Finally, Section 7 concludes the paper.

## 2 Apparently similar job polarization, actually different

Goos et al. (2009) show that employment shares by task (defined as employment in task  $i$  divided by aggregate employment) display similar evolutions in developed countries, including France and the United States: a drop in the share of routine jobs and a rise in the shares of manual and abstract jobs in total employment. In this section, we consider each element of this ratio. A close look at the separate evolutions of the numerator and denominator reveals divergent stories behind the apparent common polarization. We focus our analysis on the period corresponding to the great moderation, including the early 80s because this period witnessed technological developments and LMI drifts. We exclude episodes of deep crises caused by other elements (financial or epidemic). An analysis of these recessions is beyond the scope of this study.

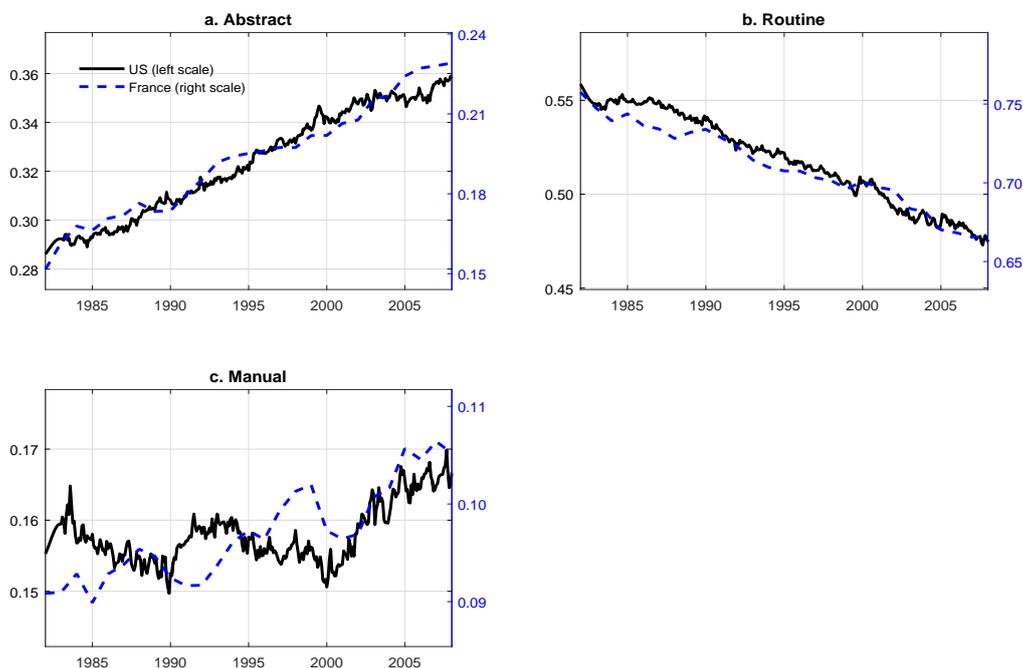
### 2.1 Based on employment share by task, job polarization seems pervasive

Figure 1 reports the evolution of employment share in the United States and France for abstract, routine, and manual jobs. We used annual CPS US data and French Labor Force Surveys from 1983 to 2007. Total employment is then disaggregated by occupational group, as in Jaimovich & Siu (2020): Based on employment shares by task, job polarization seems pervasive in the United States and France, with a rising employment share of manual service jobs<sup>12</sup> and abstract jobs, along with a decrease in routine jobs. The share of routine employment has decreased continuously, with a fall of approximately ten percentage points in both countries since the early 1980s. The shares of abstract and manual jobs increased in both countries by approximately eight and two percentage points, respectively. The similar evolutions of occupational changes, when measured in employment shares, suggest that the TBTC story is relevant in both countries. We challenge this view.

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<sup>12</sup>In the paper, we use the term “service” as a shortcut for “service occupation”.

Figure 1: Employment Share by Task



Employment level by task divided by aggregate employment. US data from the Bureau of Labor Statistics, Current Population Survey, and French Labor Surveys. See Appendix A for details.

## 2.2 Divergent changes in aggregate and routine per-capita employment levels

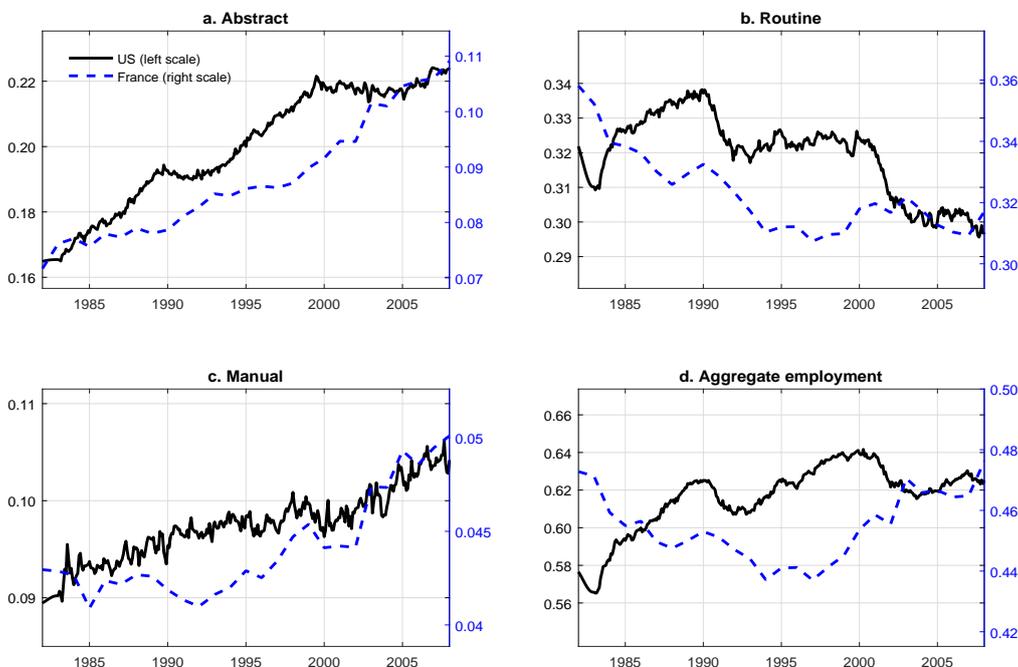
Panels a and c in Figure 2 display the per capita employment in abstract and manual jobs. Employment in these tasks in both countries displayed the same upward trend, with a flatter slope in the case of France.<sup>13</sup> We then focus on the differences across countries.

**Divergent evolutions of aggregate employment.** Aggregate per capita employment (defined as the number of all employed civilian non-institutionalized individuals aged 16

<sup>13</sup>The limited increase in manual employment share in both countries does not have the same meaning when changes in employment levels are taken into account. Given the rapid rise in US aggregate employment in the 1980s and 1990s, this limited increase in the share of manual jobs involves large labor reallocations from routine to manual jobs. The quasi-constancy of the share of manual employment seems to contradict the idea of polarization (Figure 1, panel c), but it must be interpreted in the context of increasing aggregate employment. Indeed, there is an increase in the number of manual jobs in the population (Figure 2, panel c), but at a much lower rate than that of abstract jobs. The increase in the supply of skilled workers makes this increase in the share of manual tasks even more significant. In contrast, the increasing share of workers in manual occupations in France might just mirror a mere mechanical effect of the fall in aggregate employment due to routine jobs: constant levels of jobs in manual tasks (Figure 2, panel c) are enough to lead to an increase in employment share (Figure 1, panel c).

years and over divided by the working age population)<sup>14</sup> has evolved very differently, with a striking rise in the United States and a downward trend in France until the mid-1990s followed by a rebound (Figure 2, panel d).

Figure 2: Per capita employment by task



Employment level by task divided by aggregate population. US data from the Bureau of Labor Statistics, Current Population Survey, and French Labor Surveys. See Appendix A for details.

**Divergent evolutions of routine per-capita employment.** The number of routine jobs in the population followed the opposite dynamics in the two countries (Figure 2, panel b). In the US, at the beginning of the sample period, routine per capita employment increased until the early 1980s *increased*. The decline in routine employment began in 1990. If "job polarization" refers to the decline in routine jobs, then US job polarization started in the early 1990s. Our findings on US data echo the pattern of US routine employment found in [Jaimovich & Siu \(2020\)](#). After the 1990s, in the United States, the falling share of routine jobs comes mainly from the increase in aggregate employment due to job creations in abstract and manual tasks.

In contrast, in France, from the early 1980s to the late 1990s, there has been a sharp decline in routine employment of about five percentage points, with a rebound in the late 1990s.

<sup>14</sup>This ratio is commonly referred to as the "employment rate." However, in the text, we refer to this ratio as "per capita employment," "employment level," or "employment," as opposed to the "employment share of task  $i$ ," defined as the number of employed individuals in task  $i$  divided by the total number of employed individuals.

The decrease in French routine employment share is the outcome of a fall in routine per capita employment, which leads to a decline in aggregate employment. In the late 1990s, per capita, routine employment in France rebounded: aggregate employment increased in France because routine per capita employment stabilized, abstract employment accelerated, and manual jobs started to increase.<sup>15</sup>

In Appendix M.1.1, a static search and matching model describes our identification strategy: if the dynamics of the US employment levels<sup>16</sup> allow to identify the common technology changes into both countries, given that the LMI are roughly stable in the US, then LMI must change in France in order to explain a job polarization phenomena in a context of employment decline.<sup>17</sup>

As long as the patterns in terms of employment shares for the US and France look very similar, the TBTC story seems to fit nicely with the occupational change in the US and France. However, patterns differ when looking at aggregate and occupational employment (in terms of the total working-age population). This raises the question of the relevance of a unique story for these two countries, particularly the TBTC story, that changes the distribution of occupations but also reduces firm costs and thus increases labor demand for abstract and manual jobs.

### 3 The model

Structural changes characterize both countries. We extend Autor & Dorn (2013)'s model to account for the impact of changes in TBTC, LMIs, and the supply of skilled labor.

#### 3.1 Assumptions

**Labor supply.** Skilled and unskilled workers supply labor. The skilled workers are homogeneous and perform abstract tasks ( $a$ ). Unskilled workers differ in their abilities,  $\eta$ . They can be employed in either routine tasks ( $r$ ) or manual tasks ( $m$ ). They had homogeneous (heterogeneous) skills in performing manual (routine) tasks.<sup>18</sup> For simplicity, we assume that skilled workers perform abstract tasks, whereas unskilled workers perform routine or manual tasks. This segmentation of labor is supported by data on educational

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<sup>15</sup>We show in Appendix B that divergent evolutions of routine employment are the main driver for the divergent employment levels across countries.

<sup>16</sup>Notice that information on employment shares is sufficient for the US.

<sup>17</sup>The static model suggests that, if LMIs remain stable in France, the identified common technological change does not lead to job polarization in France.

<sup>18</sup>This assumption is also in Autor & Dorn (2013) and states that blue-collar workers differ in performing their tasks, while jobs such as janitors (non-routine manual services) rarely differ in terms of productivity.

attainment by task.<sup>19</sup> An upward exogenous trend in educational attainment shifts the relative labor supply of skilled labor  $L_a \in (0; 1)$ .<sup>20</sup>

**2-sector economy with search and matching frictions.** The economy comprises two sectors. The service sector employs only unskilled labor in manual tasks,  $n_m$ . The goods sector uses three inputs: (i) skilled workers in abstract jobs  $n_a$ , (ii) unskilled workers employed in routine tasks  $n_r$ , and (iii) computer capital  $K$ . Technological change is captured by a downward trend in the price of computers,  $p_k$ . Search and Matching (SaM) frictions are introduced to include trends in LMIs that account for changes in labor market regulations.

**Occupational mobility.** In this model, mobility across task groups goes through unemployment. What is the impact on employment of this restrictive view of workers' mobility? To answer this question, we compute US counterfactual employment levels by task predicted by a counterfactual worker flow matrix that omits job-to-job transitions consistent with the restrictions imposed by our model. The results show that the counterfactual employment levels by task are very close to the observed data, suggesting that the model's mobilities capture the key features of employment levels by task.<sup>21</sup> Unemployed workers previously occupied on a routine job can search for a routine job (they are called "stayers" as they remain in the routine labor market). These unskilled workers can also change their occupations. They are called "movers" and pay mobility costs in this case. We will divide movers into two groups: "new movers" who just switched occupations and "old movers" who switched occupations and got a manual job but are still new in the manual labor market. In section 3.3, we clarify mobility costs and describe "movers."

## 3.2 Labor market frictions

Labor markets are characterized by search and matching frictions *à la* Mortensen & Pissarides (1994). There is a labor submarket for each occupation and each ability level  $\eta$  in routine jobs. Within each submarket, workers meet firms. This meeting process is random. There is no on-the-job search. The number of hires per period,  $M$ ,<sup>22</sup> in each segment of the labor market (abstract, routine for each ability level  $\eta$ , and all manual labor), is determined by constant-returns-to-scale matching function  $M_i = \Upsilon_i v_i^\psi u_i^{1-\psi}$  for task  $i = a, m, m^o$  and  $M_i(\eta) = \Upsilon_i v_i(\eta)^\psi u_i(\eta)^{1-\psi}$  for  $i = r, m^n$ , where  $\Upsilon_i > 0$  is a scale parameter that measures the efficiency of the matching function,  $v$  is the number of vacancies and  $u$  number

<sup>19</sup> Appendix C reports educational attainment by in US and French data.

<sup>20</sup>The skill composition is exogenous because educational choices are beyond the scope of this study.

<sup>21</sup>See Appendix D for more details on these counterfactuals.

<sup>22</sup>For parsimony, we drop the time subscript for contemporaneous variables. Expected variables are assigned a subscript +1.

of unemployed workers at time  $t$  in each submarket. Then,  $0 < \psi < 1$  is the elasticity of the matching function with respect to vacancies. A vacancy is filled with the probability  $q_i = M_i/v_i$ , and the job-finding probability per unit of worker search is  $f_i = M_i/u_i$ . Labor market tightness is measured by ratio  $v_i/u_i$ . A job can be destroyed for exogenous reasons at a rate  $s_i$ . Endogenous separation occurs in our model when jobs become unprofitable. They reach a scrapping time, the date after which the firm shuts down.

### 3.3 Workers' value functions, occupational choices

For abstract ( $a$ ) and routine ( $r$ ) workers with ability  $\eta$ , the value functions are

$$W_a = (1 - \tau^w)w_a + \beta[(1 - s_a)W_{a,+1} + s_a U_{a,+1}] \quad (1)$$

$$W_r(\eta) = (1 - \tau^w)w_r(\eta) + \beta \left[ \begin{array}{l} (1 - l_r(\eta))(1 - s_r)W_{r,+1}(\eta) \\ +(1 - (1 - l_r(\eta))(1 - s_r)) \max\{U_{r,+1}(\eta), U_{m,+1}^n(\eta)\} \end{array} \right] \quad (2)$$

where  $\tau^w$  denotes the tax rate for social contributions,  $w_a$  and  $w_r(\eta)$  are wages, and  $U$  is the value function for the different unemployed workers. The occupational choice is captured by the term  $\max\{U_{r,+1}(\eta), U_{m,+1}^n(\eta)\}$  when unemployed (see Equations (8) and (10)). For unskilled workers, the  $\eta$ -type matters: workers' endogenous occupational choice leads them to choose manual jobs for those with  $\eta < \tilde{\eta}$  and routine jobs for those with  $\eta \geq \tilde{\eta}$ .  $\tilde{\eta}$  is endogenous. As more routine workers switch to manual occupations,  $\tilde{\eta}$  increases endogenously over time.

For manual workers, we distinguish between three types of workers: experienced manual worker ( $W_m$ ), inexperienced manual worker entitled to an unemployment benefit indexed in the wage of a routine job ( $W_m^n(\eta)$ , "new mover") and an inexperienced manual worker entitled to an unemployment benefit indexed in the wage of a manual job ( $W_m^o$ , "old mover"). The value functions are as follows:

$$W_m = (1 - \tau^w)w_m + \beta[(1 - s_m)W_{m,+1} + s_m U_{m,+1}] \quad (3)$$

$$W_m^o = (1 - \tau^w)w_m^o + \beta\lambda[(1 - s_m)W_{m,+1} + s_m U_{m,+1}] \\ + \beta(1 - \lambda)[(1 - s_m)W_{m,+1}^o + s_m U_{m,+1}^o] \quad (4)$$

$$W_m^n(\eta) = (1 - \tau^w)w_m^n(\eta) + \beta\lambda[(1 - s_m)W_{m,+1} + s_m U_{m,+1}] \\ + \beta(1 - \lambda)[(1 - s_m)W_{m,+1}^n(\eta) + s_m U_{m,+1}^o], \quad (5)$$

where  $w_m$ ,  $w_m^n(\eta)$  and  $w_m^o$  denote the wages of each manual worker type. For unemployed

workers, the value functions are

$$U_a = z_a + \beta[(1 - f_a)U_{a,+1} + f_a W_{a,+1}] \quad (6)$$

$$U_m = z_m + \beta[(1 - f_m)U_{m,+1} + f_m W_{m,+1}] \quad (7)$$

$$U_r(\eta) = z_r(\eta) + \beta[(1 - f_r(\eta)) \max\{U_{r,+1}(\eta), U_{m,+1}^n(\eta)\} + f_r(\eta)W_{r,+1}(\eta)] \quad (8)$$

$$U_m^o = z_m + \beta[(1 - f_m^o)U_{m,+1}^o + f_m^o W_{m,+1}^o] \quad (9)$$

$$U_m^n(\eta) = z_r(\eta) + \beta[(1 - f_m^n(\eta))U_{m,+1}^n(\eta) + f_m^n(\eta)W_{m,+1}^n(\eta)] \quad (10)$$

If routine workers switch occupations when unemployed (Equation (2)), they join the pool of unemployed workers looking for manual jobs. Within this pool, we must distinguish between these three groups. The first group consists of "experienced" workers fired from a manual job. (Equation (7)) and receive unemployment benefits  $z_m$ . The second group consists of "new movers" (inexperienced manual workers) who joined the pool after being fired from a routine job. They receive unemployment benefits based on their past routine occupation and ability  $\eta$  ( $z_r(\eta)$  in Equation (10)), which affects their bargained wages when they find jobs in manual sector ( $w_m^n(\eta)$  in equation (5)). The third group consists of "old movers," who are routine workers who switched to manual jobs, had access to one manual job, got fired from this manual job, and now receive unemployment benefits  $z_m$  in Equation (9). Their bargained wage  $w_m^o$  does not depend on their ability level,  $\eta$ . "New movers" and "old movers" are not as productive as experienced manual workers (see Section 3.5., Equation (16)): This lower productivity of inexperienced workers is a part of the mobility costs.

For tractability, we use a directed search such that each type of unemployed worker in the pool (Equations (7), (9), and (10)) has the corresponding job value (Equations (3), (4), and (5)): All movers, whether old or new, can obtain regular manual jobs with probability  $\lambda$  in Equations (4) and (5), respectively.  $\lambda$  captures the probability of getting experience at the job and regulates the pace of learning. This learning process applies to routine workers who switched occupations and are not fully informed about the new tasks in the manual sector. This is consistent with the view that an important component of human capital is task and occupation-specific. (Poletaev & Robinson (2008), Kambourov & Manovskii (2009), and Cortes (2016)), which is lost by the worker who switches tasks.

### 3.4 Good-producing firm

We assumed the same production function as in Autor & Dorn (2013). However, because of wage bargaining for skilled and unskilled workers, we must preserve the constant return to scale in the wage bargaining process (see Appendix F.1). As a result, we present the good-producing firm using two separate inputs:  $Z_1$  paid at price  $p_{z1}$  is produced by abstract workers  $L_a$ , and  $Z_2$  paid at price  $p_{z2}$  is the aggregate of unskilled labor and capital. The

good-producing firm's problem is:

$$\Pi_g = \max \{Y_g - p_{z1}Z_1 - p_{z2}Z_2\} \quad \text{s.t.} \quad Y_g \leq AZ_1^\alpha Z_2^{1-\alpha}$$

with  $0 < \alpha < 1$ . The behavior of firms producing intermediate good  $Z_1$  is

$$\Pi_{z1} = \max \left\{ p_{z1}Y_{z1} - (1 + \tau_h^f)w_a n_a - c_a v_a + \beta \Pi_{z1,+1} \right\} \quad \text{s.t.} \quad \begin{cases} Y_{z1} \leq n_a \\ n_{a,+1} = (1 - s_a)n_a + q_a v_a, \end{cases}$$

where  $\tau_h^f$  denotes the payroll tax rate for the high-skilled workers. For high-tech firms, production function  $Y_{z1}$  is a linear function and firms pay a search cost to hire new workers:  $c_a$  is the cost of posting a vacancy for an abstract job, given that  $v_a > 0$ . The behavior of firms producing intermediate goods  $Z_2$  is

$$\Pi_{z2} = \max \left\{ p_{z2}Y_{z2} - p_K K - (1 + \tau_l^f) \sum_{\eta} w_r(\eta)(1 - l_r(\eta))n_r(\eta) - c \sum_{\eta} v_r(\eta) + \beta \Pi_{z2,+1} \right\},$$

$$\text{s.t.} \quad Y_{z2} \leq \left[ \left( (1 - \mu) \sum_{\eta^S} \eta (1 - l_r(\eta))n_r(\eta) \right)^\sigma + (\mu K)^\sigma \right]^{\frac{1}{\sigma}} \quad (11)$$

$$n_{r,+1}(\eta) = (1 - l_r(\eta))(1 - s_r)n_r(\eta) + q_r(\eta)v_r(\eta) \quad (12)$$

$$l_r(\eta) \leq 1 \quad (\lambda(\eta)) \quad (13)$$

$$l_r(\eta) \geq 0 \quad (\nu(\eta)) \quad (14)$$

$$v_r(\eta) \geq 0 \quad (\mu(\eta)), \quad (15)$$

where  $Y_{z2}$  denotes intermediate good production,  $\tau_l^f$  is the payroll tax rate for low-skilled workers,  $K$  is the stock of computers,  $p_k$  is the price,  $c$  is the cost of posting a vacancy, and  $l_r(\eta)$  is the fraction of fired workers (constrained by Equations (13) and (14)). As in [Autor & Dorn \(2013\)](#), TBTC is modeled as an exogenous fall in  $p_k$ . Equation (11) describes the production functions with  $\sigma$  and  $\mu \in (0, 1)$ . The elasticity of substitution between routine labor and computer capital is  $\frac{1}{1-\sigma}$  and, by assumption, is greater than 1. Equation (12) captures the evolution of labor stock given the probability  $q$  of filling a vacancy  $v$  and the endogenous rate of fired workers  $l$ . The marginal productivity of one  $\eta$ -type job does not change with the  $n_r(\eta)$  level. When the discounted sum of expected profits for this type of job becomes negative, all  $\eta$ -type workers are fired. Thus, we can deduce that  $l_r(\eta) \in (0; 1)$ . This firing decision allows us to define the scrapping time for  $\eta^S$ -type workers (see Appendix F.1); that is, the date at which endogenous separation occurs because the job becomes unprofitable ( $\frac{\partial \Pi_{z2}}{\partial n_r(\eta^S)} = 0$ ). Finally, Equation (15) allows us to distinguish between the two regimes: the first is profitable for the firm to replace exogenous separations ( $v_r(\eta) > 0$ ), and the second, where it is optimal to voluntarily reduce the workforce ( $v_r(\eta) = 0$ ).

