THE ROLE OF FIRMS IN SHAPING JOB POLARIZATION*

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Abstract

What shapes aggregate job polarization? The literature has emphasized the role of routine-biased technological change (RBTC). Through the lens of general equilibrium model that explicitly accounts for firm heterogeneity, I show that labor supply factors are relatively more important than RBTC in explaining job polarization. RBTC induces substitution of routine occupations within firms, which decreases the share of routine occupations in the aggregate. However, in contrast to a representative firm framework, it also increases the productivity of large routine intensive firms, which increases their aggregate employment share. Counterfactual experiments using the estimated model show that the net effect is to decrease the aggregate share of routine occupations by 2.34 pp, approximately 21.7% of the total decline. Substitution channel decreases the aggregate employment share of routine occupations by 5.77 pp while the productivity channel increases it by 3.38 pp. I find that the shift in the educational composition of the labor force and shifts in worker preferences explain the rest of the decline in the aggregate employment share of routine occupations.

Keywords: Job Polarization, Routine-Biased Technological Change, Educational Changes

JEL codes: J2, 03, D2

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1 Introduction

The employment share of *routine* occupations - those focused on performing procedural, repetitive tasks - declined by 10.9 percentage points (pp) between 1994 and 2015 in France. A similar trend has been documented across many industrialized countries, including the US, and in many cases it began much earlier than 1994.[1] The literature has emphasized that this phenomenon of *job polarization* - wherein the aggregate employment share of routine occupations declined, while it increased for non-routine occupations - is driven by routine-biased technological change. The main idea behind this hypothesis is simple: as information and communication technology becomes more productive in performing repetitive tasks, it replaces workers in routine occupations who previously performed these functions in the economy and raises the demand for workers in non-routine occupations who perform tasks that are complementary to routine-intensive tasks.

In this paper, I argue that routine-biased technological change (RBTC) has important macroeconomic implications, especially for aggregate welfare, but it is not the main driver of job polarization. I find that changes in the educational composition of the labor force and shifts in worker preferences play a relatively more important role in explaining aggregate job polarization. I show this to be the case for France, a country that has rapidly polarized starting from the mid-1990's.

I analyse the role of RBTC in a general equilibrium model that accounts for both firm and worker heterogeneity. Using this framework, I find that RBTC affects the aggregate employment share of routine occupations through two opposing channels. On the one hand, RBTC induces within-firm substitution of routine occupations by non-routine occupations. As a result, on average, firms shift the optimal occupational mix they employ over time away from routine occupations. This *substitution* channel, conventionally emphasized in the literature, reduces the share of routine occupations in the aggregate. On the other hand, however, RBTC has important effects on the firm-size distribution as it affects the productivity of routine and non-routine intensive firms disproportionately. Routine intensive firms, who also happen to be the largest firms in the economy in terms of the number of workers they employ, see substantial improvements in their productivity due to RBTC. As a consequence, they capture an even bigger share of aggregate employment over time. This *productivity* channel, through its impact on routine intensive firms, raises the share of routine occupations in the aggregate. A key contribution of this paper is to demonstrate that the productivity-enhancing channel is quantitatively important and partially offsets the decline in the aggregate share of routine occupations induced by the substitution channel. An important implication of this result is that it is not innocuous to abstract from firm heterogeneity while analysing the role of RBTC on aggregate job polarization.

I begin by documenting new empirical evidence on the firm-level mechanisms driving aggregate job polarization. While job polarization has been previously documented for France by Harrigan et al. (2016) and Albertini et al. (2017), surprisingly little is known about the distribution

[1] For further evidence on job polarization, see Goos and Manning (2007) for UK, Goos et al. (2009) for 16 European countries and Acemoglu and Autor (2011) for the US. See Bárány and Siegel (2018) for evidence that job polarization began as early as the 1950's in the US.

of occupational composition within and between firms, and how this has changed over time.[2] Using French administrative data, I provide answers to these questions. I decompose whether aggregate job polarization is driven by changes in the occupational composition within firms or due to changes in employment growth between firms or due to entry and exit of firms. I find that within- and between-firm changes are quantitatively important in explaining aggregate job polarization; entry and exit of firms play a relatively small role in driving aggregate polarization.