### 3.5 Service-producing firm

The representative firm's problem is:

$$\begin{aligned} \Pi_s &= \max \left\{ \begin{aligned} &p_s Y_s - (1 + \tau_l^f) \left( w_m n_m + \sum_{\eta} w_m^n(\eta) n_m^n(\eta) + w_m^o n_m^o \right) \\ &- c V_m - c \sum_{\eta} v_m^n(\eta) - c v_m^o + \beta \Pi_{s,+1} \end{aligned} \right\}, \\ \text{s.t. } Y_s &\leq A_s \left( n_s + \delta \sum_{\eta} n_m^n(\eta) + \delta n_m^o \right) \end{aligned} \quad (16)$$

$$n_{m,+1} = (1 - s_m) n_m + q_m v_m + (1 - s_m) \lambda \sum_{\eta} n_m^n(\eta) + (1 - s_m) \lambda n_m^o \quad (17)$$

$$n_{m,+1}^o = (1 - s_m)(1 - \lambda) n_m^o + q_m^o v_m^o \quad (18)$$

$$n_{m,+1}^n(\eta) = (1 - s_m)(1 - \lambda) n_m^n(\eta) + q_m^n(\eta) v_m^n(\eta), \quad (19)$$

where  $A_s > 0$  is the relative productivity parameter (with respect to the good sector). The service production function (Equation (16)) uses low-skilled workers, including new and old movers:  $n_m$ ,  $n_m^n(\eta)$ , and  $n_m^o$ . For simplicity, we assume that  $v_m, v_m^o, v_m^r(\eta) > 0$  and that there are no firings. The restrictions are always satisfied at the equilibrium.  $\delta$  captures a lower productivity of workers who switched occupations and were not fully familiar with Manual Tasks.  $\delta$  captures part of the mobility cost of switching occupations.  $p_s$  denotes the endogenous relative price of services relative to goods. This is determined at general equilibrium.

### 3.6 Wage setting

The wage is set to maximize the Nash criterion  $w_{Nash} = \operatorname{argmax}_i J_i^{1-\gamma} (W_i - U_i)^\gamma$ , with  $i = a, r, s, m, m^n$ , where  $J$  is the marginal value of a match for a firm and  $W - U$  the marginal worker's surplus from the match.  $\gamma$  denotes the worker's share of the job's value (that is, the worker's bargaining power). In the Diamond-Mortensen-Pissarides model, Nash bargaining gives the *WS* (Wage-Setting) curve: the wage is highly flexible and responds to changes in productivity and labor market tightness; however, there is a minimum wage (MW) for each task that can disconnect wages from productivity. For all jobs, we have the following Wage-Setting rule:  $w = \max\{MW, w_{Nash}\}$ , where workers consider outside opportunities for mobility to other jobs. <sup>23</sup>

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<sup>23</sup>See Appendix F.3 provides a complete description of the wage equations.

### 3.7 Household preferences and general equilibrium

We have several households in the model, one for each type of job and unemployment. All households have the same preferences. Their consumption basket  $C = [\nu C_g^\rho + (1 - \nu)C_s^\rho]^{\frac{1}{\rho}}$  includes goods  $C_g$  and services  $C_s$ , where  $\rho \in [0, 1]$  and  $\frac{1}{1-\rho}$  are the elasticity of substitution between goods and services, and  $P = \left[ \nu^{\frac{1}{1-\rho}} + (1 - \nu)^{\frac{1}{1-\rho}} (p_s)^{\frac{\rho}{\rho-1}} \right]^{\frac{\rho-1}{\rho}}$  is the consumer price index. The budget constraint for each worker is  $PC = I$  with income  $I \in \{w_a, w_r(\eta), w_m, w_m^o, w_m^n, z_a, z_m, z_r(\eta), v\}$ . The optimal demand functions are<sup>24</sup>

$$p_s = \frac{1 - \nu}{\nu} \left( \frac{C_g}{C_s} \right)^{1-\rho} \Rightarrow \begin{cases} C_g &= \nu^{\frac{1}{1-\rho}} \left( \frac{1}{P} \right)^{\frac{1}{\rho-1}} \frac{I}{P} \\ C_s &= (1 - \nu)^{\frac{1}{1-\rho}} \left( \frac{p_s}{P} \right)^{\frac{1}{\rho-1}} \frac{I}{P} \end{cases} \quad (20)$$

This model captures several endogenous phenomena that affect routine employment. Routine workers, after exogenous separation, can switch to manual jobs depending on job prospects in manual tasks. Firms can stop hiring routine low-productivity workers ( $v_r(\eta) = 0$ ). Routine jobs are destroyed when they become unprofitable (scrapping time). Each of these elements depends on the expected employment opportunities and profits, which are affected by TBTC and LMIs. In addition, the general equilibrium leads TBTC to increase the relative price of services, inducing a rise in the marginal profits of manual jobs. Consequently, the increase in labor costs induced by shifts in LMIs can be absorbed (no scrapping time in this case). This may not be the case for routine jobs because their average productivity declines, which magnifies the rise in labor costs induced by shifts in LMIs. Therefore, quantitative analysis is necessary to assess the relative importance of these different mechanisms.

## 4 Quantitative analysis

### 4.1 Calibration

First, the trends of exogenous forcing variables must be determined. Second, a strategy that helps identify each model parameter must be implemented. This leads us to choose which parameters are common to both countries and which are country-specific. Finally, we define the moments targeted by the model in the calibration procedure. Given that our objective is to capture the non-stationary process described by employment *paths* over the sample, parameter values must make the model mimic the data *over time*, not simply historical (steady-state) averages (as is usually done in the literature). However, this is a challenging task.

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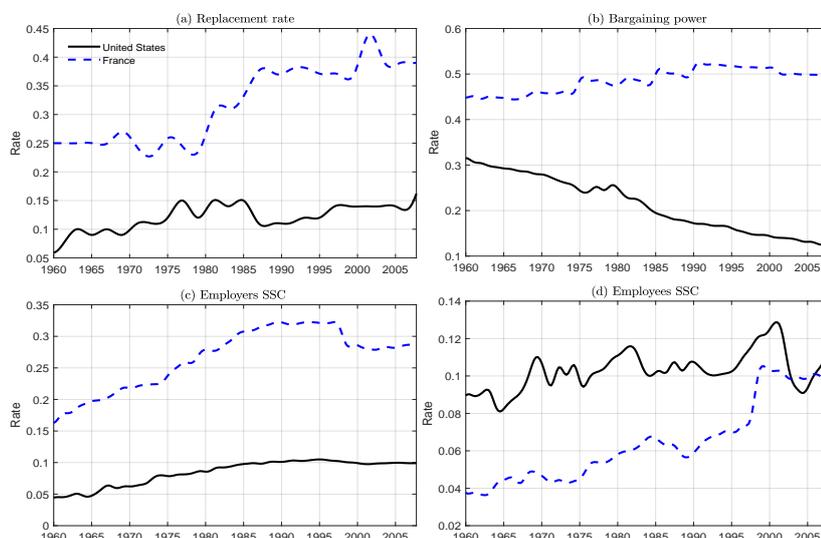
<sup>24</sup>For the sake of brevity, market clearing is reported in Appendix F.5.

### 4.1.1 Exogenous forcing variables

We consider three exogenous forces: LMI trends, the price of capital that drives TBTC, and the share of skilled workers in the population driven by increased educational attainment.

**Divergent shifts in LMIs: Rising flexibility in the United States, and rising rigidity in France.** The observed shifts in LMIs (Figures 3 - 4) were directly incorporated into the model as exogenous changes. After the early 1980s, the US and France were charac-

Figure 3: Labor market institutions I. *Replacement rate, worker bargaining power, employers' and employees' social security contribution rates*



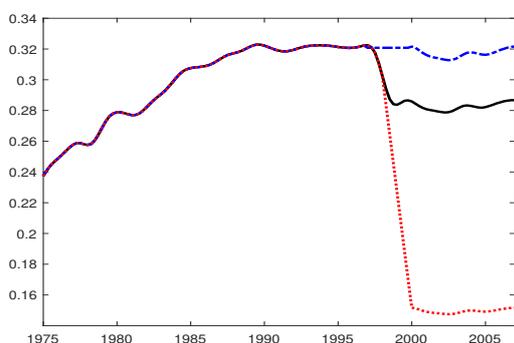
“Replacement rate” is the unemployment benefits replacement rate; “bargaining power” is workers’ bargaining power; “employer SSC” is employer social security contribution (payroll tax); and “worker SSC” is worker social security contribution. See Appendix G for data sources.

terized by opposite changes in the replacement rate and workers’ bargaining power: they both increased in France, whereas in the United States, the replacement rate was stable, and workers’ bargaining power declined. The two bottom panels of Figure 3 also underline the contrasting evolution of labor tax rates: until the mid-1990s, these tax rates largely increased in France, whereas in the US, they were stable over the entire period. Figure 3 also shows that the French payroll tax rate ("employer SSC") fell sharply in the mid-1990s. During the 1990s, tax exemptions on employer-paid payroll taxes ( $\tau^f$ ) were introduced in France to lower labor costs. This policy aimed to offset the negative impact of minimum wage legislation on employment without lowering employee wages. The subsidy increased dramatically in October 1995 and September 1996 (hereafter PTE or payroll tax exemptions). We have no information on average payroll tax by wage. Then, we consider the

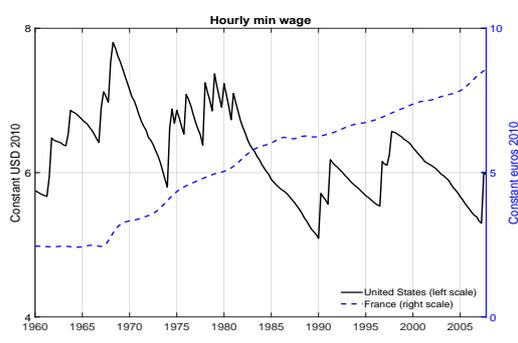
following calibration: First, the payroll tax rate is the same for all jobs (abstract, routine, and manual) until the beginning of the PTE and is identified using the data in Figure 3. Second, at the beginning of PTE, the payroll tax for abstract jobs is fixed, then adjusted in the same proportion as that described in Figure 3. Third, for routine and manual jobs, at the beginning of the PTE, payroll tax falls linearly by 50% (it reaches a 50% decline at the end of the tax exemptions, which is consistent with the actual French reform). It is then adjusted in the same proportion as that reported in Figure 3. Panel (i) of Figure 4 shows the calibrated payroll tax.<sup>25</sup> Finally, panel (ii) of Figure 4 shows that the two countries

Figure 4: Labor market institutions II (Data source: See Appendix G)

(i) French payroll tax adjusted for tax exemption



(ii) The real minimum wage



experienced very different patterns of changes in minimum wage (MW) over the period; in France, we observe a continuous increase, whereas, in the United States, it remains stable. It is important to note that the rise in the French MW began in the late 1960s, before the fall in the price of capital.

**Capital price and share of skilled workers.** Exogenous variables (price of capital and educational attainment) follow a process such that  $x(t) = x(T) + (x(0) - x(T)) \exp(-\vartheta_x(t - t_{x0})^2)$  if  $t \geq t_{x0}$ , and  $x(t) = x(0)$  if  $t < t_{x0}$ , for  $x = p_k, L_a$  in the US and France.  $T$  denotes the sample length.  $x(0)$  and  $x(T)$  for  $x = p_k, L_a$  are the initial and terminal values, respectively.  $\vartheta_x$  for  $x = p_k, L_a$  corresponds to the speed at which the variable adjusts to its final value.  $t_{x0}$  is the date on which the variable starts to evolve. Hence, for each of these two processes, four parameters  $\{t_{x0}, x(0), x(T), \vartheta_x\}$  must be calibrated. In contrast to the LMIs, we chose to calibrate these parameters using model restrictions. The resulting paths can then be compared to observed data, such as the price of investment goods, thus

<sup>25</sup>We make this simplifying assumption in order to keep the model tractable. PTE applies only to wages that lie below 1.33 times the minimum wage. In our simple calibration, PTE applies to wages above the upper bound of 1.33 minimum wage. The most productive routine workers earn these wages. We argue that this approximation has little consequence for our results because by lowering labor costs, PTE also tends to preserve routine jobs at the bottom of the productivity distribution. See [Cheron et al. \(2008\)](#) for an evaluation of this reform.

providing an opportunity to test the model's likelihood.<sup>26</sup>

#### 4.1.2 Parameter choices

The calibration was quarterly. We consider the following empirical targets.

$$\Psi_T = \left\{ n_{a,i}(0), n_{r,i}(0), n_{m,i}(0), n_{a,i}(T), n_{r,i}(T), n_{m,i}(T), E_i[n_a], E_i[n_r], E_i[n_m] \right\}_{i=US,F},$$

where  $\dim(\Psi_T) = 18$ ,  $n$  refers to the employment level,  $i$  denotes the country, and  $a, r, m$  denotes the task (abstract, routine, and manual). The beginning and end of the sample are denoted (0) and (T).  $E_i[n]$  refers to average employment over the entire sample.

The number of model parameters is greater than  $\dim(\Psi_T) = 18$ . Restrictions are required for a just-identified system. First, some parameters are considered common to all countries. These parameters include preferences and technology:

$$\Phi_1 = \{\beta, \rho, \nu, \sigma, \mu, \alpha, \eta, \bar{\eta}, A, A_s, \delta, \lambda, t_{pk0}, p_k(0), \vartheta_{pk}, p_k(T)\} \text{ where } \dim(\Phi_1) = 16.$$

Second, the labor market parameters

$$\Phi_2 = \{\psi, \Upsilon_a, \Upsilon_r, \Upsilon_m, s_a, s_r, s_m, c_a, c\}_{US,F} \text{ where } \dim(\Phi_2) = 18$$

are country-specific. Third, technological change and drift in the supply of skilled labor are also country-specific:

$$\Phi_3 = \{t_{La0}, L_a(0), \vartheta_{La}, L_a(T)\}_{US,F} \text{ where } \dim(\Phi_3) = 8.$$

Therefore, we obtained 42 parameters for the 18 targets.

**Restrictions.** To identify parameters, it is necessary to introduce  $42 - 18 = 24$  restrictions. Using external information, we calibrate  $\Phi_1^c = \{\beta, \mu, \nu\} \in \Phi_1$ , with  $\dim(\Phi_1^c) = 3$ ,  $\Phi_2^c = \{\psi, s_a, s_r, s_m, c_a, c\}_{US,F} \in \Phi_2$ , with  $\dim(\Phi_2^c) = 12$  and  $\Phi_3^c = \{L_a(0), L_a(T)\}_{US,F} \in \Phi_3$ , with  $\dim(\Phi_3^c) = 4$ . These 19 restrictions lead to the values reported in Table 5 in Appendix H.

We assume that changes in the price of capital begin in  $t_{pk}(0) = 1975$  whereas the changes in the education process begin in  $t_{La}(0) = 1960$  in the United States and  $t_{La}(0) = 1970$  in France.<sup>27</sup> Therefore, we have  $19 + 3 = 22$  restrictions.

<sup>26</sup>In section 4.1.2, we will choose different  $t_{x0}$  (for  $x = p_k, L_a$ ) for the 2 countries. This choice is made for identification purposes and is validated after the estimation procedure by comparison with the data.

<sup>27</sup>These starting dates are chosen because they correspond to the product launch of the first IBM personal computer, and the take-off of the number of students in universities. Karabarbounis & Neiman (2014) also reported a sharp decline in the price of investment goods starting in 1975.

The last two restrictions are as follows: (i) The efficiency of the labor market of high-skill workers is the same across countries ( $\Upsilon_{a,US} = \Upsilon_{a,F} \equiv \Upsilon_a$ ), and (ii) normalized to unity in the initial period ( $p_k(0) \equiv 1$ ). Hence, the model was just-identified. The solution to our non-stationary and non-linear model<sup>28</sup> can thus provide calibrated parameters based on the model restrictions. Table 1 summarizes the solution for the 18 unknown parameters, allowing us to minimize the distance between the targets and their theoretical counterparts.

Table 1: Parameter values based on empirical targets

Preferences	$\rho$					
	0.65					
Learning	$\delta$	$\lambda$				
	0.425	0.025				
Technology	$A$	$A_s$	$\sigma$	$\alpha$	$\eta$	$\bar{\eta}$
	3.5	0.3	0.74	0.3	0.48	1.44
Labor market	$\Upsilon_a$	$\Upsilon_{r,US}$	$\Upsilon_{r,F}$	$\Upsilon_{m,US}$	$\Upsilon_{m,F}$	
	0.11	0.09	0.129	0.067	0.045	
Structural changes	$\vartheta_{pk}$	$p_k(T)$	$\vartheta_{La,US}$	$\vartheta_{La,F}$		
	0.00025	0.475	0.00007	0.00005		

Note that the elasticity of substitution in the production between capital and routine workers, ( $\frac{1}{1-\sigma}$ ), is larger than the elasticity of substitution in consumption between goods and services ( $\frac{1}{1-\rho}$ ). As stressed in [Autor & Dorn \(2013\)](#), this ensures that the polarization process occurs: The falling price of capital causes routine workers to be replaced by capital. Low-skill labor flows from routine to manual jobs. Consumption complementarity between goods and services ensures that the demand for manual tasks increases with the demand for goods.

The other unknown parameters revealed by this calibration are those related to the opportunity costs of moving from routine to manual job occupations. First, we find that the productivity loss during the transition towards an experienced manual job is 42.5%. This roughly represents a wage loss of 7.3% for an American worker, and 25% for a French worker. This significant difference is mainly explained by the low bargaining power of US workers, who capture a low share of productivity. These wage losses are persistent because our estimate of  $\lambda$  means it takes ten years for a displaced routine worker to become an experienced manual worker. These large losses are consistent with the estimates provided by [Jacobson et al. \(1993\)](#), who find that, when high-tenure workers separate from distressed firms, their long-term losses average 25% per year, which was confirmed by a more recent study by [Couch & Placzek \(2010\)](#) that shows that wage falls are initially more than 30% and six years later, as much as 15%.<sup>29</sup>

<sup>28</sup>The algorithm for the model solution is presented in Appendix I.

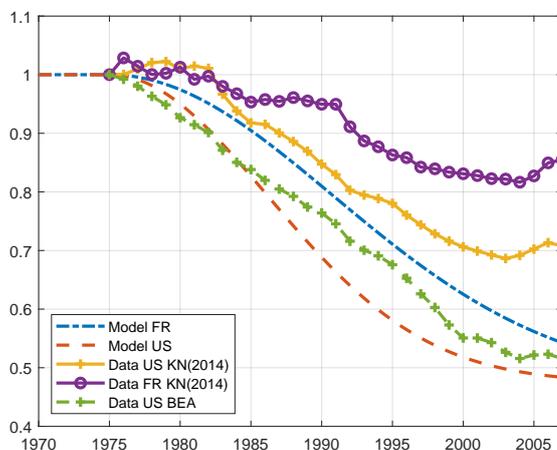
<sup>29</sup>[Cortes \(2016\)](#) shows that workers who switch from routine to manual jobs have significantly lower wage growth than stayers over short to medium-run horizons (around 14% lower over two years). These measures of wage growth are not directly comparable to our estimated wage level differences but also suggest significant wage losses for US workers.

## 4.2 Model fit

### Identified paths of Labor Supply and TBTC are consistent with external data.

The structural changes revealed by our model were consistent with external information. First, our calibrated model identifies an increase in educational attainment corresponding to a rise in the share of high-skilled workers from 18 to 24%, which is in line with US Census data indicating that the share of American college graduates has increased from 15% to 28% between 1975 and 2008. Similarly, the estimated educational attainment in France was consistent with the data. Between 1975 and 2005, the model estimation yields a rise in French college graduates from 9% to 16%, consistent with the French census data (7% and 18%).

Figure 5: Investment prices: estimation based on model-based data



Estimated investment price from the model in France (dash-dot) and in the US (dash). Data: price index based on US data from BEA (dash+), from Karabarounis & Neiman (2014) (+); French data from Karabarounis & Neiman (2014) (o). 1975-2007.

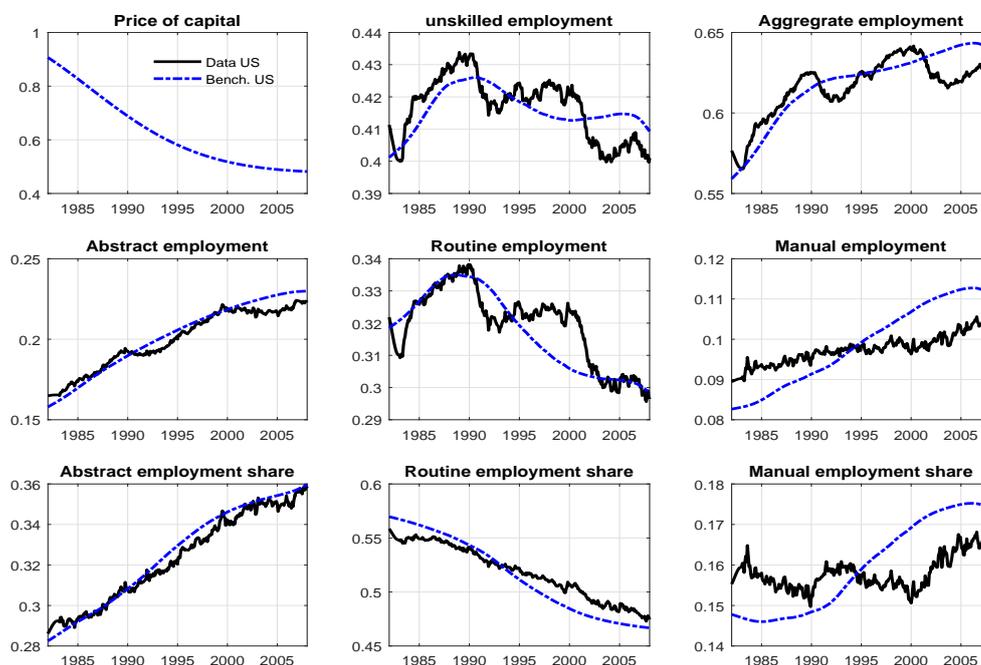
Second, we identify a shift in the price of capital ( $p_k$ ) interpreted as the source of TBTC. Figure 5 reports our estimation of this crucial structural change and compares it with the observed investment price.<sup>30</sup> The estimated price change  $p_k$  and relative price of investment goods from Karabarounis & Neiman (2014) display a very similar trend. In the model and data, the investment price has fallen dramatically since the mid-1970s, with a gradual decrease at the end of the sample. In addition, in the data as in our model, the decline in the price of investment goods is steeper in the US than in France. The gap between the two countries is roughly similar in magnitude in the model and data. These results make us confident in identifying the structural changes identified by our calibrated model.

**Employment dynamics by tasks.** Figures 6 and 7 summarize the model's predictions with regard to aggregate employment levels (for the total population and unskilled workers)

<sup>30</sup>See Appendix J for further details on the data.

and employment shares across occupational groups. For the US (Figure 6), the model

Figure 6: Employment levels and shares. *US*

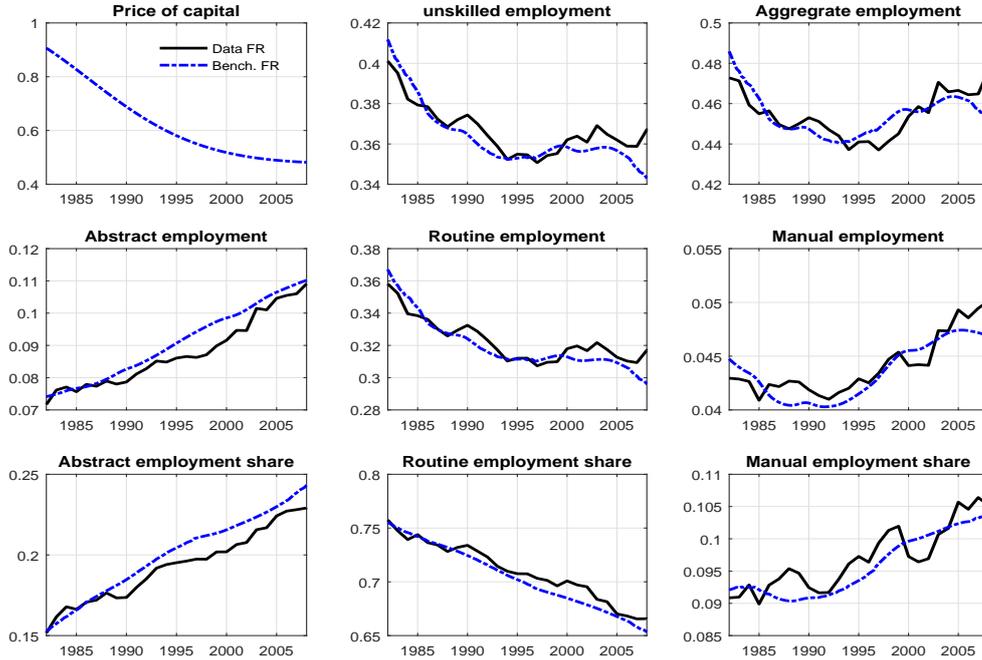


matches the aggregate upward trend and the downward trend for unskilled employment, measured in the model as the sum of routine and manual jobs. It should be noted that the model captures the hump-shaped behavior of per capita routine employment at the beginning of the sample. This hump shape is not targeted during the calibration process. These non-linear employment dynamics in routine US jobs offer an interesting test for the model's fit.

The model can also capture the fall in the French employment level until the mid-1990s and its subsequent rebound (Figure 7). This increased the employment of unskilled workers, which was explained by a stop in the decline in routine jobs and an increase in manual jobs. This rebound in per capita routine employment in France was not targeted in the calibration process. This non-linear employment dynamics in French unskilled jobs (manual and routine) in the late 1990s offers an interesting test for the model's fit.

In the model, the differences across employment by task are driven by differences in the responses of hiring decisions to exogenous changes (TBTC, LMI, etc...). Thus, when abstract and manual jobs become more profitable, their degree of tightness increases, whereas that of routine jobs declines. In Appendix E, we compute US workers' transitions across labor market states (employed in a given task, unemployed, not in the labor force). Since French quarterly labor flows cannot be computed before 2003, we focus on US labor flows. We

Figure 7: Employment levels and shares. *France*

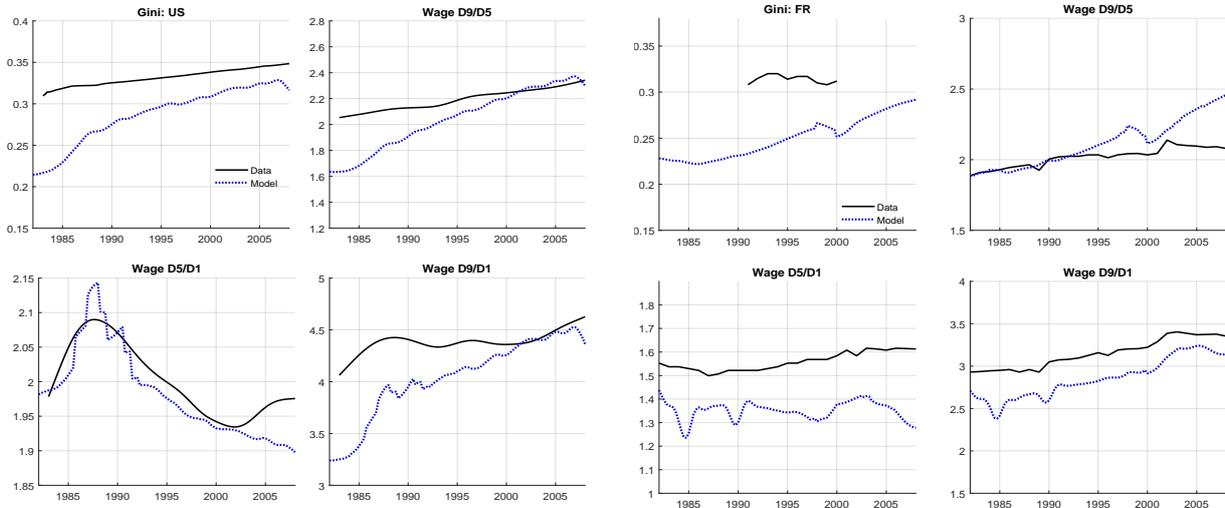


then compare the model fit with the data. The model captures the rising trend in the job finding rate of abstract jobs, as well as the hump-shaped behavior of the job finding rate of routine jobs in the 1980s and early 1990s. However, the model under-estimate these changes. The model also captures the lack of trend in separations of abstract and routine jobs, but fails to capture the slowing down of separation of manual jobs found in the US data. Further research is needed to investigate the fall in separations in US manual jobs. Finally, we perform in Appendix E a counterfactual experiment that suggests that the model can capture 90% of the rise in US manual jobs after the mid 1990s.

**Wage inequalities.** The employment dynamics generated by our model are consistent with the external information on the evolution of wage inequalities in both countries. Figure 8 shows the model’s performance in terms of wage inequality. The model predictions are compared with the data.<sup>31</sup> The model appears rather good at capturing rising wage inequality in the US and is able to capture a flatter trend in inequality in France. In addition, the model captures the average Kaitz index (the ratio of the minimum wage to average wage) in each economy (over the period 1980-2007, for France, 59% in the data versus 56% in

<sup>31</sup>The data source is CPS-MORG in the US, based on our calculations, real hourly wage. In France, we cannot use the French LFS because wages in the survey are after-tax earnings, while wages from the model are labor costs. Given the importance of labor taxes in France, the wages from LFS and the model cannot be compared. For the data, we then use wages as computed by [Bozio et al. \(2020\)](#), who report wage inequalities when wages are computed as labor costs.

Figure 8: Wage inequality: US and France



US data: CPS-MORG. French data: [Bozio et al. \(2020\)](#) and Gini from [Piketty \(2001\)](#)

the model; in the US, 34% in the data versus 33% in the model), as well as the aggregate fraction of workers paid at the minimum wage (over the period 1980-2007, for France, 14% on average in the data versus 12% in the model). In the US, 8% of the data versus 9% in the model.

## 5 Telling different stories of job polarization

In this section, we perform counterfactual simulations to determine the role of each exogenous trend (TBTC and LMI) in accounting for the job-polarization process. The benchmark model implications are compared with those obtained when one of the exogenous trends is set at a constant level (its 1975 value, instead of evolving as described in Section 4).

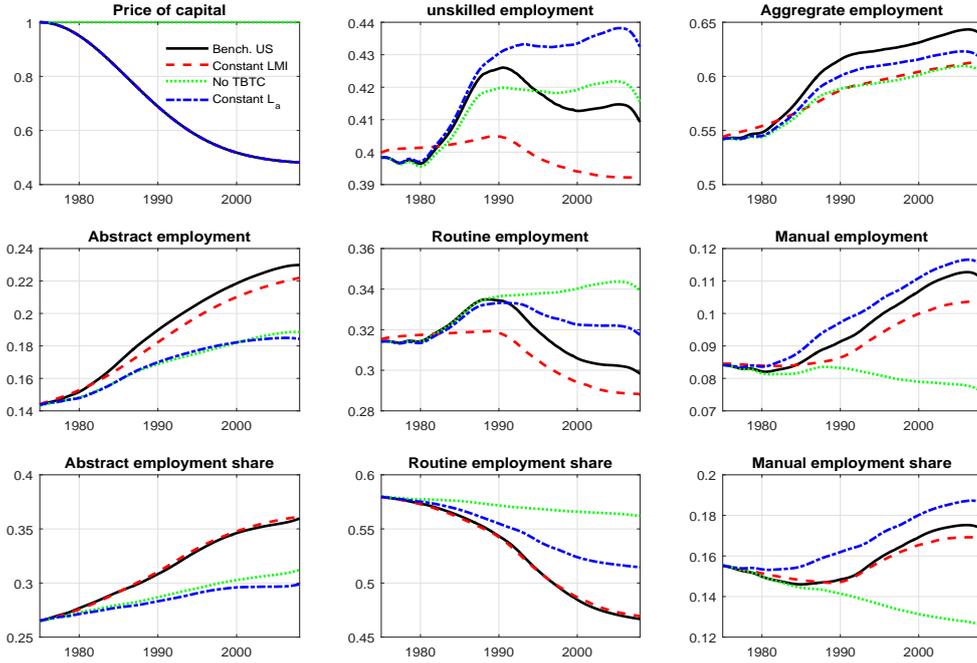
### 5.1 A tale for the US

**Until the late 1980s: De-unionization fosters unskilled per-capita employment.**

Figure 9 displays the predicted employment paths when we set the US LMIs to their 1975 level. Without a change in LMIs, US unskilled employment would have been lower in the 1970s and 1980s. Changes in LMIs fostered employment growth in the US. At the beginning of the technological transition, the story of US employment change was driven by LMIs rather than TBTC.

Figure 10 displays counterfactual employment when one specific LMI is shut off. A constant bargaining power ("BP constant" scenario) involves lower employment in routine occupations

Figure 9: Employment levels and shares *US*



“Bench US” Benchmark calibration: TBTC, rising  $L_a$  and LMI shifts. “Constant LMI” Economy with constant LMI, set at 1975 level. “No TBTC” Economy with constant price of capital, set at 1975 level. “Constant  $L_a$ ” Economy with constant supply of skilled labor, set at 1975 level.

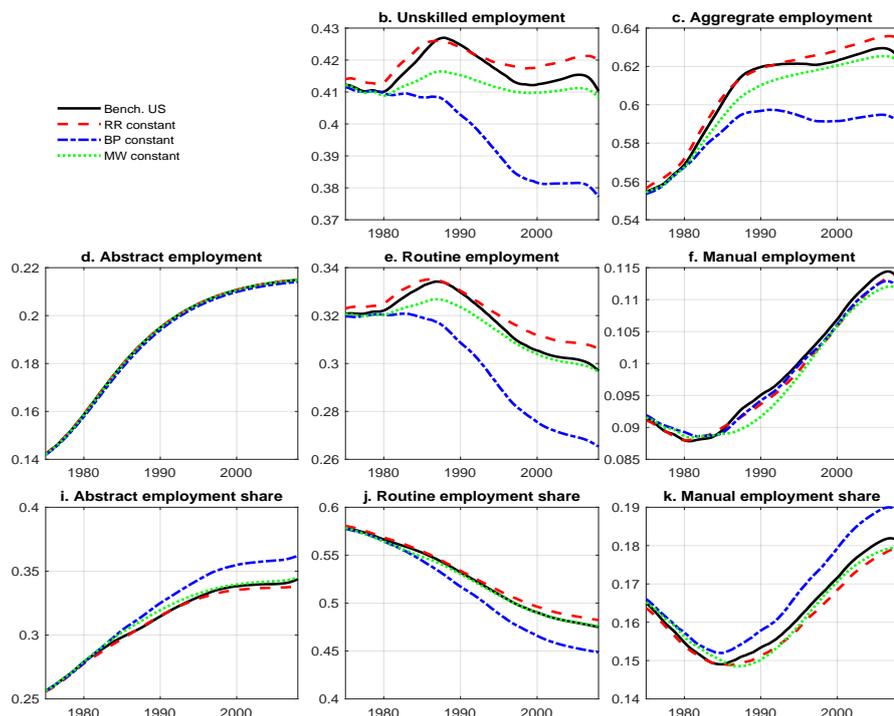
than in the benchmark case. The MW (“MW constant”) and the replacement rate (“RR constant”) scenarios produce small changes with respect to the benchmark case, as the effects of changes in bargaining power appear quantitatively predominant. This result echoes [Dinardo et al. \(1996\)](#)’s findings on the leading role of de-unionization in understanding US wages in the 1980s.

**The leading role of TBTC after the early 1990s.** Our model describes how TBTC can generate variations in employment composition, as in [Autor & Dorn \(2013\)](#), and in employment levels.

TBTC operates as a long-run trend, changing relative productivity over time and raising aggregate productivity. This leads to an increase in aggregate employment. Indeed, [Figure 9](#) shows that, without TBTC, at the end of the sample, the aggregate employment level is 4 pp lower than the benchmark employment level. This means that, without TBTC, US employment gains would have been 40% lower (4 pp divided by 10 pp employment gain between the early 1980s and 2007 in the benchmark calibration).

Employment gains are unequally shared across occupations. A decline in the price of capital reduces the marginal productivity of routine tasks, leading firms to reduce routine employment. A decrease in routine wages absorbs part of this lost competitiveness. The net effect is a decline in employment and wages for routine occupations. On the other hand, TBTC

Figure 10: Employment levels and shares. LMIs. *US*



“Bench US” Benchmark calibration: TBTC, rising  $L_a$  and LMI shifts. “RR constant” Economy with constant unemployment benefit Replacement Ratio, set at 1975 level. “BP constant” Economy with constant workers’ bargaining power, set at 1975 level. “MW constant” Economy with constant Minimum Wage, set at 1975 level.

increases the productivity of abstract tasks, owing to the rise in capital stock. Despite the offsetting effect induced by a higher wage in abstract jobs, the net effect is increased employment and wages for abstract workers. Considering the expansion in demand and endogenous rise in the relative price of manual services, this supply shock generates additional income. Demand for goods and services increases as consumers like variety in their consumption baskets. Given that a positive supply shock also affects the good market, the increase in the price of manual services is necessarily larger than that observed in the good market. Therefore, the relative price of services  $p_s$  increases, as do the marginal gains of services produced by manual workers. Hence, manual employment expands despite wage increases linked to higher labor market tightness: the expanding job opportunities in manual occupations reinforce the incentive for routine workers to move towards manual jobs.

Our US employment composition predictions are consistent with those of [Autor & Dorn \(2013\)](#), and thus their story of job polarization driven by TBTC. Figure 9 shows the counterfactual employment path when we shut down the fall in computer prices. The US labor market does not polarize: routine employment does not fall, manual employment does not expand, and abstract employment growth is limited.<sup>32</sup> Note that TBTC did not play a role in unskilled employment before 1990. The TBTC story unfolds after the early 1990s,

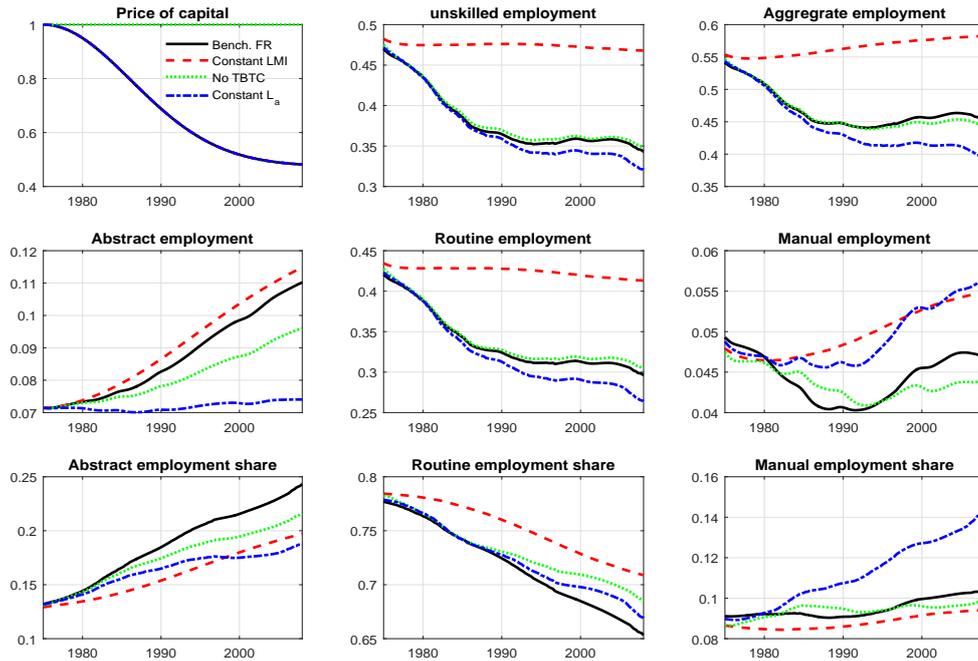
<sup>32</sup>The dynamics of productivities, wages, and job finding rates are displayed in Appendix L, with Figures 21 and 22 for the US and French economies, respectively.

consistent with the findings in Section 2.

## 5.2 A tale for France

**The marginal impact of TBTC.** In France, TBTC has no significant impact on aggregate employment (Figure 11). Indeed, when the price of capital does not fall, the counterfactual employment is close to the benchmark employment path.

Figure 11: Employment levels and shares. *France*

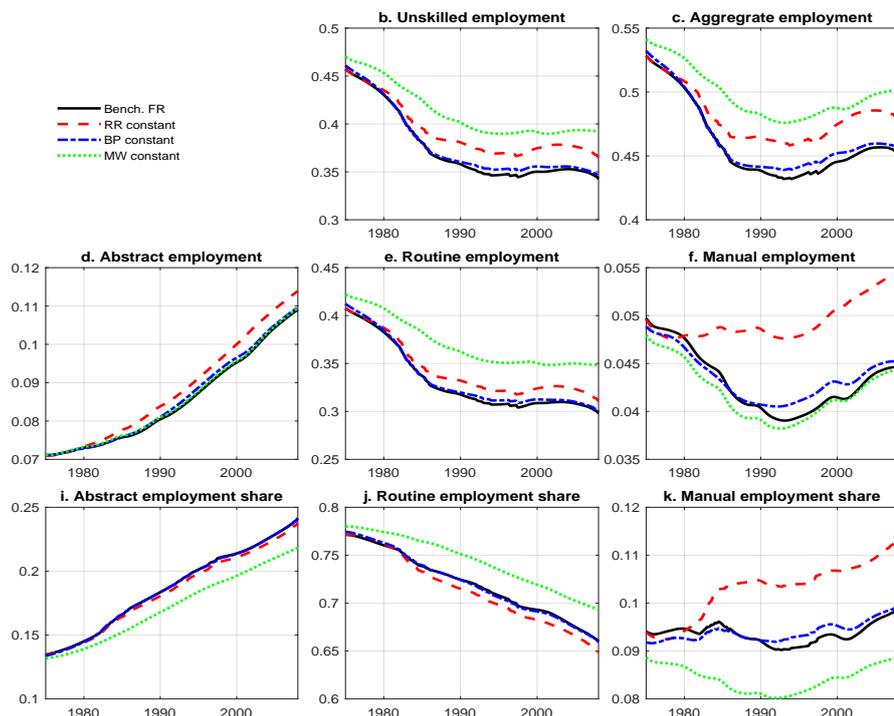


“Bench FR” Benchmark calibration: TBTC, rising  $L_a$  and LMI shifts. “Constant LMI” Economy with constant LMI, set at 1975 level. “No TBTC” Economy with constant price of capital, set at 1975 level. “Constant  $L_a$ ” Economy with constant supply of skilled labor, set at 1975 level.

**Rising minimum wage (MW) and replacement ratio until the mid-1990s.** In France, LMIs lowered employment, thereby reducing the overall profitability of employment (see Figure 11). Interestingly, the quantitative model shows that the impact of LMI is quite different according to the type of job and accounts for the much more pronounced disappearance of routine jobs in France.

Indeed, these jobs are characterized by large heterogeneity. In particular, the bottom of the distribution of these jobs is highly sensitive to the increasing trend in the Minimum Wage (MW) and unemployment replacement ratio. The sizeable increases in the MW and replacement ratio lead to the displacement of a large fraction of workers previously employed in routine occupations. LMIs also slow down the creation of manual jobs, particularly for inexperienced workers in routine occupations.

Figure 12: Employment levels and shares. LMIs. *France*



“Bench FR” Benchmark calibration: TBTC, rising  $L_a$  and LMI shifts. “RR constant” Economy with constant unemployment benefit Replacement Ratio, set at 1975 level. “BP constant” Economy with constant workers’ bargaining power, set at 1975 level. “MW constant” Economy with constant Minimum Wage, set at 1975 level.

Figure 12 shows that LMI changes mostly explained the dynamics of French employment over the past 40 years. Employment adjustments induced by LMI changes are more sizeable than the pace impelled in the US, especially for unskilled labor. Routine jobs are particularly affected by the increase in MW. Manual jobs would have increased considerably if the replacement ratio had remained constant. Note that the impact of LMI trends on the employment of abstract jobs is modest, which is expected. Let us notice that the trend in workers’ bargaining power explains little of the employment dynamics in France, while the opposite is true in the US (Figures 12 and 10).

**Payroll tax cuts of the late 1990s.** This decline in French routine employment occurred until the mid-1990s. Since the mid-1990s, and until the end of the sample period, the drop in the level of routine jobs stopped, and aggregate employment started to rise again. Figure 20 in Appendix K shows that this is due to the policy of subsidies for low-paid jobs, which limits the effects of the MW on labor cost. This subsidy policy has helped support unskilled employment in France, which would otherwise have continued to fall due to the rising MW.

In Appendix M.2, we present a simulation in which all French LMIs are held constant at their 1975 levels. In this scenario, the model fails to generate job polarization in the context of declining employment, as observed in France. This underscores the significance of LMI

changes in explaining trends in employment by tasks.

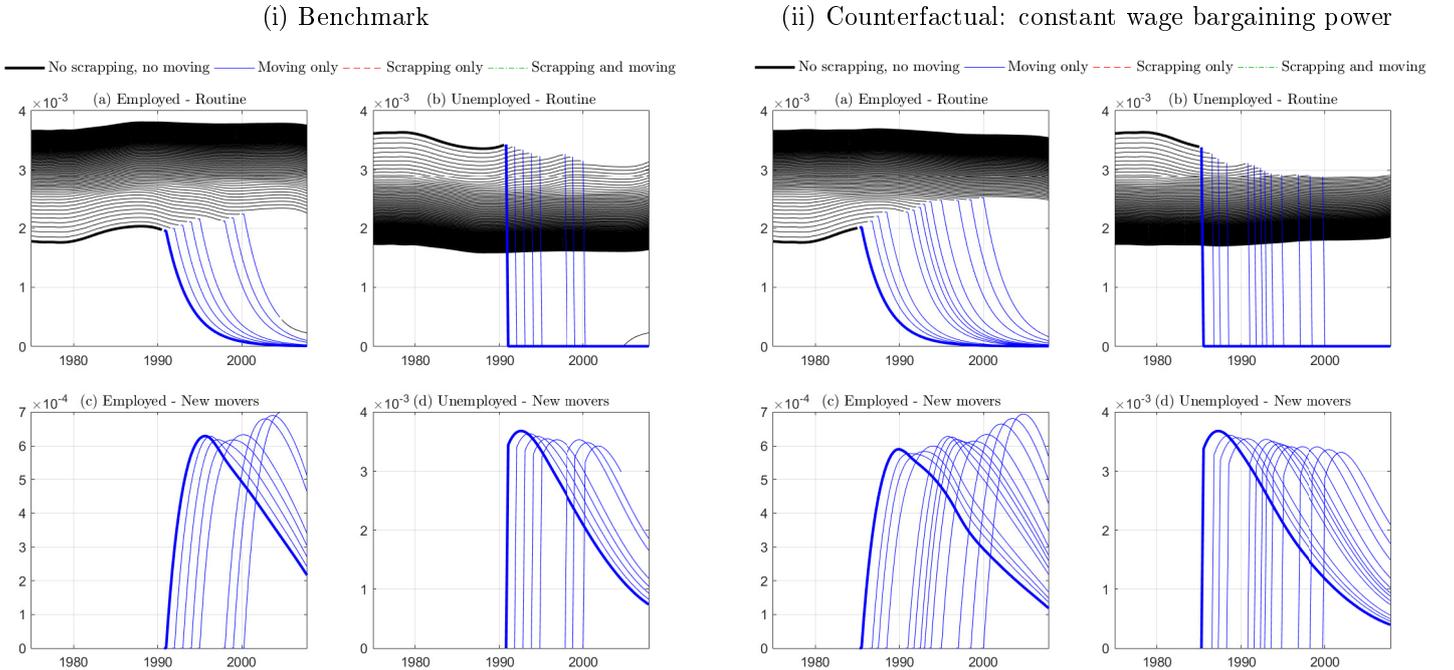
## 6 Job polarization from workers' point of view

In this section, we propose to go beyond the analysis of employment aggregate dynamics by analyzing the choices made by workers along technological and LMI transitions. For the US, we show that TBTC modifies labor market equilibrium by generating voluntary employment reallocation in an economy that creates new jobs. In France, the story is different and is characterized by numerous involuntary reallocations induced by firings.