Motivated by these facts, I construct a static, general equilibrium model to rationalize the empirical evidence and to quantify the role of RBTC shocks in explaining them. Given the importance of between-firm effects in explaining job polarization, I depart from a representative-firm framework and explicitly account for firm heterogeneity in the model. A firm produces its output by combining abstract, routine and manual occupations. These occupations are imperfectly substitutable in the production technology of the firm. RBTC is modelled as a shift in the relative distribution of firm *and* occupation-specific factor-augmenting productivity over time. On the other side of the market, there are two types of workers, high and low-skilled, who endogenously sort themselves into one of three occupations. In equilibrium, aggregate job polarization and changes within- and between-firm are explained by the interaction of two forces: non-neutral technological change that makes workers in routine occupations relatively more productive; and supply shocks that change the educational composition of the labor force and the disutility cost of working in routine occupations over time.

Equipped with the model I estimate the key structural parameters from the data. Estimating production function parameters from a cross-section is challenging due to endogeneity issues: firms choose their optimal labor demand conditional on their knowledge of technology shocks that are unobserved by the econometrician. Similar issues make it challenging to identify supply-side parameters. In general, estimating the slope of the demand and the supply curve requires at least two instruments. However, in specific cases, economic theory provides sufficient restrictions on demand and supply equations such that the two slopes can be identified by a single instrument. I rely on the insights developed in a recent paper by Zoutman et al. (2018) and instrument wages in the model by employer's payroll taxes to estimate the key elasticity parameters of the model. Following the literature, I use a nested-CES specification to model the firm's production technology. The estimate for the elasticity of substitution between abstract and routine occupations is 1.75 and for the composite of abstract and routine occupations with manual occupations is 2.64.[3] Conditional on model primitives, theory provides a direct link between quantities observed in the data and unobserved technology shocks. Having estimated the structural parameters, I infer technological change through the lens of my model.

Finally, I perform counterfactual exercises to quantify the importance of RBTC in explaining

[2] A notable exception is Cortes and Salvatori (2019).

[3] This is high compared to the values found in the literature. To the best of my knowledge, the only other estimate of the elasticity of substitution in the literature is by Goos et al. (2014), who find a value between 0.53 and 0.80 depending on their specification. They estimate it with 21 occupations (compared to three in this model) in a partial equilibrium framework. The key results of the paper do not change if I use the estimated values from Goos et al. (2014).

the observed facts. To do so, I hold supply and occupation-specific tax parameters fixed to their level in 1994 and let RBTC shocks evolve as they do in the data. Given that occupational choice is endogenous in the model, if RBTC is the key driver of aggregate job polarization then this counterfactual should be able to explain the changes in the employment shares as observed in the data. I find that the share of routine occupations decreased by 2.34 pp compared to 10.9 pp decline in the data. This result is driven by the counteracting effects of the substitution and productivity channels mentioned at the beginning of this section. Quantitatively, the substitution channels accounts for 5.77 pp decline in the aggregate share of routine occupations. The productivity channel, on the other hand, increases the share of routine occupations by 3.38 pp.

Changes in the educational composition of the labor force explain an additional 3.05 pp decline in the share of routine occupations. In the case of France, like in other industrialized countries, the share of college-educated workers increased substantially over time. As this share increased, there were increasingly more workers who had a comparative advantage in performing non-repetitive tasks that required problem-solving, persuasion and managerial skills. Workers equipped with such skills sorted into abstract (non-routine cognitive) occupations, which required a high-level of analytical aptitude and paid higher wages on average. Changes in occupation-specific tax rates' play a relatively small role in explaining the changes in the employment share of routine occupations.