### 6.1 Moving to new job opportunities in the US

Panel (i) of Figure 13 depicts the evolution of the stock of American workers. We focus on heterogeneous routine workers with respect to the ability level  $\eta$ . Years are displayed on the horizontal axis. Each line represents the employment dynamics of a particular ability level  $\eta$ . On the graphs, the lowest line (top line) captures the dynamics of the lowest-ability (top ability) worker. Aggregate routine employment is the sum of all the routine workers.

Figure 13: US occupational switch along the transition



The black lines represent workers that do not change occupation. The blues lines represent workers that change occupation following a voluntary choice to move ( $\eta$ -type s.t.  $U_m^n(\eta) > U^r(\eta)$ ). Panel (a): Employment level on routine jobs ( $n_t^r(\eta) \forall \eta > \hat{\eta}$ ); Bottom line:  $n_t^r(\hat{\eta})$  lowest-ability worker; Upper line is  $n_t^r(\bar{\eta})$  Top-ability worker. Panel (b): Unemployed workers searching for a routine job  $\forall \eta \in [\hat{\eta}, \bar{\eta}]$ . Panel (c): Newly employed workers on manual jobs. These new employees appear after a time period of search on the submarket of inexperienced manual jobs. They join the stock of regular manual workers as they gain experience in manual jobs (with probability  $\lambda$ ). Panel (d): Newly unemployed workers searching for manual jobs. These workers appear in this submarket when  $\hat{\eta} > \eta$ .

**Gradual occupational switches along the transition path.** Panel (a) in Figure 13(i) shows that, in 1990, the least-productive routine workers switched occupations to manual jobs. These decisions (switch from routine to manual occupations) are voluntary and taken by unemployed workers that have lost their routine jobs for exogenous reasons. The first wave of reallocation to manual occupations occurred in 1990. Then, there was one per year until 1995, with a pause in 1996. Then, the reallocation from routine to manual occupation resumes in 1997 and occurs each year until 2000 (see the blue line in panel (a) in Figure 13)-(i)). The least-productive unemployed routine worker chooses to search for another occupation. Routine firms stop opening their vacancies directed on the least productive workers ( $v^r(\eta) = 0$ ), and the scrapping time is never reached. Thus, the stock of employed routine workers gradually declines as they become separated at the exogenous rate  $s_r$  (see the decreasing blue lines) in panel (a) of Figure 13)-(i). All these adjustments appear earlier and for a wider range of abilities among routine workers when bargaining power is maintained at a higher level in the 70s (see panel (a) of Figure 13-(ii)). Moreover, the reallocation process in the US occurs in a context where the employment rate of high-ability routine workers increases because of the decline in worker bargaining power (compare panel (a) of Figures 13-(i) with 13-(ii)).

**Gradual employment increase in manual jobs.** Unemployment episodes allow routine workers to move to new occupations in an expanding labor market of manual jobs. Panel (b) of Figure 13(i) shows that the number of low-productive unemployed workers seeking a routine job then falls to zero. These individuals seek employment in another occupation, which mechanically increases the number of unemployed looking for manual jobs (Panel (d) in Figure 13-(i)). They have gradually joined the pool of employed workers in manual jobs (panel (c) in Figure 13). The number of manual jobs increases in the economy with a proportion of "new movers" (inexperienced manual workers) declines with the rate of promotion in manual jobs.

Routine workers at the bottom of the ability distribution bear costs of occupational changes (unemployment spells and periods paid as inexperienced manual workers). This feature echoes Autor and Dorn's model, in which lowest-ability routine workers also switch to manual jobs. In our model, this costly choice was the best option for displaced routine workers (voluntary choice); they expect expanding employment opportunities in manual occupations. These labor adjustments results in a gradual decline in the total stock of routine workers in the economy and a gradual increase in manual employment, consistent with the data.

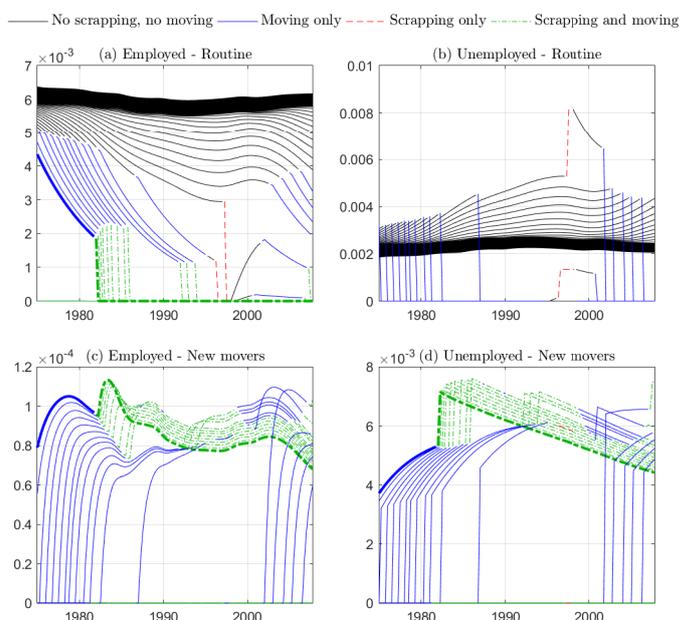
**Counterfactual exercise: strong de-unionization in the 1980s has maintained the lowest ability workers on their routine jobs for approximately five years.** Panel (a) in Figure 13(i) shows that the model generates an increase in routine per capita

employment until late 1980s. By comparing this figure with Panel (a) of Figure 13(ii), where the observed decline in worker bargaining power is muted, it appears that the strong de-unionization observed in the US during this period has maintained the lowest-ability workers in their routine jobs for at least five years. All  $\eta$ -type workers benefit from improved employment prospects. In the 1980s, the speed of change in LMIs outraced the speed of change in TBTC.

## 6.2 Labor market rigidities and job destructions in France

The story of job polarization differs for France during the transition. Indeed, Figure 14 suggests that the erratic trajectories respond to changes in the LMIs rather than to the smooth diffusion of technology (TBTC).

Figure 14: French occupational switch and job destruction along the transition



The black lines represent workers that do not change occupation. The blue lines represent workers that change occupation following a voluntary choice to move ( $\eta$ -type s.t.  $U_m^n(\eta) > U^r(\eta)$ ). The dashed red lines represent workers that lose their jobs involuntarily after the scrapping (firing) of their jobs ( $\eta$ -type s.t.  $\eta < \eta^S$ ) and that choose not to move towards new opportunities, preferring a situation of permanent unemployment (inactivity). The dashed green lines represent workers that lose their jobs involuntarily after the scrapping (firing) of their jobs ( $\eta$ -type s.t.  $\eta < \eta^S$ ) and immediately choose to move to the manual labor market segment. Panel (a): Employment level on the routine jobs ( $n_t^r(\eta) \forall \eta > \bar{\eta}$ ; Bottom line:  $n_t^r(\bar{\eta})$  lowest-ability worker; Top line is  $n_t^r(\bar{\eta})$  Top-ability worker. Panel (b): Unemployed workers searching for a routine job  $\forall \eta \in [\bar{\eta}, \bar{\eta}]$ . Panel (c): Newly employed workers on manual jobs. These new employees appear after a time period of search on the submarket of inexperienced manual jobs. They join the stock of regular manual workers as they gain experience in manual jobs (with probability  $\lambda$ ). Panel (d): Newly unemployed workers searching for manual jobs. These workers appear in this submarket when  $\bar{\eta} > \eta$ .

**Successive waves of firings, starting in the early 1980s.** Panel (a) of Figure 14 suggests that, in the 1970s, low-ability routine workers face a declining probability of maintaining their job. At the beginning of the 1980s, the least productive routine workers were

fired. Their matches reached the scraping time and became unprofitable. As time passes, the scraping time is gradually reached for other low-productivity routine matches. The 9 the least productive types of routine workers fired between 1980 and 1985 (green vertical lines in panel (a) of Figure 14).

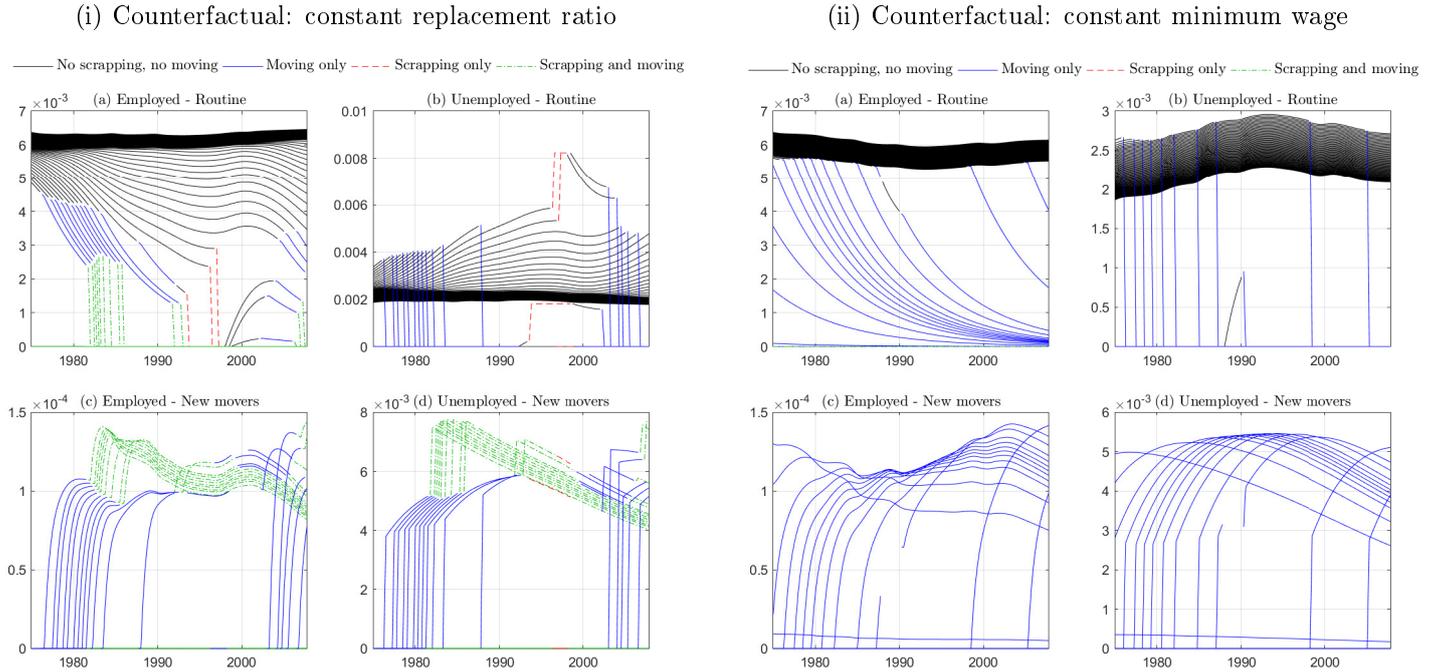
**Counterfactual exercise: the rise in the minimum wage accelerates routine job destruction.** The early 1980s corresponded to the legislature that decided to largely increase the Minimum Wage and the unemployment replacement rate. Panel (a) in Figure 15(i) shows that, even if the replacement rate had remained at its level in the 1970s, this would not have preserved the jobs of these low-ability workers. However, the generosity of unemployment benefits maintained at their level in the 70s would have made it possible to increase the employment rate in the most skilled segments of the routine labor market.

Panel (a) of Figure 15-(ii) shows that none of these job destructions have occurred in France, with a minimum wage maintained at the 70s level (relative to average productivity). Note that the shift in the Minimum Wage affects only low-ability workers. The rise in the unemployment-benefit replacement ratio induces a decline in the employment rate of high-ability workers in France.

Low-ability, displaced routine workers choose to move to the manual labor market segment (see panel (b) in Figure 14). Therefore, France experienced the phenomenon of displaced routine workers in the early 1980s, ten years before the US. This is consistent with the trends observed in routine employment as described in Section 2. The timing of This employment reallocation from routine to manual jobs was driven to a large extent owing to the changes in labor costs in France during this period (see Figure 15(ii)). Panel (c) in Figure 14 shows that in the 1980s, displaced routine workers gradually joined the pool of Inexperienced manual worker. Another important difference between the US lies in the persistence of the transition period induced by an Occupational change: Unemployment duration before hiring a new manual job is longer than that in the US (see panel (c) in Figure 14).

**Counterfactual exercise: The fall in employers' contributions, starting in 1996, saved low-productivity routine jobs.** An interesting French episode is a fall in the employers' contributions starting in 1996. This policy stops the continuous increase in labor costs (through increases in MW and unemployment benefits) (see the red line in the panels (a) and (b) in Figure 14). Prior to 1996 reform, routine jobs were destroyed, but the newly unemployed routine workers decided to keep looking for routine jobs rather than switching occupations. Payroll tax subsidies implemented in 1996 allowed these unemployed workers to find new routine jobs, which became profitable again through the fall in labor costs. Panel (a) of Figure 15(i) shows that this policy would have had a larger impact if the generosity of unemployment benefits had remained at the 70s level.

Figure 15: French occupational switch and job destruction: counterfactuals



With a gradual increase in minimum wage, the French worker is fired before any voluntary occupational switch (before an exogenous separation gives routine workers a choice to move to manual occupation). The decline in the employment rate of high-ability routine workers was due to the observed increase in unemployment benefits. Therefore, the timing of worker firing is driven by shifts in labor demand and constrained by faster LMI changes than the speed of changes in TBTC.

## 7 Conclusion

First, we shed light on job polarization using US and French data. Dynamics of employment *shares* for abstract, routine, and manual jobs appear similar across countries. This similarity hides major differences in employment *levels* by tasks. In particular, routine employment levels fell in France until the mid-1990s and then rebounded in the late 1990s. The evolution of routine US employment went in the opposite direction relative to that of the French economy. Despite these huge differences, the dynamics of employment share are close.

Using data on employment levels, our contribution shows how to identify two stories that account for the job polarization process. First, the story of employment reallocation driven by TBTC, as described by [Autor & Dorn \(2013\)](#), fits the post-1990 trends in US employment because this positive supply shock is consistent with a rise in the aggregate employment

rate over this period. However, this cannot account for French employment trends because the aggregate employment rate declined during this period. The second story shows that the French decline in routine employment is driven mainly by LMI changes, which have a heterogenous impact on jobs, although their changes apply to all employees. Hence, beyond explaining the evolution of aggregate employment, we show that the observed shifts in LMIs also explain a large part of the changes in the employment composition, particularly in the job polarization process. Therefore, our analysis suggests that the relevance of the TBTC story should be assessed in relation to LMI changes.

# ONLINE APPENDIX

## A Annual data on employment by task

### A.1 US data

As in [Jaimovich & Siu \(2020\)](#), we consider only individuals aged 16 and more. Occupations in farming, fishing, forestry, and military are excluded. Occupations are categorized into three groups, each corresponding to the main tasks performed on the job. In doing so, we follow [Jaimovich & Siu \(2020\)](#). Starting in 1983, the classification is based on the categorization of occupations in the 2000 Standard Occupational Classification system. Employment data from January 1983 onwards are taken from FRED. Non-routine cognitive workers are those employed in “management, business, and financial operations occupations” and “professional and related occupations.” Routine workers are those in “sales and related occupations,” “office and administrative support occupations,” “production occupations,” “transportation and material moving occupations,” “construction and extraction occupations,” and “installation, maintenance, and repair occupations.” Non-routine manual occupations are “service occupations.” We checked that employment stocks by task are similar to Figure 4 in [Jaimovich & Siu \(2020\)](#).

### A.2 French data

We repeat the US procedure on French data in order to ensure comparability across countries. We use the LFS from 1983 through 2007. The survey was redesigned in 2003. Prior to 2003, the survey was annual. Individuals were surveyed each year, for three years in a row. Since 2003, the survey is quarterly. Each individual is surveyed every quarter, for six quarters in a row. The survey is designed to be representative of the French population, with more than 130,000 observations in year 1983 and approximately 70,000 each quarter for year 2007. As in [Jaimovich & Siu \(2020\)](#), we consider only individuals aged 16 and more.

As for occupations, we apply the procedure used for US data. Occupations in farming, fishing, and forestry are excluded. Occupations are categorized into three groups, each corresponding to the main tasks performed on the job. We base our categorization on the two-digit occupational codes.<sup>33</sup> We want our assignment of occupations to tasks to match the one used in [Jaimovich & Siu \(2020\)](#).

Abstract jobs are management, business, science, and arts occupations; this includes occu-

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<sup>33</sup>[Harrigan et al. \(2021\)](#) argue that two-digit codes used in French data are economically meaningful. Each code is the aggregation of 10 to 20 four-digit sub-occupations with stark differences in the susceptibility of jobs to automation.

pation codes 23 large business heads, 31 licensed professionals, 33 civil servant, executives, 34 scientific professional, 35 creative professional, 37 top managers and professionals, 38 technical manager, engineers, 42 teacher, and 43 health workers. <sup>34</sup>

Routine jobs are sales and office occupations; construction and maintenance occupations, and production, transportation, and material moving occupations; this includes occupation codes 45 mid-level professionals in the public sector, office worker, 46 mid-level professionals in the corporate sector, office workers, 47 technician, 48 foremen, supervisors, 52 civil servants, office workers, mid-level and low level, 53 security workers, 54 office workers in the corporate sector, 55 retail worker, 62 skilled industrial workers, 63 skilled manual laborers, 64 drivers, 65 skilled distribution worker (dispatch, dockers, warehousemen, ...), 67 low skill workers, in manufacturing, food industries, press, ... 68 low skill laborers, craftsmen

Manual jobs are service occupations. This includes occupation codes 56 Personal service workers and 22 heads of small businesses (selling food, tobacco, services, and other items)

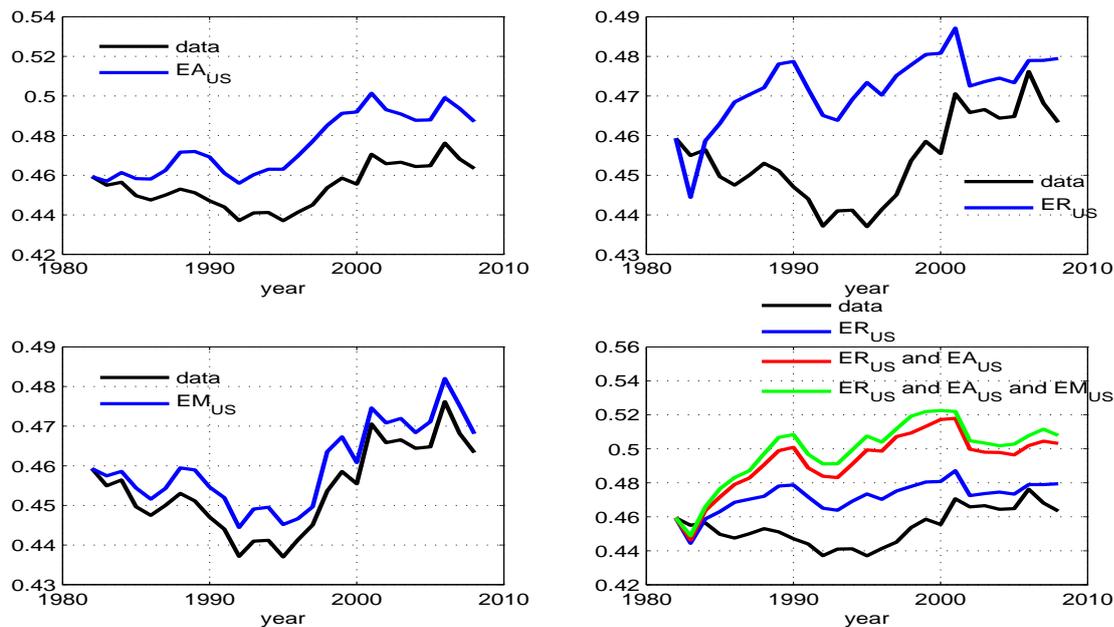
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<sup>34</sup>Some could argue that occupation 43 could also be considered to be part of manual non-routine jobs. We choose to consider them in the abstract group, as [Charnoz & Orand \(2015\)](#). These authors consider the same group of occupations in the abstract group and checked that these jobs are indeed characterized by abstract-intensive tasks. In addition, [Jaimovich & Siu \(2020\)](#) also consider medical occupations as part of non-routine cognitive jobs.

## B Key role of routine employment in accounting for cross-country divergence in employment levels

The dynamics of routine employment explains the main difference in the evolution of employment levels in France and the United States. Figure 16 shows it explicitly, using counterfactual exercises. Each curve corresponds to the counterfactual French employment level that would have been observed in the employment growth has been that observed in the United States. Changes in the US employment of abstract and services do not significantly change the dynamics of the French employment compared to that observed. On the other hand, if France had experienced the US dynamics of routine employment, changes in the French aggregate employment would have been radically changed, and indeed quite constant over the whole period. We would have missed the sharp downturn in routine employment until the mid-1990s and then the upturn prior to the last recession.

Figure 16: Counterfactual employment levels: France



“Data” French data; “ $EA_{US}$ ”: counterfactual French employment with US employment growth in abstract jobs; “ $ER_{US}$ ”: counterfactual French employment with US employment growth in routine jobs; “ $EM_{US}$ ”: counterfactual French employment with US employment growth in manual jobs.

## C Educational attainment by task

We report in this appendix the educational attainment by task in France and in the US (Table 2). The descriptive statistics suggest that our assumption (that abstract workers are skilled workers, while routine and manual workers are unskilled workers) is supported by the data.

Table 2: Educational attainment by task

France	Abstract	Routine	Manual
diplôme supérieur	0.422	0.025	0.026
baccalauréat + 2	0.296	0.065	0.032
High School (baccalauréat)	0.139	0.132	0.093
Less Than High School	0.144	0.778	0.849 <sup>(a)</sup>
US	Abstract	Routine	Manual
College (4 years and more)	0.570	0.114	0.070
Some college	0.247	0.285	0.261
High School	0.156	0.440	0.398
Less Than High School	0.027	0.162	0.271

Data sources: French Labor Force Surveys (1984-2018) and US CPS MORG (1979-2018). Average educational attainment by task. (a) : In France, on average over the sample period, 84.9% of Manual workers did not have any degree.

In France, the vast majority of routine and manual workers did not have any degree. In contrast, the vast majority of Abstract workers had either completed a University degree or a 2-year program. Notice that, in France, 2-year post-High School programs are selective programs.

The majority of routine and manual workers were high school graduates or did not complete high school, while the majority of abstract workers completed college. Notice that, in the US survey data, the education variable categorizes into "some college" several types of individuals: those who completed short programs (such as associate degrees) and those who did not complete college.

## D Counterfactual employment levels by tasks

### D.1 Data

Drawing on [Charlot et al. \(2019\)](#), we compute labor flows across tasks using monthly US-CPS (1985m6-2007m12). The sample starts in 1985, after a major redesign of the CPS occupational classification.

The Current Population Survey (CPS) Basic Monthly Data provides information on labor market status. The survey is conducted on a monthly basis. A housing unit in the CPS is interviewed for four consecutive months and then dropped out of the sample for the next eight months and is brought back in the following four months. We use the data on labor market status, occupation, and hours worked. Individuals are matched from one month to the next, so that we can then track individual’s labor market transitions.

We follow the literature by using occupational data to categorize workers into 3 task-groups.

### D.2 Measuring labor flows across task groups

We consider three labor market statuses : employment, unemployment (measured according to the ILO definition) and non-participation. When looking at employed individuals, their occupations are categorized into three groups, each corresponding to the main task performed on the job: abstract, routine or manual. In a nutshell, we classify individuals in each quarter into one of 5 mutually exclusive categories: unemployed ( $U$ ), not in the labor force ( $N$ ), and for those employed, we have three task groups (abstract ( $A$ ), routine ( $R$ ) and manual ( $M$ )).

We thus rely on a 5-state Markov model of labor market adjustments, where the corresponding stocks are denoted as:

$$X_t = (A_t; R_t; M_t; U_t; N_t),$$

and evolve as follows:

$$X_t = \ell_t X_{t-1}, \tag{21}$$

where  $\ell_t$  denotes a square matrix of size 5, whose elements  $\ell_{i,j}$  capture the probability of transition from labor market status  $i$  to labor market status  $j$ . Using month-to-month matched data, we compute gross flows across employment states.<sup>35</sup>

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<sup>35</sup>We then apply the usual treatment of the data in the literature. We adjust the data along three dimensions. We first seasonally adjust gross flows using x13. As in [Elsby et al. \(2013a\)](#), we then compute transition probabilities that are consistent with the observed changes in stocks (correction for margin error). Finally, as gross flows provide transition probabilities observed at discrete points of time, in order to correct these measures for possible transitions occurring between consecutive surveys, we correct gross flows for time aggregation bias ([Shimer \(2012\)](#)). We then get instantaneous transition rates.

### D.3 Omitted worker transitions are small in the data

We compute the average transition probabilities across labor market statuses. We report in Table 3 below the average monthly probability of job-to-job transitions, across task groups. On average 0.92 % of routine workers take an abstract job, from one month to the next. 1.31% of abstract workers take a routine job the next month. We report in bold the transitions that are absent from the model ( $A \rightarrow R$ ,  $A \rightarrow M$ ,  $R \rightarrow A$ ,  $R \rightarrow M \rightarrow R$ , and  $M \rightarrow A$ ). All transition probabilities that are omitted from the model are rather small (around 1% or less).

Table 3: Job-2-Job transitions from month  $t - 1$  to month  $t$

		$t$		
		$A$	$R$	$M$
$t - 1$	$A$	95.78	<b>1.31</b>	<b>0.27</b>
	$R$	<b>0.92</b>	93.79	<b>0.52</b>
	$M$	<b>0.78</b>	<b>1.89</b>	89.48

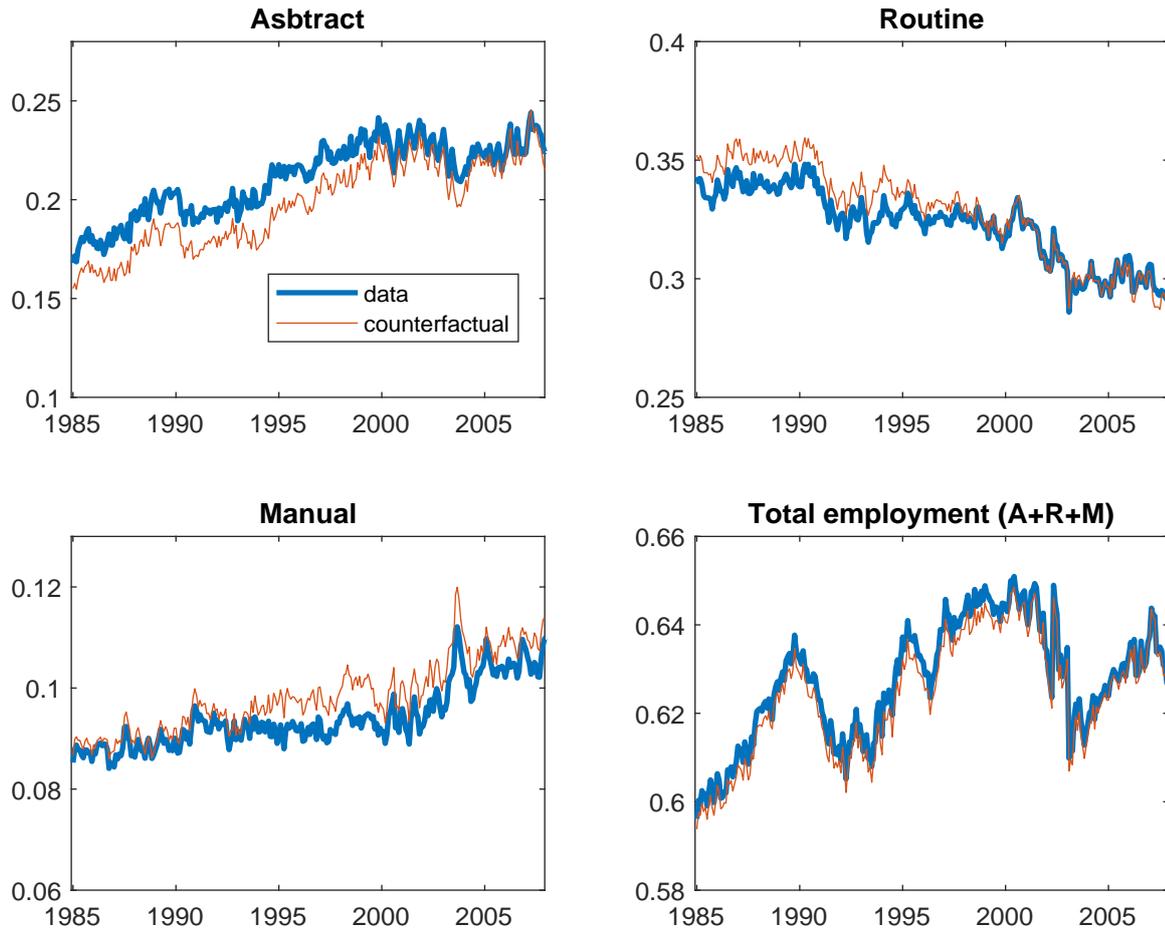
Data: monthly CPS (1985m1-2007m12). Authors' calculations. Counterfactual: Counterfactual steady-state evolution as predicted by Markov matrix when flows ( $A \rightarrow R$ ,  $A \rightarrow M$ ,  $R \rightarrow A$ ,  $R \rightarrow M \rightarrow R$ , and  $M \rightarrow A$ ) are set to zero, and the diagonal element in the Markov matrix adjusts so that each line sums to 1.

### D.4 Do these omitted worker flows play a large in the data? A counterfactual exercise

Job-to-job transitions in Table 3 appear small. However, in order to make sure that these small numbers are innocuous for the evolution of employment stocks, we compute counterfactual steady-state employment stocks when the flows omitted in the model ( $A \rightarrow R$ ,  $A \rightarrow M$ ,  $R \rightarrow A$ ,  $R \rightarrow M \rightarrow R$ , and  $M \rightarrow A$ ) are set to zero in the data. In other words, in matrix  $\ell_t$  (equation (21)), transitions  $A \rightarrow R$ ,  $A \rightarrow M$ ,  $R \rightarrow A$ ,  $R \rightarrow M \rightarrow R$ , and  $M \rightarrow A$  are set to zero. The diagonal element in the Markov matrix adjusts so that each line sums to 1.

Results are reported in Figure 17 below. Employment stocks are barely affected. For the sake of parsimony, we then decide to keep the model unchanged.

Figure 17: US employment by tasks: data and counterfactuals



Data: monthly CPS (1985m1-2007m12). Authors' calculations. Counterfactual: Counterfactual steady-state evolution as predicted by Markov matrix when flows ( $A \rightarrow R$ ,  $A \rightarrow M$ ,  $R \rightarrow A$ ,  $R \rightarrow M$ ,  $M \rightarrow R$ , and  $M \rightarrow A$ ) are set to zero, and diagonal in the Markov matrix adjusts so that each line sum to 1. "A" Abstract employment, "R" Routine employment, "M" Manual employment, "A+R+M" total employment.

## E Model fit on worker flows

### E.1 Consistent measurement in the data and in the model

In order to compare worker flows from the model to their empirical counterparts, we pay attention to several elements.

- First, the model is calibrated on a quarterly frequency, while we computed monthly labor market transitions. We need to transform, in US data, monthly labor market transitions into quarterly transitions. We obtain the quarterly Markov matrix by calculating the monthly Markov matrix to the power of 3.
- Secondly, the model is about employment levels, so that agents who are not employed in the model are unemployed or out of the labor force. So separation in the model captures transitions to non-employment: E-to-U + E-to-N.

### E.2 Model predictions on worker flows

Figure 18 reports the evolution of worker flows from the model and from the data.

#### E.2.1 Separation rates.

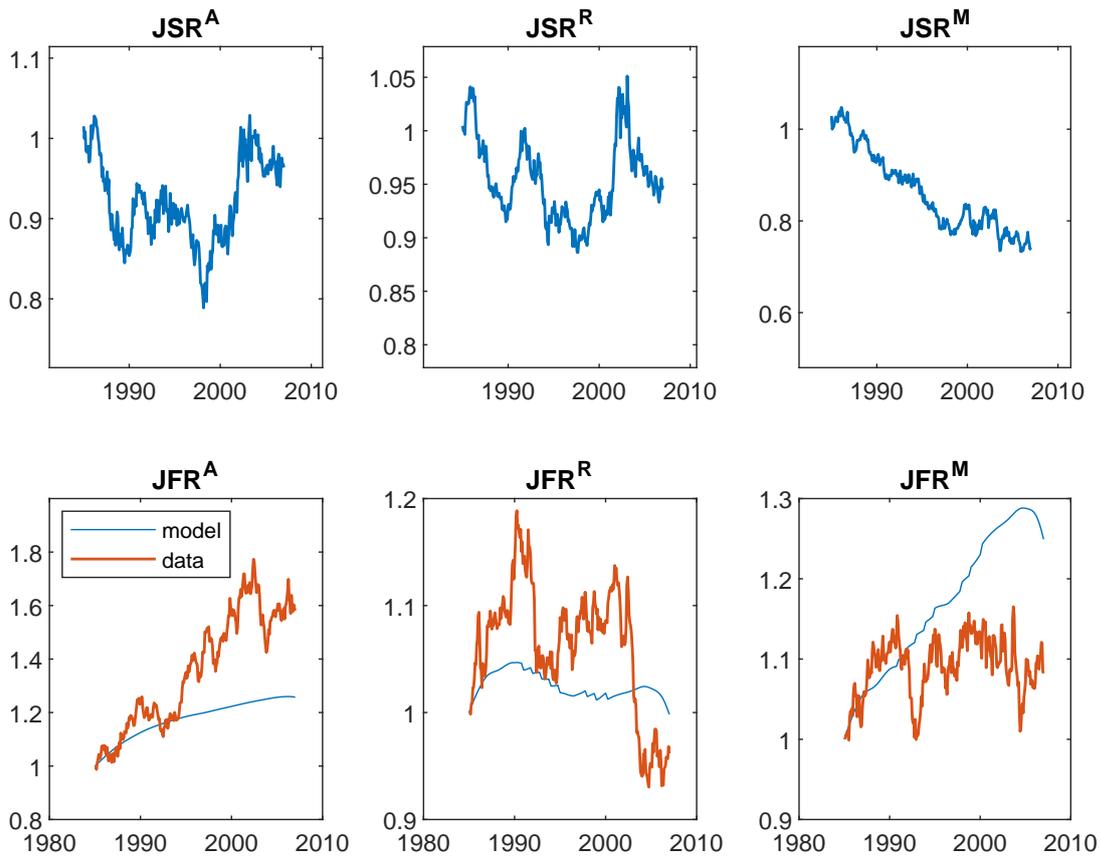
**Abstract jobs:** In the model, there is no endogenous separation for abstract jobs: the separation rate is constant, at the calibrated value. In US data, there is indeed no observed trend in the US separation rate of abstract jobs (see  $JSR^A$  in Figure 18).

**Routine jobs:** Concerning routine jobs, there is no endogenous separations in the model calibrated on US data: the separation rate is constant for these jobs. Indeed, the model predicts that, following an exogenous separation, unemployed workers switch occupations to manual jobs when the technological changes make manual jobs more attractive, after the early 1990s (section 6.1.). Consistently, there is indeed no observed trend in the data of the US separation rates of routine jobs (see  $JSR^R$  in Figure 18).

**Manual jobs:** Finally, the separation rate of manual jobs is also exogenous in the model calibrated on US data. However, in US data, the separation rate for manual jobs displays a downward sloping trend, which is not the case in the model (see  $JSR^M$  in Figure 18).

In order to understand what is missed in the model, we perform the following counterfactual exercise. In the Markov labor market transition rates, we fix the separation rates of manual

Figure 18: US worker flows

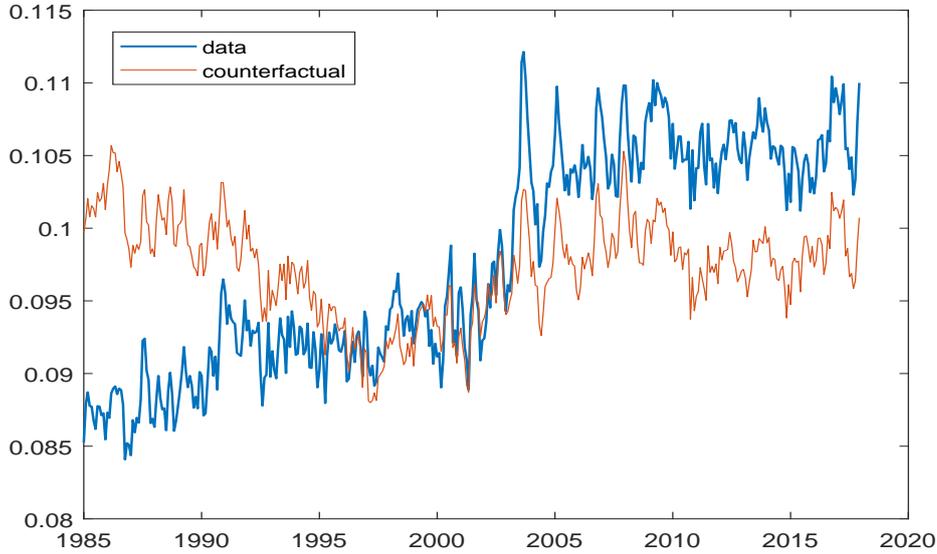


Level 1985 = 100.  $JSR^A$ : Job separation rate, Abstract jobs.  $JSR^R$ : Job separation rate, Routine jobs.  $JSR^M$ : Job separation rate, Manual jobs.  $JFR^A$ : job finding rate, Abstract jobs.  $JFR^R$ : job finding rate, Routine jobs.  $JFR^M$ : job finding rate, Manual jobs.

jobs to its average over the sample, we then compute the counterfactual manual employment. Hence, like in the model, the manual (counterfactual) employment is generated with constant separation rates (E-to-U and E-to-N).

The result is displayed in Figure 19: contrary to the observed data (continuously growing since the beginning of the sample), the counterfactual manual employment is decreasing before 1995, and increasing afterwards. This means that the model is better suited to capture the rise in manual employment after the mid-1990s. Nevertheless, this gap between the model implications and the data with respect to the dynamics of manual jobs before the 1990s is not large enough to reverse our main findings. After the mid 1990s, the average employment in manual jobs is approximately 0.1025 in US data and approximately 0.095 in the counterfactual, which means that the model can predict  $0.095/0.1025 = 93\%$  of the rise in manual jobs.

Figure 19: Counterfactual manual jobs when separation rate is constant



### E.2.2 Job finding rates

The definition of the job finding rate (JFR) from the data is model-consistent: we compute the probability to find a job when a worker is not employed (whether from U or from N). Job finding rate is computed as  $\frac{\text{total hiring from U or N}}{U+N}$ , or  $\frac{(U-to-E) \times U + (N-to-E) \times N}{U+N}$ .

**For abstract jobs:** The model captures the upward trend in the job finding rate. The model tends to underestimate the rise in JFR after the mid-1990s (see  $JFR^A$  in the Figure 18).

**For routine jobs:** The model captures the main features of the dynamics of JFR. JFR of routine jobs first increases until 1990, falls to an approximately constant rate from 1990 to 2000 and then declines. The model captures the rise in routine employment in the 1980s, even if the model increase underestimates its observed counterpart. The model also correctly captures the constancy of the 1990s and the decline of the 2000s, which triggers the decline in routine employment (see  $JFR^R$  in Figure 18). The gap between simulated and observed JFR data of the routine jobs are consistent with gaps in employment rates (simulated and observed) of routine jobs. In Figure 6 of the paper, the model under-predicts routine employment from 1995 to 2002, which is consistent with the evolutions of theoretical routine JFR (below the observed JFR).

**For manual jobs:** The model correctly captures the rise in the JFR of manual jobs. In the data, the rise in manual employment is explained by lower separations and higher JFR. Our model correctly predicts the rise in manual employment by having high JFR in manual jobs (see  $JFR^M$  in Figure 18). This highlights that further research is needed to investigate the trend in separation in manual jobs, which is not captured in the model.

## F Model

### F.1 Good-producing firms

#### F.1.1 Abstract jobs

If we denote  $J_a = \frac{\partial \Pi_{z1}}{\partial n_a}$ , the Bellman equations of a filled abstract job write, when  $v_a > 0$ :

$$J_a = y_a - (1 + \tau_h^f)w_a + (1 - s_a)\beta J_{a,+1}$$

where  $y_a = p_{z1}$ . The FOC for vacant jobs writes:

$$0 = -c_a + \beta q_a J_{a,+1}$$

#### F.1.2 Routine jobs

First, let us notice that the firm program can be solved in two steps, given the homogeneity of degree one of the production function and the exogenous process of the capital price. This property of the firm program allows us to show that if the firm chooses to fire, it is optimal to fire all of the  $\eta$ -type workers simultaneously.

**Marginal productivity of routine jobs.** The FOC with respect to  $K$  is

$$p_{z2} \frac{\partial Y_{z2}}{\partial K} = p_k \quad (22)$$

Using the homogeneity of the production, we have  $Y_{z2} = \frac{\partial Y_{z2}}{\partial K} K + \sum_{\eta} \frac{\partial Y_{z2}}{\partial L_r(\eta)} L_r(\eta) \Rightarrow p_{z2} Y_{z2} - p_k K = p_{z2} \sum_{\eta} \frac{\partial Y_{z2}}{\partial L_r(\eta)} n_r(\eta)$ . Given (11), Equation (22) can be rewritten as follow:

$$p_k = p_{z2} \mu k^{\sigma-1} (1 - \mu + \mu k^{\sigma})^{\frac{1}{\sigma}-1} = p_{z2} \mu k^{\sigma-1} g(k)$$

where  $k \equiv \frac{K}{\sum_{\eta} \eta n_r(\eta)}$  is determined by this equation each period, given  $\{p_k, p_{z2}\}$ . Therefore, we have  $\frac{\partial Y_{z2}}{\partial n_r(\eta)} = \eta(1 - \mu)g(k) \equiv \Upsilon(p_k, p_{z2})$ , showing that productivity cannot be manipulated during the negotiation process. Thus, we deduce that

$$p_{z2} Y_{z2} - p_k K = p_{z2} (1 - \mu) g(k) \sum_{\eta} \eta n_r(\eta)$$

the marginal productivity of one  $\eta$ -type job does not change with the level of  $n_r(\eta)$ .

This result will be also key when we will show below that when it is optimal to fire one  $\eta$ -type worker, it is optimal to fire all of them, at one period in the time (the scrapping

time).

**Hiring and firing decisions.** The problem of a firm with routine jobs can be rewritten as follows:

$$\begin{aligned}
\Pi_{z2} &= \max \left\{ p_{z2}Y_{z2} - p_k K - (1 + \tau^f(\eta)) \sum_{\eta} w_r(\eta)(1 - l_r(\eta))n_r(\eta) - c \sum_{\eta} v_r(\eta) + \beta\Pi_{z2,+1} \right\}, \\
\text{s.t. } Y_{z2} &\leq \left[ \left( (1 - \mu) \sum_{\eta^S}^{\bar{\eta}} \eta(1 - l_r(\eta))n_r(\eta) \right)^{\sigma} + (\mu K)^{\sigma} \right]^{\frac{1}{\sigma}} \\
n_{r,+1}(\eta) &= (1 - l_r(\eta))(1 - s_r)n_r(\eta) + q_r(\eta)v_r(\eta) \\
l_r(\eta) &\leq 1 && (\lambda(\eta)) \\
l_r(\eta) &\geq 0 && (\nu(\eta)) \\
q_r(\eta)v_r(\eta) &\geq 0 && (\mu(\eta)),
\end{aligned}$$

The FOCs of this problem are w.r.t.  $\{v_r(\eta), l(\eta), n_r(\eta)\}$  are

$$\begin{aligned}
0 &= -c + \mu(\eta)q_r(\eta) + \beta\Pi'_{z2,+1}q_r(\eta) \\
0 &= -\frac{\partial Y_{z2}}{\partial n_r(\eta)} + (1 + \tau^f(\eta))w_r(\eta) - \beta\Pi'_{z2,+1}(1 - s) + \nu(\eta) - \lambda(\eta) \\
\Pi'_{z2} &= (1 - l_r(\eta))p_{z2}\frac{\partial Y_{z2}}{\partial n_r(\eta)} - (1 - l_r(\eta))(1 + \tau^f(\eta))w_r(\eta) + \beta\Pi'_{z2,+1}(1 - s)(1 - l_r(\eta)) \\
&\quad + \nu(\eta)l_r(\eta) + \lambda(\eta)(1 - l_r(\eta))
\end{aligned}$$

**Regime 1: Hiring regime.** In this regime, we have  $v_r(\eta) > 0 \Rightarrow \mu(\eta) = 0$  and thus  $l_r(\eta) = 0 \Rightarrow \nu(\eta) = 0$  and  $\lambda(\eta) \geq 0$ . Including these conditions in the FOCs lead to

$$\begin{aligned}
\frac{c}{q_r(\eta)} &= \beta\Pi'_{z2,+1} \\
\lambda(\eta) &= -\frac{\partial Y_{z2}}{\partial n_r(\eta)} + (1 + \tau^f(\eta))w_r(\eta) - \beta\Pi'_{z2,+1}(1 - s) \\
\Pi'_{z2} &= p_{z2}\frac{\partial Y_{z2}}{\partial n_r(\eta)} - (1 + \tau^f(\eta))w_r(\eta) + (1 - s)\beta\Pi'_{z2,+1}
\end{aligned}$$

where the first equation gives  $\theta_r(\eta)$ , the second  $\lambda(\eta)$  and the last the value of the marginal job.