Finally, shifts in worker preferences lead to a decline of 5.60 pp in the share of routine occupations. Through the lens of the model, these shifts in worker preferences capture changes in occupation-specific non-pecuniary factors such as disutility costs. Such a shift induces workers, especially those that are low-skilled, to switch from routine occupations to non-routine manual occupations that require situational adaptability, visual and language recognition and in-person interactions. However, these preference parameters might also capture forces that have occurred in the French economy that I do not directly account for in my model which affect worker's occupational choice and employment during the time period under study. Potentially relevant factors that I have abstracted from include changes in policy affecting the incentive to participate in the labor market, offshoring, changes in the minimum wage and changes in occupation-specific monopsony power. In my view, the generality of the model provides a useful template for future quantitative research in evaluating the role of RBTC and other factors in contributing to the labor market outcomes discussed in the paper.

Relation to Literature. This paper contributes to two strands of the literature. The first strand of the literature documents aggregate job polarization and highlights the role of RBTC in driving this phenomenon. Autor et al. (2003) showed that ICT raises demand for non-routine cognitive tasks, reduces it for routine tasks and has very little impact on manual tasks. Autor et al. (2006) and Goos and Manning (2007) subsequently documented, in line with the predictions of RBTC hypothesis, high employment growth in low-paying service and high-paying professional and managerial jobs, and a decline in the number of jobs in the middle of the income distribution.[4] Goos et al. (2014) showed that job polarization is pervasive across European economies and has within-industry and between-industry components that are both important. They develop a partial equilibrium model to explain these facts and showed that RBTC is relatively more important compared to offshoring in explaining job polarization and changes within- and between-industry.[5]

In contrast to this strand of the literature, using administrative firm-employee-level data, I show that aggregate job polarization is not exclusively a within-industry, within-firm phenomenon; changes in employment growth *between* firms (within-industries) is an important channel in understanding aggregate job polarization. An implication of this empirical finding is that models that rely on within-firm substitution of routine occupations by non-routine occupations to explain job polarization are missing out on an important margin of firm adjustment to biased technological change, their size. Moreover, by not explicitly accounting for firm heterogeneity in their analysis, these papers apportioned a larger role to RBTC compared to labor supply shifts in explaining aggregate job polarization.

Closer to this paper, a more recent strand of the literature has focused on accounting for firm heterogeneity in their analysis of aggregate job polarization. Notably, Heyman (2016) and Harrigan et al. (2016), using Swedish and French administrative data, respectively, perform a similar decomposition as in this paper and highlight the importance of within- and between-firm changes in explaining aggregate job polarization.[6] In a reduced-form setting, they analyze how the observed patterns of changes within firms and between firms are related to prominent explanations for job polarization such as routine-biased technological change, offshoring and trade. Heyman (2016) finds that the degree of routineness is the most important explanation for the within-firm patterns observed in the data. Accounting for endogeneity issues in firm-level regressions, an issue not directly addressed in Heyman (2016), Harrigan et al. (2016) reach similar conclusion. They find that those firms that had a higher employment share of *techies* - engineers and technicians with skills and experience in sciences, technology, engineering and math (STEM) - in 2002 saw greater within-firm polarization and grew faster, from 2002 to 2007.

In this paper, I expand their analysis to a longer time frame and find that their conclusion concerning the importance of within- and between-firm changes in explaining aggregate job polarization remains intact.[7] However, in contrast to the reduced-form approach adopted by this strand of the literature, given the emphasis of this paper to disentangle the effects of technology shocks and labor labor supply shocks in explaining job polarization, I use a more structural approach. I construct a general equilibrium model where job polarization can be driven either due technological change, as emphasized by these two papers, or due to compositional changes of the

[4] Asplund et al. (2011) used administrative micro-data for Finland, Norway and Sweden and documented job polarization for these countries. Adermon and Gustavsson (2015) used Swedish administrative data to document job polarization in Sweden.

[5] To measure RBTC and offshoring, they rely on the extent to which an occupation consists of repetitive tasks and the extent to which it can be offshored. They collect this information from DOT.

[6] Unlike this paper, Harrigan et al. (2016) do not aggregate occupations into three groups.

[7] Harrigan et al. (2016) focus on the period between 1994 and 2007 while Heyman (2016) focuses on 1997 and 2013.

labor force that increases the supply of high-skilled workers in the economy. The key advantage of my approach is that it allows me to quantify the importance of each of these drivers in explaining aggregate job polarization and its split into within-firm and between-firm components.

Methodologically speaking, this paper is most closely related to Bárány and Siegel (2020). The key motivation of their paper is to study drivers of employment reallocation across sectors and occupations. They adopt a general equilibrium model and infer occupation-sector specific productivity using the production side of their model. I adopt a similar strategy in this paper and use the relative first order conditions and labor demand equations to infer RBTC shocks. However, there are two differences between their work and this paper. While Bárány and Siegel (2020) are interested in quantifying the importance of neutral-, sector-, and occupation-specific technological change in explaining employment reallocation across sectors, I am interested in quantifying the importance of RBTC and supply shocks in explaining job polarization. Second, unlike Bárány and Siegel (2020), who calibrate the elasticity of substitution parameters, I estimate them using an instrumental variable approach. In this paper, I show how one can use the aggregate variation over time in payroll tax rates as instruments to identify *both* supply and demand elasticities.

Outline. The remainder of the paper is structured as follows. Section 2 presents the data and empirical analysis. Section 3 builds a general equilibrium model to rationalize the facts and quantify the importance of RBTC and supply shocks in explaining job polarization. Section 4 lays out the estimation strategy followed by results of the counterfactual exercises in Section 5. The last section concludes. Additional details are found in the Appendix.

2 Empirical evidence

In this section, I begin by providing further information concerning the administrative data used in the paper. I then proceed to document facts pertaining to aggregate job polarization and changes in the wage structure in France.

Data description. I consider the period between 1994 and 2015 and use two sources of French administrative data: the DADS Postes and FICUS/FARE.[8] Additionally, I also use information from the French Labor Force Survey (*Enquête Emploi*) to collect information on the educational composition of the workforce by occupation and labour force participation. The worker-level information is obtained from DADS Postes. It reports information on wages, hours worked and occupation for the universe of workers and allows me to identify the firm at which each individual worker is employed. Consequently, I am able to observe the entire workforce of a given firm between 1994 and 2015. No individual characteristics of workers, such as the level of education, worker identifier or labor market experience is available in the DADS Postes. There is no additional information

[8] DADS stands for Déclaration Annuelle des Données Sociales in French. DADS Postes is restricted data set and it is administered by the French National Statistical Institute (INSEE)

concerning the firm beyond the firm identifier and firm-level aggregates pertaining to firm size and average wages. I merge DADS Postes with FICUS/FARE (using the unique firm identifier "SIREN" in both datasets) which contains balance sheet data of firms. From it, I extract measures of total employment, value-added and industry affiliation of firms. I keep all workers between the age of 18 and 65 and include all firms that hire at least one worker in each of the three occupations: abstract, routine and manual. Further details on classifying occupations into abstract, routine and manual groups are provided in Appendix A.

Aggregate job polarization in France. In Table 1, I document the level of the employment share of the three occupations and its change over time for France and the US. I find that routine employment constitutes the bulk of aggregate employment in both the countries. In 1994, 64% of aggregate employment was routine employment in France while in the US it was 54%.

Between 1994 and 2015, I observe that the employment share of routine occupations fell by 10.9 percentage points (pp), similar to what is observed in the US. In Figure 1, I show that the employment share of routine occupations has steadily declined over time. While in the US, a bulk of the decline in routine occupations is compensated by an increase in employment share of abstract occupations, in France we see that the 56% of the decline in routine occupation is compensated by an increase in manual occupations and the rest by abstract occupations.

In Figure A1, I document that a majority of the decline in the employment share of routine occupations in France is driven by a decline in the employment share of construction workers, electrical machinery operators, foremen and assembly line workers. The increase in the employment share of abstract occupations is explained due to the increase in the employment share of engineers, professional and managerial workers. Finally, similar to the US, the increase in the employment share of manual occupations is explained by the increase in the employment share of personal service occupations such as restaurant servers, food preparation workers, hotel employees, barbers, hair-stylists, beauty-shop managers, child-care specialists and residential building janitors.