**Regime 2: inactivity regime.** In this regime, the flow cost to open a vacancy ( $c$ ) is too high with respect to the expected gains if it will be matched. Thus, we have  $v_r(\eta) = 0 \Rightarrow \mu(\eta) \geq 0$  and thus  $q_r(\eta) \rightarrow 1$ , the maximal value for a probability. But the marginal value of employment is still positive, leading to  $l_r(\eta) = 0 \Rightarrow \nu(\eta) = 0$  and  $\lambda(\eta) \geq 0$ . Including these

conditions in the FOCs lead to

$$\begin{aligned}\mu(\eta) &= c - \beta\Pi'_{z2,+1} \\ \lambda(\eta) &= -\frac{\partial Y_{z2}}{\partial n_r(\eta)} + (1 + \tau^f(\eta))w_r(\eta) - \beta\Pi'_{z2,+1}(1 - s) \\ \Pi'_{z2} &= p_{z2}\frac{\partial Y_{z2}}{\partial n_r(\eta)} - (1 + \tau^f(\eta))w_r(\eta) + (1 - s)\beta\Pi'_{z2,+1}\end{aligned}$$

where the first equation gives  $\mu(\eta)$ , the second  $\lambda(\eta)$  and the last the value of the marginal job.

**Regime 3: firings regime.** For the declining firms, we also have  $v_r(\eta) = 0 \Rightarrow \mu(\eta) \geq 0$ , but firings can occur, ie.  $0 < l_r(\eta) \leq 1$ . If  $l_r(\eta) < 1 \Rightarrow \lambda(\eta) = 0$  and  $\nu(\eta) \geq 0$ , then the FOCs lead to

$$\begin{aligned}\mu(\eta) &= c - \beta\Pi'_{z2,+1} \\ \nu(\eta) &= \frac{\partial Y_{z2}}{\partial n_r(\eta)} - (1 + \tau^f(\eta))w_r(\eta) + (1 - s)\beta\Pi'_{z2,+1} \\ \Pi'_{z2} &= (1 - l_r(\eta))p_{z2}\frac{\partial Y_{z2}}{\partial n_r(\eta)} - (1 - l_r(\eta))(1 + \tau^f(\eta))w_r(\eta) + (1 - s)\beta\Pi'_{z2,+1}(1 - l_r(\eta)) + \nu(\eta)l_r(\eta)\end{aligned}$$

By combining the second and the third equation, we obtain

$$\Pi'_{z2} = p_{z2}\frac{\partial Y_{z2}}{\partial n_r(\eta)} - (1 + \tau^f(\eta))w_r(\eta) + (1 - s)\beta\Pi'_{z2,+1}$$

These three equations give  $\mu(\eta)$ ,  $\nu(\eta)$  and the value of the marginal job, but  $l_r(\eta)$  stills undetermined. We deduce that the solutions for  $l_r(\eta)$  can take only two values, zero or one. Hence, in the regime 3, the only solution is  $l_r(\eta) = 1 \Rightarrow \lambda(\eta) \geq 0$  and  $\nu(\eta) = 0$  and the FOCs are

$$\begin{aligned}\mu(\eta) &= c - \beta\Pi'_{z2,+1} \\ \lambda(\eta) &= -\frac{\partial Y_{z2}}{\partial n_r(\eta)} + (1 + \tau^f(\eta))w_r(\eta) - (1 - s)\beta\Pi'_{z2,+1} \\ \Pi'_{z2} &= 0\end{aligned}$$

They provide the solutions for  $\mu(\eta)$ ,  $\lambda(\eta)$  and  $\nu(\eta)$ .

**Synthetic expressions of the FOCs.** If we abstract for the solutions of multipliers, then

the complete solution of the firm is given by

$$\begin{aligned} \frac{c}{q_r(\eta)} &= \beta J_{r,+1}(\eta) \quad \text{If } \beta J_{r,+1}(\eta) > c, \text{ otherwise } q_r(\eta) = 1 \\ J_r(\eta) &= \max \left\{ 0; p_{z2} \frac{\partial Y_{z2}}{\partial n_r(\eta)} - (1 + \tau^f(\eta))w_r(\eta) + (1 - s)\beta J_{r,+1}(\eta) \right\} \end{aligned} \quad (23)$$

where we denote  $J_r(\eta) = \Pi'_{z2} \equiv \frac{\partial \Pi_{z2}}{\partial N_r(\eta)}$ .

*Scrapping time.* The expression of  $J_r(\eta)$  allows us to determine  $\eta^S$ , such that  $0 = p_{z2} \frac{\partial Y_{z2}}{\partial n_r(\eta^S)} - (1 + \tau^f(\eta^S))w_r(\eta^S) + (1 - s)\beta J_{r,+1}(\eta^S)$ . This gives us the  $\eta$ -type workers that are fired at time  $t$ . Therefore, this condition determines the scrapping time for the  $\eta$ -type workers.

## Service-producing firms

Let us denote  $J_m = \frac{\partial \Pi_s}{\partial n_m}$ ,  $J_m^o = \frac{\partial \Pi_s}{\partial n_m^o}$  and  $J_m^n(\eta) = \frac{\partial \Pi_s}{\partial n_m^n(\eta)}$ , the associated Bellman equations of a filled job write, when  $v_m > 0$ ,  $v_m^o > 0$  and  $v_m^n(\eta) > 0$ :

$$J_m^n(\eta) = p_s \delta A_s - (1 + \tau_h^f)w_m^n(\eta) + (1 - s)\beta \left( (1 - \lambda)J_{m,+1}^n(\eta) + \lambda J_{m,+1} \right) \quad (24)$$

$$J_m^o = p_s \delta A_s - (1 + \tau_h^f)w_m^o + (1 - s)\beta \left( (1 - \lambda)J_{m,+1}^o + \lambda J_{m,+1} \right) \quad (25)$$

$$J_m = p_s A_s - (1 + \tau_h^f)w_m + (1 - s)\beta J_{m,+1} \quad (26)$$

The FOCs for a vacant job write:

$$0 = -c + \beta q_m^n(\eta) J_{m,+1}^n(\eta)$$

$$0 = -c + \beta q_m^o J_{m,+1}^o$$

$$0 = -c + \beta q_m J_{m,+1}$$

## F.2 Job creation equations

Together with the firm present values of a filled job, we obtain the following job creation condition for skilled workers when  $v_a > 0$ :

$$\frac{c_a}{q_a} = \beta \left[ y_{a,+1} - (1 + \tau_{h,+1}^f)w_{a,+1} + (1 - s_a) \frac{c_a}{q_{a,+1}} \right]$$

whereas, for unskilled workers, job creation conditions are, when  $v_r(\eta) > 0$ ,  $v_m^n(\eta) > 0$ ,  $v_m^o > 0$  and  $v_m > 0$ :

$$\begin{aligned}\frac{c}{q_r(\eta)} &= \beta \left[ y_{r,+1}(\eta) - (1 + \tau_{l,+1}^f) w_{r,+1}(\eta) + (1 - s_r) \frac{c}{q_{r,+1}(\eta)} \right] \\ \frac{c}{q_m^n(\eta)} &= \beta \left[ p_{s,+1} \delta A_s - (1 + \tau_{l,+1}^f) w_{m,+1}^n(\eta) + (1 - s_m) \left( \frac{c(1 - \lambda)}{q_{m,+1}^n(\eta)} + \frac{c\lambda}{q_{m,+1}} \right) \right] \\ \frac{c}{q_m^o} &= \beta \left[ p_{s,+1} \delta A_s - (1 + \tau_{l,+1}^f) w_{m,+1}^o + (1 - s_m) \left( \frac{c(1 - \lambda)}{q_{m,+1}^o} + \frac{c\lambda}{q_{m,+1}} \right) \right] \\ \frac{c}{q_m} &= \beta \left[ p_{s,+1} A_s - (1 + \tau_{l,+1}^f) w_{m,+1} + (1 - s_m) \frac{c}{q_{m,+1}} \right]\end{aligned}$$

### F.3 Wage equations

**Abstract jobs:**

$$w_a = \frac{\gamma}{1 + \tau^f} \left( y_a + \Gamma(\tau_{+1}^f, \tau_{+1}^w) \frac{\phi_{+1}}{\phi} c_a \theta_a + (1 - s_a) \frac{c_a}{q_a} \left( 1 - \frac{\phi_{+1}}{\phi} \Gamma(\tau_{+1}^f, \tau_{+1}^w) \right) \right) + \frac{1 - \gamma}{1 - \tau^w} z_a$$

where  $\phi = \frac{\gamma}{1 - \gamma}$  and  $\Gamma(\tau_{+1}^f, \tau_{+1}^w) = \frac{1 + \tau^f}{1 + \tau_{+1}^f} \frac{1 - \tau_{+1}^w}{1 - \tau^w}$ . This equation shows that the bargained surplus captured by employees is the sum of (i) the marginal productivity, and (ii) the search returns. For the worker, the returns on the search process are equal to the discounted time duration to find a job offer; for the firm, returns are instead equivalent to the discounted time duration to find a worker. These relative time spans cannot be approximated by the ratio of the average duration for these two search processes ( $\theta_a = \frac{f_a}{q_a}$ ), as would be the case when bargaining powers or tax rates are constant.<sup>36</sup> However, if workers expect that their future bargaining power is close to zero ( $\phi_{t+1} \approx 0$ ), the evaluation of the current match surplus is only driven by the search costs saved by the firm if the job is not destroyed ( $(1 - s) \frac{c_a}{q_a}$ ). In contrast, when workers' bargaining power increases ( $\phi_{t+1} > \phi_t$ ), or if they pay more taxes, the match value must be depreciated by the firm (it expects a decrease in its bargaining power), whereas the relative time spans must be over-estimated by the worker because its bargaining power increases. Thus, the value of the search cost is a function of the bargaining power and taxes, which themselves change over time. Finally, the reservation wage includes the home production with the non-employment incomes.

**Unskilled workers.**

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<sup>36</sup>More formally, in these two cases, we have  $\phi_{+1}/\phi = 1$  in the first and  $\Gamma(\tau_{+1}^f, \tau_{+1}^w) = \frac{1 + \tau^f}{1 + \tau_{+1}^f} \frac{1 - \tau_{+1}^w}{1 - \tau^w} = 1$  in the second case

(i) Routine:

$$w^r(\eta) = \frac{\gamma}{1 + \tau^f} \left( y_r(\eta) + \Gamma(\tau_{+1}^f, \tau_{+1}^w) \frac{\phi_{+1}}{\phi} c\theta_r(\eta) + \frac{c}{q_r(\eta)} (1 - s_r) \left( 1 - \Gamma(\tau_{+1}^f, \tau_{+1}^w) \frac{\phi_{+1}}{\phi} \right) \right) + \frac{1 - \gamma}{1 - \tau^w} (z_r(\eta) + (1 - s_r - f_r)\beta \max\{0, U_{m,+1}^n(\eta) - U_{r,+1}(\eta)\})$$

With respect to the wages of abstract jobs, the novelty comes from the reservation wage. If unemployed, workers know that they can move from routine to manual occupations if manual jobs are more profitable: they take into account this new opportunity in their reservation wage. When  $U_m^n > U_r(\eta)$ , this surplus is obtained only if an unemployed worker does not find a job (with a probability  $1 - f_r$ ), net of the chance to obtain it directly after a separation (with probability  $s$ ). This opportunity to move is offered only to unemployed workers: thus, this increases the reservation wage.

When  $U_m^n(\eta) > U_r(\eta)$  and given that  $U_m^n(\eta)$  is increasing whereas  $U_r(\eta)$  is decreasing, the wage on a routine job is

$$w^r(\eta) = \frac{\gamma}{1 + \tau^f} \left( y_r(\eta) + \Gamma(\tau_{+1}^f, \tau_{+1}^w) \frac{\phi_{+1}}{\phi} c\theta_m^n(\eta) + \frac{c}{q_r(\eta)} (1 - s_r) \left( 1 - \Gamma(\tau_{+1}^f, \tau_{+1}^w) \frac{\phi_{+1}}{\phi} \right) \right) + \frac{1 - \gamma}{1 - \tau^w} z_r(\eta)$$

This wage is paid to workers on routine jobs, after  $\eta$ -type unemployed workers had moved to the market of manual jobs.

(ii) Manual (incumbent or experienced workers):

$$w_m = \frac{\gamma}{1 + \tau^f} \left( p_s \delta A_s + \Gamma(\tau_{+1}^f, \tau_{+1}^w) \frac{\phi_{+1}}{\phi} c\theta_m + \frac{c}{q_m} (1 - s_m) \left( 1 - \Gamma(\tau_{+1}^f, \tau_{+1}^w) \frac{\phi_{+1}}{\phi} \right) \right) + \frac{1 - \gamma}{1 - \tau^w} z_m$$

These workers are incumbent: they do not expect any mobility, except the one associated to the unemployment risk. Thus, the wage equation is the same as for the “abstract” workers.

(iii) Manual (new movers or inexperienced workers):

$$w_m^n(\eta) = \frac{\gamma}{1 + \tau^f} \left( p_s \delta A_s + \Gamma(\tau_{+1}^f, \tau_{+1}^w) \frac{\phi_{+1}}{\phi} c\theta_m^n(\eta) + \left( \frac{c(1-\lambda)}{q_m^n(\eta)} + \frac{c\lambda}{q_m} \right) (1 - s_m) \left( 1 - \Gamma(\tau_{+1}^f, \tau_{+1}^w) \frac{\phi_{+1}}{\phi} \right) \right) + \frac{1 - \gamma}{1 - \tau^w} \left( z_r(\eta) + \beta \left( \lambda(U_{m,+1}^n(\eta) - U_{m,+1}) + s(1 - \lambda)(U_{m,+1}^n(\eta) - U_{m,+1}^o) \right) \right)$$

The value of the opportunity to become an experienced worker is included in the reservation wage of the new movers (inexperienced workers): this changes workers'

outside option  $U_{m,+1}^n(\eta) - U_{m,+1}$  with a probability  $\lambda$ . Workers also know that they can lose the state of “new mover” even if they do not become experienced: they can lose their “new mover” jobs and become “old mover” unemployed workers, implying a change in their outside options  $U_{m,+1}^n(\eta) - U_{m,+1}^o$ . This event can appear with a probability  $s(1 - \lambda)$ . In the “regular” case, we have  $U_{m,+1}^n(\eta) < U_{m,+1}$  and  $U_{m,+1}^n(\eta) > U_{m,+1}^o$ : the expectation of the promotion leads workers to reduce their reservation wage to increase their opportunities to access this labor market state, whereas the loss of their unemployed benefits indexed to the wage of a routine job is a risk shared with the firm that hires an “new mover.”

(iv) Manual (old movers):

$$w_m^o(\eta) = \frac{\gamma}{1 + \tau^f} \left( p_s \delta A_s + \Gamma(\tau_{+1}^f, \tau_{+1}^w)^{\frac{\phi+1}{\phi}} c \theta_m^o \right) + \left( \frac{c(1-\lambda)}{q_m^o} + \frac{c\lambda}{q_m} \right) (1 - s_m) \left( 1 - \Gamma(\tau_{+1}^f, \tau_{+1}^w)^{\frac{\phi+1}{\phi}} \right) + \frac{1 - \gamma}{1 - \tau^s} (z_m + \beta \lambda (U_{m,+1}^o - U_{m,+1}))$$

With a probability  $\lambda$ , these workers become experienced manual workers and then access this new labor market: this changes their outside option by an amount of  $U_{m,+1}^o - U_{m,+1}$ . Note that, if  $U_{m,+1}^o < U_{m,+1}$ , this leads them to accept lower wages when they are “old movers.”

## F.4 Unemployment Dynamics

The law of motion for the unemployed in each occupation is as follows:

$$u_a = L_a - n_a \quad (27)$$

$$u_{r,+1}(\eta) = \mathbb{I}\{U_r(\eta) > U_m^n(\eta)\} \left[ u_r(\eta)(1 - f_r(\eta)) + s_r n_r(\eta) + n_r(\eta)(s_r + (1 - s_r)\mathbb{I}\{J_r(\eta) > 0\}) \right] \quad (28)$$

$$u_{m,+1}^n(\eta) = u_m^n(\eta)(1 - f_m^n(\eta)) + u_r(\eta)\mathbb{I}\{U_r(\eta) \leq U_m^n(\eta)\} \quad (29)$$

$$u_{m,+1}^o = u_{m,+1}^o(\eta)(1 - f_m^o) + s_m(1 - \lambda)(n_m^o + \sum_{\eta} n_m^n(\eta)) \quad (30)$$

$$u_m = 1 - L_a - (n_m + n_m^o + u_m^o + \sum_{\eta} u_r(\eta) + n_r(\eta)) \quad (31)$$

where  $\mathbb{I}\{\cdot\} = 1$  when the inequality inside the brackets is satisfied.

## F.5 Market clearing conditions

The production equals demand on each market:

$$\begin{aligned}\tilde{Y}_g &= \sum_k C_g^k \equiv C_g \quad \text{with } k \in \{ae, re(\eta), me, me^o, me^n, au, mu, ru(\eta), v\} \\ Y_s &= \sum_k C_s^k \equiv C_s,\end{aligned}$$

where  $\tilde{Y}^g$  is the production of the intermediate goods net of hiring and entry costs:

$$\tilde{Y}_g = Y_g - p_k K - c_a V_a - c \sum_{\eta} V_r(\eta) - c V_m - c \sum_{\eta} V_m^n(\eta) - c V_m^o,$$

and the index  $v$  relates to the agent that receives the income  $I = S_g + \Omega$ , which are respectively government surplus and firm dividends. Government fiscal revenues and expenditures are given by:

$$\begin{aligned}\Theta &= (\tau^w + \tau_l^f) \left( \sum_{\eta} w_r(\eta) L_r(\eta) + w_m L_m + \sum_{\eta} w_m^n(\eta) L_m^n(\eta) + w_m^o L_m^o \right) + (\tau^w + \tau_h^f) w_a L_a \\ \Gamma &= z_a U_a + \sum_{\eta} z_r(\eta) U_r(\eta) + z_m (U_m + U_m^o) + \sum_{\eta} z_m^n(\eta) U_m^n(\eta)\end{aligned}$$

with unemployment benefit being a function of productivity:<sup>37</sup>  $z_i = \rho_i y_i$ . This allows us to define government surplus  $S_g = \Theta - \Gamma$ . Finally, dividends are defined as  $\Omega = \Pi_{z1} + \Pi_{z2} + \Pi_s$ .

## F.6 General equilibrium

Our model is a general equilibrium as labor income affects demand for goods and services, which leads to an endogenous relative price of service. However, to make the model tractable, we discard savings<sup>38</sup> and discussion on the structure of public spending. Without savings, we cannot deal with welfare implications of changes in public debt or firm dividends. The general equilibrium is reached through the economic agent that receives government surplus and firm dividends and spends it on the good and service markets.<sup>39</sup> Alternatively, we could have shared government surplus and firm dividends among workers, using lump-sum transfers. However, we consider this assumption as unrealistic. Tax rates are all taken from institutional data. We therefore leave aside the question of the impact of changes in LMI

<sup>37</sup>While unemployment benefits are usually proportional to wages, we simplify the definition of  $z_i$  for keep the model tractable. However, it does not matter so much since wage are mainly driven by movements in productivity.

<sup>38</sup>Dealing with savings is left for future research as the size of the model is already very large

<sup>39</sup>In Annexe D.3, this agent is denoted by subscript  $v$ .

(replacement ratios) on tax rates or public spending. Any fiscal feedback from LMI shifts is left for future research.

## G Labor market institutions : Data sources

**Data sources.** Table 4 reports data sources for measurement of LMIs.

Table 4: Labor market institutions

LMI	Notation	Source	
		USA	France
Unemployment benefits Replacement rate	$rr$	OECD replacement rate	OECD replacement rate
Bargaining power	$\gamma$	ICTWSS <sup>a</sup>	ICTWSS
Employer social security contribution	$\tau^f$	MacDaniel (2007)	MacDaniel (2007)
Employees social security contributions	$\tau^w$	MacDaniel (2007)	MacDaniel (2007)
Minimum wage	$\frac{w_{\min}}{\text{mean}(w)}$	FRED, gross hourly	INSEE, equivalent annual

a: Database on Institutional Characteristics from Trade Unions, Wage Settings, State Intervention and Social Pact (ICTWSS) average of union density and union coverage. OECD replacement rate measures the proportion of previous in-work income maintained after 5 years of unemployment.

**Worker’s bargaining power.** Our measure of worker’s bargaining power draws on [Langot & Pizzo \(2019\)](#) who consider data from the Institutional Characteristics of Trade Unions, Wage Settings, State Intervention and Social Pact (ICTWSS) database. Two statistical indicators provide an indirect measure of the bargaining power of the employee during the wage bargaining process: union coverage (UC) and union density (UD). These two indicators are closely linked to bargaining power: wide UC or high UD enable the worker to make counteroffers during the bargaining process.

We choose to evaluate the worker’s bargaining power by averaging UC and UD, as in [Langot & Pizzo \(2019\)](#).

In a Nash-bargaining problem, there are no institutions and the wage contract is signed by two parties. Hence, bargaining power can be interpreted as a measure of relative impatience. One can link this theoretical framework to wage bargaining by assuming that the relative impatience of workers is dampened when they can share information in a union. Therefore, a natural way to measure the bargaining power of workers is to use an indicator of union size. The ICTWSS database provides a measure of UD. Alternatively, even if the union is small, information on the other contracts can be large (thus reducing the worker’s impatience) if certain state rules imply a large coverage of the decisions of this small number of union members. The ICTWSS database also provides a measure of UC.

In the United States, UD is similar to the collective bargaining coverage. Therefore, in this country, there is no problem relating UC and/or UD to the bargaining power of workers.

This is not the case in European countries, such as France. Only 7.7% of French workers are union members, while 98% are covered by collective bargaining agreements. The coverage rates are thus substantially higher than union membership. We then choose to keep the two pieces of information on unions (i.e., UD and UC) and build an indicator of the bargaining power of workers as their average.

These measures are also widely used in the literature to assess the importance of labor unions (that are representatives of wage earners) on labor market (see textbook on Labor Economics, by Cahuc et al, MIT Press, chap 7, 2014; [Blanchard & Wolfers \(2001\)](#))

UC and UD are also commonly used in reports and studies that use structural models of search and matching for policy evaluations (such as [Lombardi et al. \(2020\)](#) and [Auray et al. \(2020\)](#)). It is worth noting that numerous studies, including [Nickell \(1997, 1998\)](#), [Belot & Van Ours \(2001\)](#), [Bertola et al. \(2007\)](#), [Baker et al. \(2004\)](#), [Nickell et al. \(2005\)](#) and [Bassanini & Duval \(2009\)](#), showed that union density and union coverage wield significant influence over unemployment through their impact on the wage-setting mechanism. These papers also emphasize that changes in these labor market indicators have contributed to diverging unemployment trends.<sup>40</sup>

**Replacement rate.** The replacement rates for unemployment benefits are computed by the OECD. To be consistent with our model, we need the gross replacement rate, which is available from 1963 until 2005; from 2005 onward we use information on the net replacement rate in order to reconstruct the gross one. Both measures refer to the average replacement rate of income during unemployment over a five-year period (for details, see the [OECD website](#)). For a discussion on the link between unemployment benefits and non-employment incomes, see also appendix C of [Langot & Pizzo \(2019\)](#).

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<sup>40</sup>Nickell (1997, 1998) showed, through an analysis of the Log of aggregate unemployment rates for a sample period spanning 1983-1994 and encompassing 20 OECD countries, that both union density and coverage exerted a significant impact on aggregate unemployment. [Belot & Van Ours \(2001\)](#) investigated aggregate unemployment rates spanning from 1960 to 1995 across 18 OECD countries. Their findings indicate that union density and union coverage held significant influence on these rates. [Bertola et al. \(2007\)](#) examined aggregate unemployment data from 1960 to 1995/96, involving 20 OECD countries. Their research revealed that changes in institutional factors, particularly union density and coverage, played a role in explaining diverging unemployment trends, with the expected signs in their baseline specification. [Baker et al. \(2004\)](#) focused on a dataset covering the years 1960 to 1999 and including 20 OECD countries. Their research underscored the high significance of coordination and interaction between union density in understanding unemployment patterns. [Nickell et al. \(2005\)](#) conducted an analysis using aggregate unemployment rates from 1961 to 1995, spanning 20 OECD countries. Their findings emphasized that interactions between union density and coordination accounted for a substantial fraction of the increase in European unemployment observed over the sample period. [Bassanini & Duval \(2009\)](#) focused on aggregate unemployment data spanning from 1982 to 2003 across 20 OECD countries. Their research highlighted that interactions between union density and corporatism contributed to increase unemployment.

## H Model calibration

Table 5 summarizes the 19 calibrated parameters.  $\Phi_1^c$  relates to preferences,  $\Phi_2^c$  to matching calibration and  $\Phi_3^c$  to the supply of skilled labor. There is a first set of parameters that is

Table 5: 19 Model parameters values based on external information

$\Phi_1^c$ Preferences		$\Phi_3^c$ Supply of skilled labor	
$\beta$	4%	$L_{a,US}(0)$	0.17
$\mu$	0.5	$L_{a,F}(0)$	0.085
$\nu$	0.5	$L_{a,US}(T)$	0.238
		$L_{a,F}(T)$	0.1513
$\Phi_2^c$ Matching			
$s_{a,US}$	0.05	$c_{a,US}$	0.5
$s_{a,F}$	0.04	$c_{a,F}$	0.5
$s_{r,US}$	0.085	$c_{US}$	0.3
$s_{r,F}$	0.045	$c_F$	0.3
$s_{m,US}$	0.13	$\psi_{US}$	0.5
$s_{m,F}$	0.11	$\psi_F$	0.5

not country-specific. The discount factor  $\beta$  is such that the annual real interest rate is 4%. The elasticity of the matching function is set to 0.5, which is consistent with the estimates reported in [Petrongolo & Pissarides \(2001\)](#). The calibration of the vacancy posting costs  $\{c_a, c\}$  are based on the results of [Barron et al. \(1997\)](#) and [Barron & Bishop \(1985\)](#). These authors suggest that an amount to 17% of a 40-hour workweek.<sup>41</sup> For low-skilled workers, we set  $c = 0.3$  because this corresponds to 17% of the average production of workers on routine and manual occupations. For skilled workers, we suppose that the work time required to process each application is 1.66 larger, leading us to set  $c_a = 0.5$ .<sup>42</sup> This value lies within the range found in the literature: [Acemoglu \(2001\)](#) and [Krause & Lubik \(2006\)](#) suggest  $\frac{c_a}{c} > 1$ . [Hagedorn et al. \(2016\)](#) set  $\frac{c_a}{c} = 4$ . We consider an intermediate value of 5/3. Finally, we arbitrary set to  $\mu = \nu = 0.5$  the values of the share parameters respectively in the production and utility functions.

The second set of parameters are country-specific: these are job separation rates and the shift of the labor supply composition.

- *Job separation rates.* We use information on worker flows. Since French quarterly labor flows cannot be computed before 2003, we focus on US labor flows. As explained in [Appendix D](#), we build US monthly labor flows with 5 labor statuses Employed in each task ( $A, R, M$ ), Unemployed and Not in the labor force, using monthly CPS

<sup>41</sup>More precisely, nine applicants for each vacancy filled, with two hours of work time required to process each application

<sup>42</sup>Job creation costs consist of costs for recruitment, screening, and training. [Acemoglu \(2001\)](#) argue that job creation costs are likely to be larger for high-wage jobs. This supports the view that job creation costs for abstract jobs are larger than for low-wage jobs.

data (1985m6-2007m12). The model is calibrated on a quarterly frequency, while we computed monthly labor market transitions from US data. We need to transform, in US data, monthly labor market transitions into quarterly transitions. We obtain the quarterly Markov matrix by calculating the monthly Markov matrix to the power of 3. The model is about employment levels, so that agents who are not employed in the model are unemployed or out of the labor force. So the calibration of separation shall actually be based on transitions to non-employment. In the sample (1985Q1-2007Q4), average quarterly transitions rates to non-employment (E-to-U + E-to-N) for abstract, routine and manual workers are, respectively, 7.40%, 12.08% and 18.60%. In addition, [Simmons \(2023\)](#) points out that, in US data (1996m4-2013m5, SIPP), less than a third of transitions E-to-U are involuntary (which corresponds to endogenous separations in the model). This means that the calibration of exogenous separations shall consider 70% the separations rates from the data. Taking into account this result and assuming the same rate for all separations, the exogenous separation rate in our model should be, in the US,  $s_a = 0.074 \times 0.7 = 0.0518 \approx 0.05$ ,  $s_r = 0.1208 \times 0.7 = 0.0846 \approx 0.085$ ,  $s_m = 0.186 \times 0.7 = 0.1302 \approx 0.13$ . For the French economy, we only know that the aggregate job separation rate is 0.05. Therefore, we arbitrary chose  $s_a, s_r, s_m$  such that  $share_a \times s_a + share_r \times s_r + share_m \times s_m = 0.05$  where  $share_a = 0.2$ ,  $share_r = 0.72$  and  $share_m = 1 - share_a - share_r$ . One solution is  $s_a = 0.04$ ,  $s_r = 0.045$  and  $s_m = 0.11$ .

- *Share of the labor supply for abstract jobs.* We choose to pin down  $L_a$  that is consistent with the observed employment level in abstract jobs  $N_a$  and the non-employment rate in the pool of abstract jobs, denoted  $nn_a$ . Hence,  $L_a = N_a / (1 - nn_a)$ . We choose to approximate the rate of people that are not employed in the segment of the abstract tasks as the non-employment rate of the bachelor's degree or more. These rates has been stable in the United States, around 20%, whereas in France, they slightly increase from 15% in the 80s to 18% in 2008. Using the formula  $L_{a,US}(\tau) = N_{a,i}(\tau) / (1 - nn_{a,i}(\tau))$ , for  $i = US, F$  and  $\tau = 0, T$ , we obtain the values reported in [Table 5](#).

**Estimation.** For the estimation, the unknown parameters  $\Phi^u$  are the solutions of  $\min_{\Phi^u} \|\Psi(\Phi^u) - \Psi_T\|$ , with  $\Phi^u = \{\Phi_1^u, \Phi_2^u, \Phi_3^u\}$ . The model is non-stationary and non-linear, which requires an innovative solution method. The algorithm is presented in [Appendix I](#).

# I Numerical method used to solve the model

## I.1 Overview of computational difficulties

Solving the model is challenging. As pointed out by [Petrosky-Nadeau & Zha \(2017\)](#), a rigorous solution method is required to capture non-linearities. Several elements make the computation of the dynamic challenging.

- First, the job polarization involves a non-stationary environment because of structural changes in the economy. The main difficulty is the occurrence of regimes only during the transitional path, and not at the steady. As a result, standard solution methods involving approximation of the dynamics around a unique steady state are inappropriate.
- Second, we have heterogeneous agents. The problem is currently solved with 100 ability levels  $\eta \sim \mathcal{U}(\underline{\eta}, \bar{\eta})$ , which makes the computation burdensome.
- Third, along the transitional path, we face a highly non-linear environment. The reasons behind the non-linearity is threefold:
  1. Along the transitional path, the minimum wage can bind or not in some segments of the labor market, leading to several regimes in the economy.
  2. The existence of rigid wage in the form of a minimum wage may cause firms to run negative surplus, thereby leading to firms' closure and introducing a scrapping-time.
  3. Occupational choices involves also discontinuities as workers of different abilities leave the routine labor market.

We then have to deal with occasionally binding constraints for each ability level. Changes in occupations, binding minimum wages and firms' closure are all endogenous events.

- Fourth, there are general equilibrium effects: the relative price of service is such that good and service markets clear. This relative price also affects the relative productivity levels across sectors, which feeds back on occupational choices, employment levels in each sector and the supply in the good and service markets. In turn, those changes are likely to affect the relative price of service, and so on. As a result, we need to find a fixed point over general equilibrium effect for each period along the transitional path.

## I.2 Overview of the algorithm

Standard procedures can no longer be used because of the huge number of discontinuities. This leads us to propose an original algorithm for the numerical solution of the model. The algorithm aims at finding a “fixed point” for a trajectory between an initial steady state and a terminal steady state, given that, during this adjustment process, exogenous variables, such as the policy tools, can change. The numerical method is presented in the case of perfect forecast for the policy instruments.

We use the block-recursive aspect of the Diamond–Mortensen–Pissarides (DMP) model that is cast into two sub-routines. We first solve for the paths of the forward variables, given an initial guess one the dynamics of backward variables. Thereafter, the backward variables trajectories are obtained by iterating on their law of motion. Given new trajectories for the state variables, a new trajectory for the forward variable is calculated. This procedure is repeated until convergence of both the backward and the forward variables.

## I.3 Detailed algorithm

### I.3.1 Notations

- $T$  is the simulation length.
- $\{x_t\}_{t=0}^T$  stacks the trajectory of all **endogenous** state (backward) variables.  $x$  corresponds to all different employment and unemployment stocks.
- $\{y_t\}_{t=0}^T$  stacks the trajectory of all **endogenous** control (forward) variables.  $y$  corresponds to all different value functions, tightness, prices, wages, productivity values, capital levels and consumption levels.
- $\{z_t\}_{t=0}^T$  stacks the trajectory of all **exogenous** disturbance that for which we perfectly know their value. It corresponds to the value of the observed LMIs (replacement rate, minimum wage, bargaining powers as well as employers and employees social security contributions).
- $\{p_{k,t}\}_{t=0}^T$  and  $\{L_{a,t}\}_{t=0}^T$  are two disturbances whose law of motion are define is the core of the paper. The important aspect here is that they do not depend on endogenous variable or exogenous disturbances.
- $\Theta$  stands for the set of parameters.

### I.3.2 General problem

The general problem can be summarized by the following system of equations:

$$\begin{aligned}x_t &= g(x_{t-1}, y_{t-1}; \Theta) \\y_t &= f(x_{t+1}, y_{t+1}, z_{t+1}; \Theta) \\p_{k,t} &= h_1(t; \Theta) \\L_{a,t} &= h_2(t; \Theta)\end{aligned}$$

### I.3.3 Step-by-step algorithm

**Step 1** Set the parameters  $\Theta$  and get the trajectories for the shocks  $\{p_{k,t}\}_{t=0}^T$  and  $\{L_{a,t}\}_{t=0}^T$ .

**Step 2** Guess an initial trajectory<sup>43</sup> for the state variables  $\{x_t^0\}_{t=0}^T$  and for the control variables  $\{y_t^0\}_{t=0}^T$ . For simplicity, we assume in a first time that they are all constant. Since the states variables correspond to the stocks of employment and unemployment, the only constraint that must be imposed is  $\sum x_t = 1$  every period. For the controls, they are all set to one  $\forall t$  in the first place.

**Step 3** Given the terminal condition of the shocks  $p_{k,T}$  and  $L_{a,T}$ , the terminal condition of state variables  $x_T^0$  and the shock processes  $z_t$  at time  $t = T$ , recalculate the terminal condition for the control variables  $y_T$  using a fixed-point method.

**Step 4** Given the exogenous shock and the initial trajectory of the state variables  $\{x_t^0\}_{t=0}^T$ , solve for the path of the control variables by iterating backward<sup>44</sup>:

$$\begin{aligned}y_{T-1} &= f(x_T^0, y_T, z_T; \Theta) \\y_{T-2} &= f(x_{T-1}^0, y_{T-1}, z_{T-1}; \Theta) \\y_{T-3} &= f(x_{T-2}^0, y_{T-2}, z_{T-2}; \Theta) \\&\vdots \\y_0 &= f(x_1^0, y_1, z_1; \Theta)\end{aligned}$$

<sup>43</sup>Superscript zero to  $x_t^0$  and  $y_t^0$  stands for the initial guesses.

<sup>44</sup>It should be noted that given the highly non-linear nature of the system of equations in  $f(\cdot)$ , we need a root-finding procedure to pin down some control variables at each period  $t$ . For that purpose, we use a Newton–Raphson algorithm. Furthermore, this step involves the checking of whether the aforementioned constraints (minimum wage, occupation, scrapping) are binding or not. This involves an adaptive algorithm which tests for the binding constraints.

**Step 5** Given the initial condition of the shocks  $p_{k,0}$  and  $L_{a,0}$ , the new initial condition of control variables  $y_0$  and the shock processes  $z_t$  at time  $t = 0$ , recalculate the initial condition for the control variables  $x_0$  using a fixed-point method.

**Step 6** Given the initial conditions of the states  $x_0$  (from **Step 2**) and the new path of the controls  $\{y_t\}_{t=0}^T$ , solve for the path of the state variables by iterating forward using the laws of motion:

$$\begin{aligned} x_1 &= g(x_0, y_0; \Theta) \\ x_2 &= g(x_1, y_1; \Theta) \\ &\vdots \\ x_{T-1} &= g(x_{T-2}, y_{T-2}; \Theta) \\ x_T &= g(x_{T-1}, y_{T-1}; \Theta) \end{aligned}$$

**Step 7** Check if the new trajectories of the states  $\{x_t\}_{t=0}^T$  and the controls  $\{y_t\}_{t=0}^T$  are different from the one in **Step 2** (i.e.,  $\{x_t^0\}_{t=0}^T$  and  $\{y_t^0\}_{t=0}^T$ , respectively). We use a Euclidian norm and target and criterion of  $10^{-8}$ :

$$\begin{aligned} \frac{\|x - x^0\|}{\|x^0\|} &\leq 10^{-8} \\ \frac{\|y - y^0\|}{\|y^0\|} &\leq 10^{-8} \end{aligned}$$

**Step 8** If it is not the case, then define:

$$\begin{aligned} \{x_t^0\}_{t=0}^T &= \{x_t\}_{t=0}^T \\ \{y_t^0\}_{t=0}^T &= \{y_t\}_{t=0}^T \end{aligned}$$

and go back to **Step 3**.

## J Computing ICT prices

We report on Figure 5 several investment prices.

**Relative price of investment goods from Karabarbounis & Neiman (2014).** We use data from Karabarbounis & Neiman (2014) who compute the relative price of investment goods (price of investment divided by the domestic price of consumption) from the Penn World Tables (which provides comparable data across countries with the purchasing power parity exchange rates).

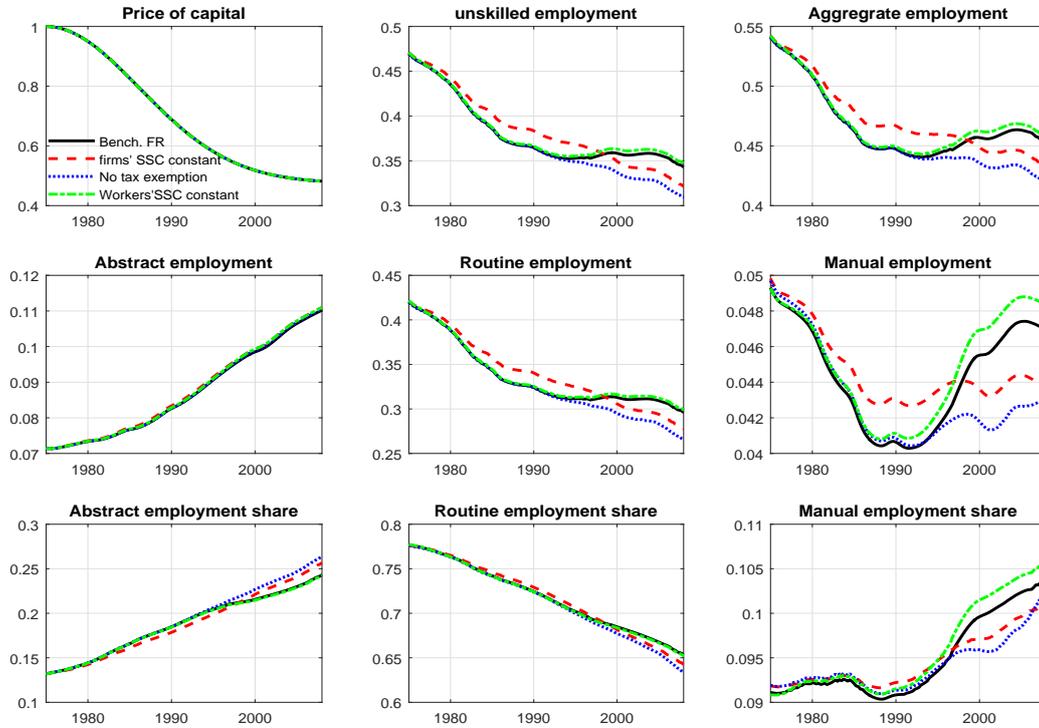
**US ICT price from the BEA.** As investment goods include ICT equipment as well as machinery, one can construct an index of the investment price shift (*i*) by weighting the ICT component of this index by the share of ICT investments in total investments, and (*ii*) by assuming that only the price of ICT change in this index, this last assumption being supported by Karabarbounis & Neiman (2014) where the price of investment goods is stable before the ICT revolution.

For simplicity, we assume a Cobb Douglas index for investment goods price, i.e.  $p_{k,t} = p_m^{1-s_{ICT,t}} p_{ICT,t}^{s_{ICT,t}}$  where  $p_m$  is constant and normalized to unity,  $p_{ICT,t}$  is the US BEA price index of private fixed investment in information processing equipment and software (B679RG3Q086SBEA, divided by the Personal Consumption Expenditures deflator, PCEPI) and  $s_{ICT,t}$  denotes the share of ICT investment in total investments. For computing  $s_{ICT,t}$ , we use Private fixed investment in information processing equipment and software (A679RC1Q027SBEA) and Private Nonresidential Fixed Investment (PNFI). We could not find a similar ICT data for France for the time span that we consider.

Figure 5 shows that the price shifts identified by our model matches quite well this measure of changes in capital price induced by the reduction of investment price in ICT.

# K Payroll tax cuts experience in France

Figure 20: The role of subsidies for low-paid jobs *France*

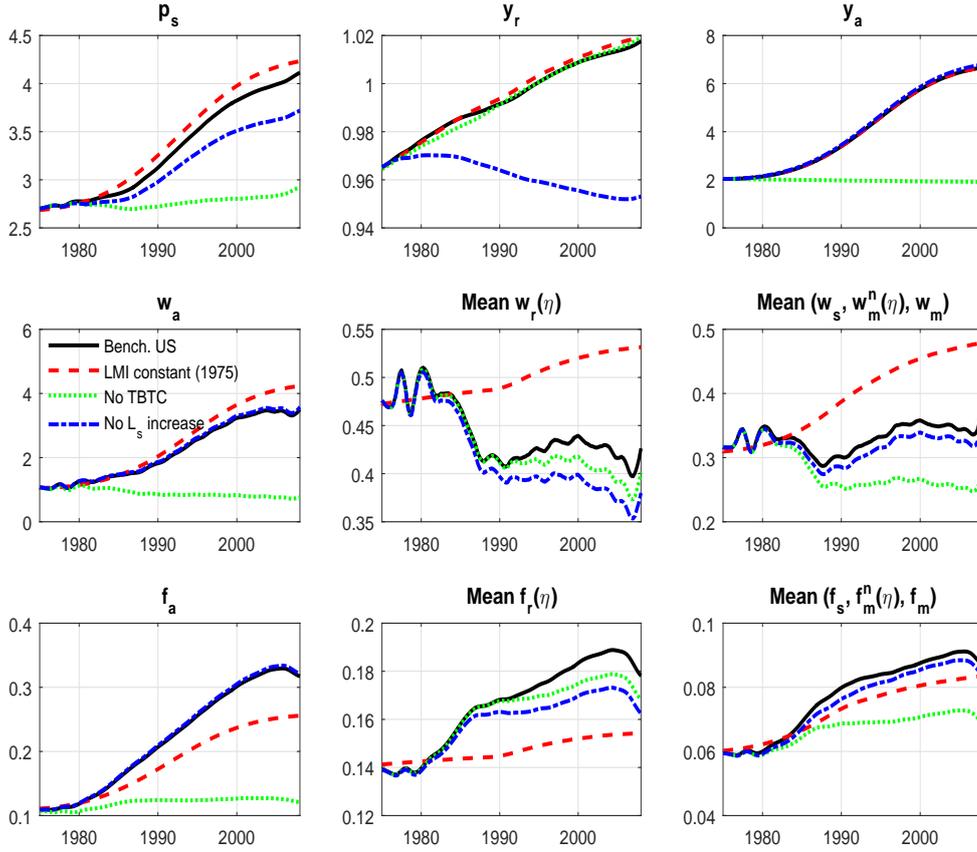


“Bench FR” Benchmark calibration: TBTC, rising  $L_a$  and LMI shifts; “firms’ SSC Constant” Economy with constant  $\tau^f$ , set at 1975 level; “No tax exemption” Economy with a homogenous tax rate  $\tau^f$  even after 1996; “Workers’ SSC Constant” Economy with constant  $\tau^w$ , set at 1975 level.

# L Additional graphs on the polarization analysis: Benchmark case

For routine jobs and manual job wage are averaged using the employment weight for each categories.<sup>45</sup>

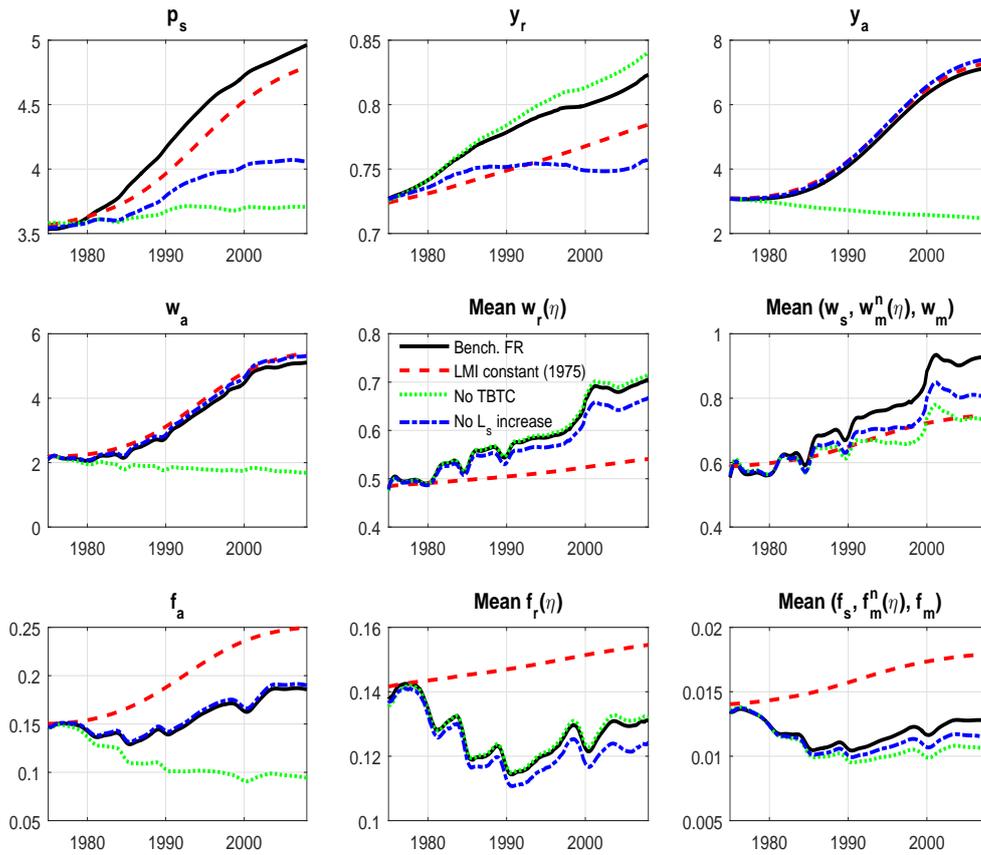
Figure 21: Productivity, average wages, and job finding rates. *US*.



<sup>45</sup>“Bench US” Benchmark calibration: TBTC, rising  $L_a$  and LMI shifts. “Constant LMI (1975)” Economy with constant LMI, set at 1975 level. “No TBTC” Economy with constant price of capital, set at 1975 level. “No  $L_s$  increase” Economy with constant supply of skilled labor  $L_a$ , set at 1975 level.

<sup>45</sup>The productivity for routine job does not include the skill component  $\eta$ . By multiplying  $y_r$  by  $\eta$ , we have the productivity for each skill  $y_r(\eta)$ .

Figure 22: Productivity, average wages, and job finding rates. *France*.



“Bench FR” Benchmark calibration: TBTC, rising  $L_a$  and LMI shifts. “Constant LMI (1975)” Economy with constant LMI, set at 1975 level. “No TBTC” Economy with constant price of capital, set at 1975 level. “No  $L_s$  increase” Economy with constant supply of skilled labor  $L_a$ , set at 1975 level.

## M Identification scheme: intuitions and illustrations

The model draws from the textbook by Shimer (Labour Market and Business Cycle, 2010). This textbook model is now used in teaching modern labor macroeconomics (Benjamin Moll's class notes at LSE, for instance). In order to be transparent, we use the same notations as in Benjamin Moll's classnotes.

The textbook model is extended to capture 3 tasks (Abstract, Routine and Manual) and technological change. We first look at the initial steady state of 2 hypothetical countries (called France and the US). To simplify, at the initial steady state, both countries share the same employment levels, hence the same employment shares by task. We define the final steady state as the steady state prevailing after the technological change has taken place. Using this model, at the final steady state, we show that employment shares alone cannot provide enough information to account for opposite evolutions of aggregate employment in France and in US. The model also suggests that, without change in LMI, France's aggregate employment would have increased, which is counterfactual. Only changes in LMI can account for changes in employment levels consistent with French data.

### M.1 Intuition of identification using a static matching model

#### M.1.1 Static matching model

**Matching function.** The number of new jobs is given by the Cobb-Douglas matching function :  $m = \mu v^\eta u^{1-\eta}$  with  $0 < \eta < 1$ .  $\theta$  is defined as  $\frac{v}{u}$ .

**Vacancy filling rate for firms** Firms that considers posting vacancy need to know the vacancy filling rate, which is the probability of filling a given vacancy. This is given by  $\frac{m}{v} = \bar{\mu}\theta^{\eta-1}$  with  $v$  the vacancies posted by a firm. The employment level  $n$  of an individual firm is determined by

$$n = n_0 + \mu(\theta)v \quad \text{with } \mu(\theta) = \bar{\mu}\theta^{\eta-1}$$

with  $n_0$  the number of workers employed (matched) before the start of period. Labor force is fixed so that  $u = 1 - n$ .

**Firm's problem.** The production function is  $y = An$ , where  $A$  captures the technological level. The profits of a firm with  $n_0$  workers are

$$\Pi = \max_v \{An - wn - \kappa v\}, \quad \text{s.c. } n = \mu(\theta)v + n_0$$

We assume that the cost of posting job vacancies  $\kappa v$  is paid to households. The optimality condition for job vacancies  $v$  is:

$$A = w + \frac{\kappa}{\mu(\theta)}$$

The marginal product of a match equals the labor cost  $w$  plus the recruiting cost per new worker.

**Households** There is a representative household with a large number of members. A fraction  $n$  are employed, a fraction  $u = 1 - n$  are unemployed. Household utility is

$$E(n) = U(c) - V(n)$$

The marginal value of an extra employed member is  $E'(n) = U'(c)w - V'(n)$

**Wage determination** Nash bargaining outcome is

$$w = \phi A + (1 - \phi) \left( \frac{V'(n)}{U'(c)} + b \right) \quad \text{where } 0 \leq \phi \leq 1$$

$\phi$  is the worker's bargaining power. We assume that  $U(c) - V(n) = c - \gamma n$  so that  $\frac{V'(n)}{U'(c)} = \gamma$ . Here, we use a linear utility function to simplify the analytical results. Hence, wage is

$$w = \phi A + (1 - \phi)(\gamma + b)$$

**Equilibrium** Using  $v = \theta(1 - n)$ , labor market equilibrium with search frictions is defined by 3 equations in three unknowns ( $w, n, \theta$ ):

$$\begin{array}{ll} \text{Optimality for } v: & \frac{\kappa}{\mu(\theta)} = A - w \\ \text{Wage determination:} & w = \phi A + (1 - \phi)(\gamma + b) \\ \text{Employment:} & n = \mu(\theta)\theta(1 - n) + n_0 \end{array}$$

Using the optimality condition for  $v$  and the wage equation, we deduce  $\theta$  from

$$(1 - \phi)(A - \gamma - b) = \frac{\kappa}{\bar{\mu}}\theta^{1-\eta} \Rightarrow \theta = \left( \frac{\bar{\mu}(1 - \phi)(A - \gamma - b)}{\kappa} \right)^{\frac{1}{1-\eta}}$$

Finally, using the law of motion for employment, we deduce that  $n = \frac{\mu(\theta)\theta + n_0}{1 + \mu(\theta)\theta}$ . Let us define  $\Theta \equiv \mu(\theta)\theta = \bar{\mu}\theta^n = \bar{\mu}^{\frac{1}{1-\eta}} \left( \frac{(1-\phi)(A-\gamma-b)}{\kappa} \right)^{\frac{\eta}{1-\eta}}$ . We then have

$$n(\Theta) = \frac{\Theta + n_0}{1 + \Theta} \quad \text{with} \quad n' = \frac{1 - n_0}{(1 + \Theta)^2} > 0$$

with

$$\Theta'_A > 0 \quad \Theta'_\phi < 0 \quad \Theta'_b < 0 \quad \Theta'_\gamma < 0 \quad \Theta'_{\bar{\mu}} > 0$$

**Equilibrium by task.** We extend this static model to a setting consistent with our paper. First, we will consider the steady equilibrium for 2 countries, France and the US. Secondly, in each country, we consider 3 tasks  $j = A, R, M$ . The 3-equation equilibrium applies to each task  $j$ . We define employment level by task as  $n_A, n_R, n_M$ , and employment shares as  $s_j = \frac{n_j}{\sum_j n_j}$  for  $j = A, R, M$ .

Notations are then the following :  $n_j^{US}$  ( $n_j^{FR}$ ) refers to employment level in the US (in France) in task  $j$ .

We capture technological change through the term  $A_j$  in the production function  $y_j = A_j n_j$ . We also allow labor market institutions (LMI) to be country-specific.

### M.1.2 Identifying technological vs institutional changes thanks to employment levels

We will use the model to characterize 2 steady states:

- Steady state 1: Before the technological transition.
- Steady state 2: After the technological change.

We make very stark assumptions in order to make our point clearer.

#### Steady state 1: Before the technological transition

*Identifying restrictions.* We assume that

- 1) Employment levels are the same across countries  $n_j^{US} = n_j^{FR} \forall j$ ,
- 2) LMIs are identical in France and the U.S. at the initial steady state.

Remark that 1) implies that employment shares  $s_j = \frac{n_j}{\sum_j n_j}$  are identical across countries (a restriction made only for the initial steady state, to make our point clearer).

*Identified parameters:*

- We assume that  $A_M > 0$ ,  $A_R = A_A > 0$ , and  $n_{0,R} > 0$ ,  $n_{0,A} = n_{0,M} = 0$ .

Employment levels in each task  $n_j$  are known. We can then deduce  $\Theta_j$  as follows:

$$\begin{aligned} n(\Theta_j) = \frac{\Theta_j}{1 + \Theta_j} \quad j = A, M &\Rightarrow \Theta_j = \frac{n_j}{1 - n_j} \\ n(\Theta_R) = \frac{\Theta_R + n_{0,R}}{1 + \Theta_R} &\Rightarrow \Theta_R = \frac{n_R - n_{0,R}}{1 - n_R} \end{aligned}$$

- With these values of  $\{\Theta_M, \Theta_R, \Theta_A\}$ , we deduce those of  $A_j$ :

$$\begin{aligned} \Theta_j &= \bar{\mu}^{\frac{1}{1-\eta}} \left( \frac{(1-\phi)(A_j - \gamma - b)}{\kappa} \right)^{\frac{\eta}{1-\eta}} \\ \Rightarrow A_j &= \frac{\kappa}{1-\phi} \left( \Theta_j \bar{\mu}^{\frac{-1}{1-\eta}} \right)^{\frac{1-\eta}{\eta}} + \gamma + b \end{aligned}$$

- **Identifying restrictions for the steady state 1.** In the U.S. and in France,
  - the matching technology is the same across countries, so parameters  $\{\bar{\mu}, \eta, \kappa\}$  are identical, with  $\bar{\mu} = 1$  (normalization).
  - we assume no disutility from work:  $\gamma = 0$
  - unemployment benefits are such that  $b = \rho w$ , so that, using the wage equation,  $b = \frac{\phi\rho}{1-(1-\phi)\rho}A \equiv \Phi A$

The solution is then given by:

$$\begin{aligned} A_j^{ini} &= \pi (\Theta_j)^{\frac{1-\eta}{\eta}} \quad \text{with } \pi = \frac{\kappa}{(1-\Phi)(1-\phi)} \quad \text{for } j = A, M \\ n_{0,R}^{ini} &= n_R - (1 - n_R) \left( \frac{A_R^{ini}}{\pi} \right)^{\frac{\eta}{1-\eta}} \quad \text{with } A_R = A_A \end{aligned}$$

- **Property.** Employment shares, given by  $s_j = \frac{n(\Theta_j)}{\sum_j n(\Theta_j)}$ , provide exactly the same information as employment levels in this identification scheme, and therefore lead to the same values of  $\{A_M^{ini}, A_R^{ini}, n_{0,R}^{ini}\}$ .

## Steady state 2: After the technological change

- We want to match  $n_j^{US}$  et  $n_j^{FR}$  for  $j = M, R, A$ . We assume that  $n_j^{US} \neq n_j^{FR}, \forall j$ . However,  $n_j^{US}$  and  $n_j^{FR}$  are such that  $s_j^{US} = s_j^{FR}$ .

In fact, if we only had only the employment shares, we could not identify different parameters for France and the U.S. We could only reproduce what is done for the initial steady state and then wrongly conclude that only technological progress explains the evolution of labor markets identically in both countries.

- **Identification hypothesis:**

- The new steady states values of  $\{A_M^{end}, A_R^{end}, A_A^{end}\}$  will be identified from U.S. data because institutions in the U.S. are assumed to remain stable.
- We assume that these changes in technological progress are common to both countries: France therefore has the same values for  $\{A_M^{end}, A_R^{end}, A_A^{end}\}$ .
- In the data, US and French aggregate employment has evolved very differently: an increasing aggregate US employment, versus an decline in French until the late 1990s. In order to match divergent employment levels, French institutions must have changed given that the US LMI are stable.

- **Step 1.** We identify  $\{A_M^{end}, A_R^{end}, A_A^{end}\}$  from US employment rates. To match  $n_j^{US}$ , with  $n_0^{end} = 0$ , we use the system

$$A_j^{end} = \pi (\Theta_j^{US})^{\frac{1-\eta}{\eta}} \quad j = M, R, A \quad \text{with } \Theta_j^{US} = \frac{n_j^{US}}{1-n_j^{US}}$$

- **Step 2.** We identify  $\{\phi^{FR}, \bar{b}^{FR}, w_{min}^{FR}\}$  using French employment levels. We assume that (i) bargaining power changes identically for all occupations (the parameter  $\phi$  of the steady state 1 becomes  $\phi^{FR}$ ), (ii) a specific unemployment benefit is paid to workers in declining occupations (the parameter  $b_R = \rho w_R$  of the steady state 1 becomes  $b_R^{FR} = \rho w_R + \bar{b}^{FR}$ ) and (iii) manual jobs are paid at the minimum wage (the bargained wage  $w_M$  of the steady state 1 becomes  $w_{min}^{FR}$ ).

- Step 2.1: We compute the French workers' bargaining power ( $\phi^{FR}$ ) at the final steady state:

$$\Theta_A^{FR} = \left( \frac{(1 - \phi^{FR})(1 - \rho) A_A}{1 - (1 - \phi^{FR})\rho} \frac{A_A}{\kappa} \right)^{\frac{\eta}{1-\eta}}$$

$$\phi^{FR} = (1 - \rho) \frac{1 - \frac{\kappa}{A_A} (\Theta_A^{FR})^{\frac{1-\eta}{\eta}}}{\rho \frac{\kappa}{A_A} (\Theta_A^{FR})^{\frac{1-\eta}{\eta}} + 1 - \rho}$$

- Step 2.2: We compute the specific unemployment benefit is paid to Fench workers in declining occupations at the final steady state. We assume that  $b_R = \rho w_R + \bar{b}^{FR}$

where  $w_R = \phi^{FR}A_R + (1 - \phi^{FR})(\rho w_R + \bar{b}^{FR})$ . This leads to  $b_R = \Phi^{FR} \left( A_R + \frac{\bar{b}^{FR}}{\rho\phi^{FR}} \right)$  with  $\Phi^{FR} = \frac{\phi^{FR}\rho}{1 - (1 - \phi^{FR})\rho}$ . Given that the employment rates  $n_j^{FR}$  provide  $\Theta_j^{FR} = \frac{n_j^{FR}}{1 - n_j^{FR}}$ , we deduce

$$\begin{aligned}\Theta_R &= \left( \frac{(1 - \phi^{FR})((1 - \Phi^{FR})A_R - B)}{\kappa} \right)^{\frac{\eta}{1-\eta}} \quad \text{with } B = \frac{\Phi^{FR}}{\rho\phi^{FR}}\bar{b}^{FR} \\ \frac{\Theta_A}{\Theta_R} &= \left( \frac{(1 - \Phi^{FR})A_A}{(1 - \Phi^{FR})A_R - B} \right)^{\frac{\eta}{1-\eta}} \\ \Rightarrow B &= (1 - \Phi^{FR}) \left[ A_R - A_A \left( \frac{\Theta_R^{FR}}{\Theta_A^{FR}} \right)^{\frac{1-\eta}{\eta}} \right] \rightarrow \bar{b}^{FR} = \frac{\rho\phi^{FR}}{\Phi^{FR}}B\end{aligned}$$

- Step 2.3: We assume that manual workers are paid at the minimum wage. We compute the French minimum wage at the final steady state as follows:

$$\begin{aligned}\Theta_M^{FR} &= \left( \frac{A_M - w_{min}}{\kappa} \right)^{\frac{\eta}{1-\eta}} \\ w_{min}^{FR} &= A_M - \kappa (\Theta_M^{FR})^{\frac{1-\eta}{\eta}}\end{aligned}$$

### M.1.3 A simple numerical application

We perform a simple quantitative exercise to illustrate the model's implications.

- **Simple quantitative exercise** We assume the following calibration
  - Unemployment benefit replacement ratio:  $\rho = 0.4$
  - Workers' bargaining power and matching function parameter:  $\phi = \eta = 0.5$ ,
  - Cost of vacancy posting:  $\kappa = 0.2$  so that  $n = \frac{\Theta}{1+\Theta} = 65\%$
- **Scenarios.** We choose our hypothetical data such that
  - US aggregate employment increases between the initial and final steady states
  - French aggregate employment decreases between the initial and final steady states
  - In both countries, the changes in employment levels imply polarization of employment shares:  $s_M$  and  $s_A$  increase while  $s_R$  decreases.
  - Even if the changes in employment levels are different, the changes in employment shares are approximately identical, not allowing for the identification of 2 different labor markets dynamics.

Table 6: Hypothetical scenarios

	$j = M$	$j = R$	$j = A$
Beginning of the sample (Initial SS)			
Levels US = FR ( $n_j$ )	0.10	0.40	0.20
Shares ( $s_j$ )	0.1429	0.5714	0.2857
End of the sample (final SS)			
Levels US ( $n_j^{US}$ )	0.15	0.25	0.35
Shares US ( $s_j^{US}$ )	0.2000	0.3333	0.4667
Levels FR ( $n_j^{FR}$ )	0.10	0.15	0.23
Shares FR ( $s_j^{FR}$ )	0.2083	0.3125	0.4792

- **Results.** Using the simple model, we identify the technological trend on US data, following the procedure described above. Table 7 shows that the technological progress must be biased against the routine jobs in order to generate the hypothetical US job polarization:  $A_R$  increase by 33% between the two steady states whereas  $A_M$  and  $A_A$  increase by 59% and 115% respectively.

Table 7: Numerical results

Technological progress	$A_M$	$A_R$	$A_A$	$n_{0,R}$
Initial SS	0.0593	0.1333	0.1333	0.25
Final SS (US & FR)	0.0941	0.1778	0.2872	0
LMI	$b^{FR}$	$\phi^{FR}$	$w_{min}^{FR}$	$\rho$
Initial SS (US & FR)	0	0.5	0	0.4
Final SS FR	0.0049	0.6955	0.0719	0.4

Obviously, if the LMI does not change in France, employment levels in France would be exactly the same as in the U.S. in the final steady state.

In order to explain simultaneously the job polarization and the aggregate employment decline in France, LMI must change: *(i)* workers' bargaining power increase, *(ii)* specific unemployment benefits are provided to workers on declining occupations and *(iii)* manual jobs are paid at the minimum wage.

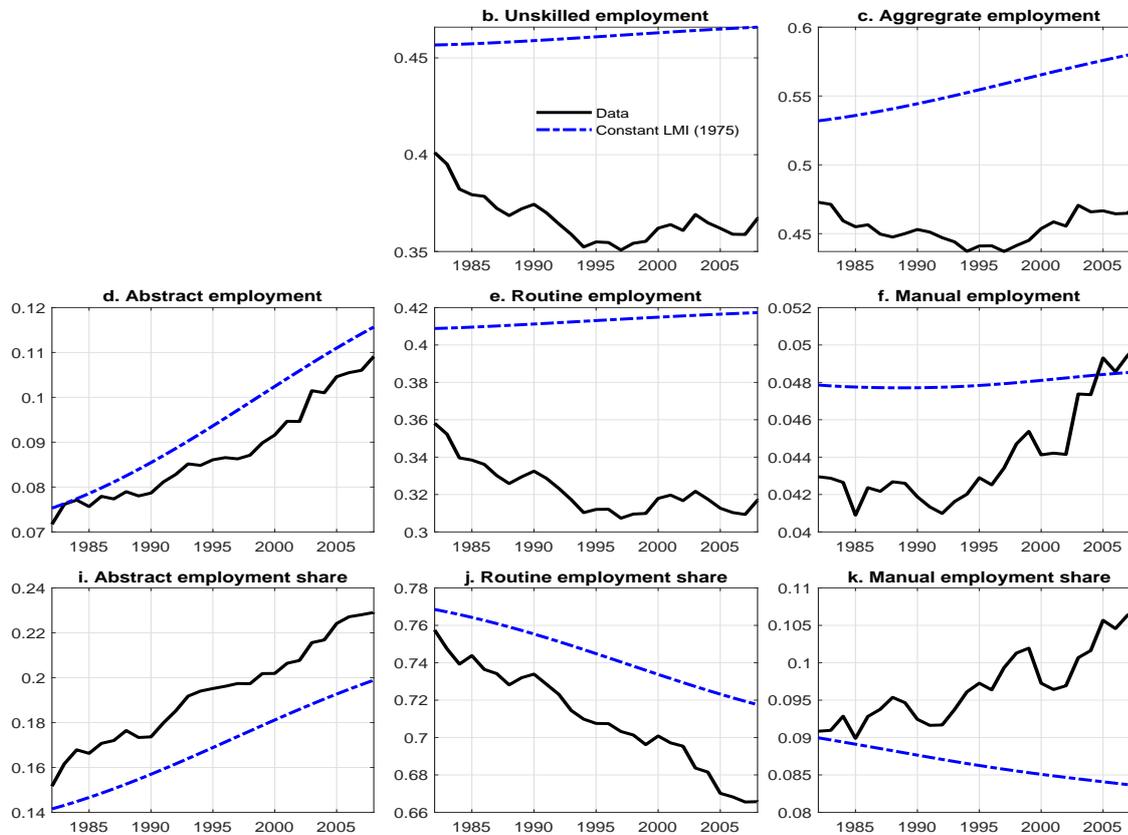
If we assume that only LMI change in France, assuming that the technological progress increases homogeneously for all  $A_j$  by 33% (the increase of  $A_R$  in Table 7), then the employment levels in France would be  $n_M = 3.34\%$ ,  $n_R = 32.58\%$  and  $n_A = 24.9\%$  and there would be no job polarization.

## M.2 Illustration using our quantitative model

We simulate our quantitative model by introducing in France only the technical progress common to both countries, while keeping the labor market institutions constant throughout

the simulation.

Figure 23: France : LMIs remain fixed at their 1975 values



Model's predictions when all French LMIs are constant.

Panel (c) in Figure 23 shows that if LMIs had remained at their 1975 level, French aggregate employment  $n$  would have been higher and continuously increasing, which is counterfactual. More interestingly, Figure 23 shows that the model implies (i) an increase in the abstract employment level (panel (d)), as seen in the data (although the levels and elasticities are poorly replicated in this experiment with constant LMIs), (ii) a near-stagnation in the manual employment level (panel (f)), thus failing to replicate the decline followed by an increase from the mid-1990s observed in the data, and (iii) an increase in routine employment (panel (e)), which contradicts what is observed in France. Nevertheless, this counterfactual simulation leads to a fall in the share of routine employment (panel (j)) thereby giving a false impression that the model is consistent with data on employment share, whereas this fall in the share of routine jobs (at the heart of the polarization process) does not come from the disappearance of routine jobs (on panel (e), with constant LMIs, routine employment increases) but a rise in aggregate employment  $n$  (panel (c)).

**On "the importance of looking at LMI".** The U.S. data on employment levels allows the model to identify the size of the technological change because the data on LMI are roughly stable over the sample in this country.

Considering that both countries share a common technological progress pattern (as an observed restriction), the differences in employment levels between France and the U.S. can be attributed to the observed shifts in LMIs within France, while LMIs in the U.S. remained roughly stable. This is the scenario that is tested in the paper. Our quantitative analysis shows that it can not be rejected. Furthermore, by simultaneously altering technological progress and Labor Market Institutions (LMI) in accordance with observed data trends, our aim is to uncover the appropriate magnitude of changes in these two explanatory factors necessary to match observed employment dynamics. Specifically, if Skill-Biased Technological Change (SBTC) is nonexistent, the extent of changes required in LMI to align with the data would differ, potentially resulting in a biased assessment of the influence of LMI on employment dynamics (the observed shift in French LMI cannot adequately account for the observed employment levels in France). This becomes especially significant in cases where the labor market equilibrium exhibits a high degree of nonlinearity.

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