Finally, the decline in the employment share of routine occupations is not limited to shift in the sectoral composition of the economy away from routine-intensive industries like manufacturing. In Appendix A, Figure A2, I replicate the graph in Figure 1 separately for manufacturing and non-manufacturing industries. I find that the share of routine occupations declines in both these industries. Compared to 1994, in manufacturing, the employment share of routine occupations decline by approximately 7 pp, while in non-manufacturing declined by more than 10 pp.

Decomposing aggregate job polarization. To better understand the change in the aggregate employment share of routine occupations, I decompose whether this is driven by changes in the occupational composition within firms or due to changes in employment growth between firms or both. This, it tells us if the decline in the aggregate share of routine occupations is driven by within-firm substitution of routine occupations by abstract and manual occupations or due to low

Table 1: **Aggregate Job Polarization: France vs. US**

	Level of employment share (in %)				**Change in employment share** (in pp)	
	France		U.S.		France	U.S
	1994	2015	1994	2015	1994-2015	1994-2015
Abstract	13.0	17.6	32.0	40.0	4.6	8.0
Routine	64.0	53.1	54.0	43.0	-10.9	-11.0
Manual	22.0	28.2	14.0	17.0	6.2	3.0

Notes: Author's own calculations using DADS Postes. Aggregate employment share of occupation o is measured as the total number of worker employed in occupation o divided by total workers employed in the economy at time t. The numbers from the U.S. are borrowed from Foote and Ryan (2015).

employment growth of routine-intensive firms.

Denoting the aggregate share of occupation o at time t as s_{ot}, this can be written as:

$$s_{ot} = \sum_{j} s_{ojt}\psi_{jt}$$

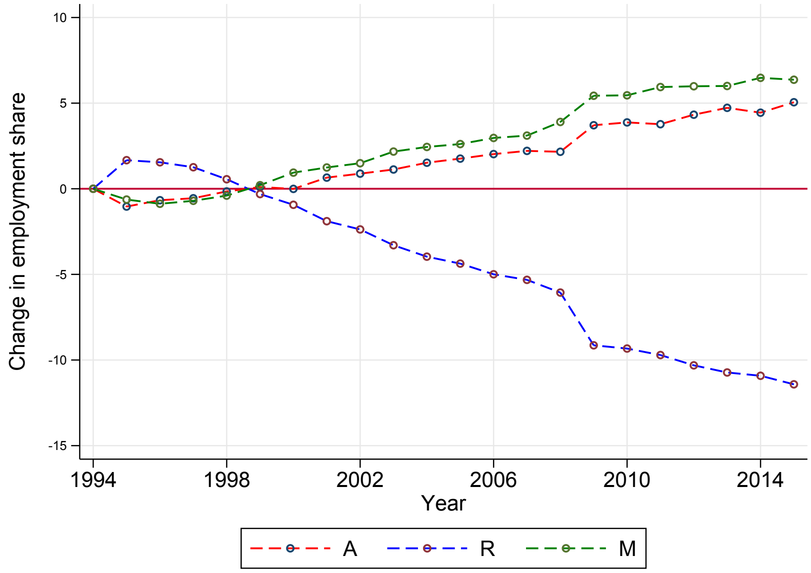
where s_{ojt} is the share of employment of occupation o in firm j at time t and ψ_{jt} is the employment share of firm j in the aggregate at time t. The change in the employment share of occupation o can be written as:

$$\Delta s_{ot} = \underbrace{\sum_{j \in \mathcal{C}} \overline{\psi}_j \Delta s_{ojt}}_{\Delta \text{ Within}} + \underbrace{\sum_{j \in \mathcal{C}} \overline{s}_{oj} \Delta \psi_{jt}}_{\Delta \text{ Between}} + \underbrace{\underbrace{\psi_t^{\mathcal{N}}(s_{ot}^{\mathcal{N}} - s_{ot}^{\mathcal{C}})}_{\text{Entry}} + \underbrace{\psi_{t-1}^{\mathcal{X}}(s_{ot-1}^{\mathcal{C}} - s_{ot-1}^{\mathcal{X}})}_{\text{Exit}}}_{\text{Net Entry}} \tag{1}$$

where Δ indicate change over time, $\mathcal{C}$ denotes the set of continuing firms, i.e. those firms that are present in period t and $t-1$ of the decomposition, $\mathcal{N}$ denotes the set of entering firms, i.e. those firms that are present in period t but not in period $t-1$, $\mathcal{X}$ denotes the set of exiting firm, i.e., those firms that are present in period $t-1$ but not in period t, $s_{ot}^{\mathcal{G}}$ denotes the share of occupation o in total employment of set $\mathcal{G} \in \{\mathcal{C}, \mathcal{N}, \mathcal{X}\}$ and $\psi_t^{\mathcal{G}}$ denotes the employment share of set $\mathcal{G}$.

The first term denotes the within-firm effect. It tells us how much of the aggregate change is due to changes in the occupational composition within firms, holding fixed the employment share of the firm. The second component is a between-firm effect and it tell us how much of the aggregate change is driven due changes in the employment share of firms, holding fixed the occupational composition within firms. The third component indicates the contribution of entry to the aggregate change in employment share. It is positive when the employment share of occupation o in new firms is higher than in continuing firms in period t. The fourth term denotes the contribution of exit. It is positive if the share of occupation o in exiting firms is lower in surviving firms

Figure 1: **Job Polarisation in France between 1994 and 2015**



Notes: Author's own calculations using DADS Postes. I normalize the share of each occupation to 0 in 1994 and plot the difference in share over time relative to the initial period.

in period $t-1$. The result of this decomposition is documented in Table 2.

We can draw three conclusions from Table 2. First, the decline in the aggregate employment share of routine occupations is explained by changes in the occupational composition within firms. On average, firms reduced the employment share of routine occupations by 8.5 pp and increased it by 7.1 pp for abstract occupations. The share of manual occupations increased within firms by 1.3 pp, on average. This shows that firms have shifted their optimal occupational mix away from routine occupations towards abstract occupations. Furthermore, this evidence is consistent with the hypothesis of routine-biased technological change proposed by Autor et al. (2003). As firms introduce ICT capital in the workplace, this new technology replaces routine workers and complements abstract workers.

Second, the increase in the aggregate share of manual occupations is due to changes in employment growth between firms. Table 2 shows that the employment share of routine and abstract-intensive firms declined by 3.0 pp and 1.6 pp, respectively, while that of manual-intensive firms increased by 4.6 pp. This evidence is puzzling in light of RBTC. Firms that are intensive in routine occupations should see a larger decrease in relative costs and output prices leading to a shift in product demand towards these firms. Therefore, we should expect to see growth in the employment share of routine-intensive firms, but we the opposite in the data.

Third, new firms entering the labor market have a lower share of routine occupations and a higher share of abstract and manual occupations compared to continuing firms. As a result, entry contributes negatively to the change in the aggregate share of routine occupations (and positively

Table 2: **Decomposing Aggregate Job Polarization**

	Δs_{ojt}	Δ Within	Δ Between	Entry	Exit	Net Entry	$\frac{W+B}{\Delta}$
Abstract	4.6	7.1	-3.0	0.40	0.08	0.49	89.1%
Routine	-10.9	-8.5	-1.6	-2.05	1.26	-0.79	92.6%
Manual	6.2	1.3	4.6	1.64	-1.34	0.29	95.1%

Notes: Author's own calculations. Δ indicates the change in employment share over time. The figures are calculated using DADS Postes. $\frac{W+B}{\Delta}$ documents the contribution of within and between components (in percentage terms) in explaining the aggregate decline in the share of occupation $o \in \{A, R, M\}$

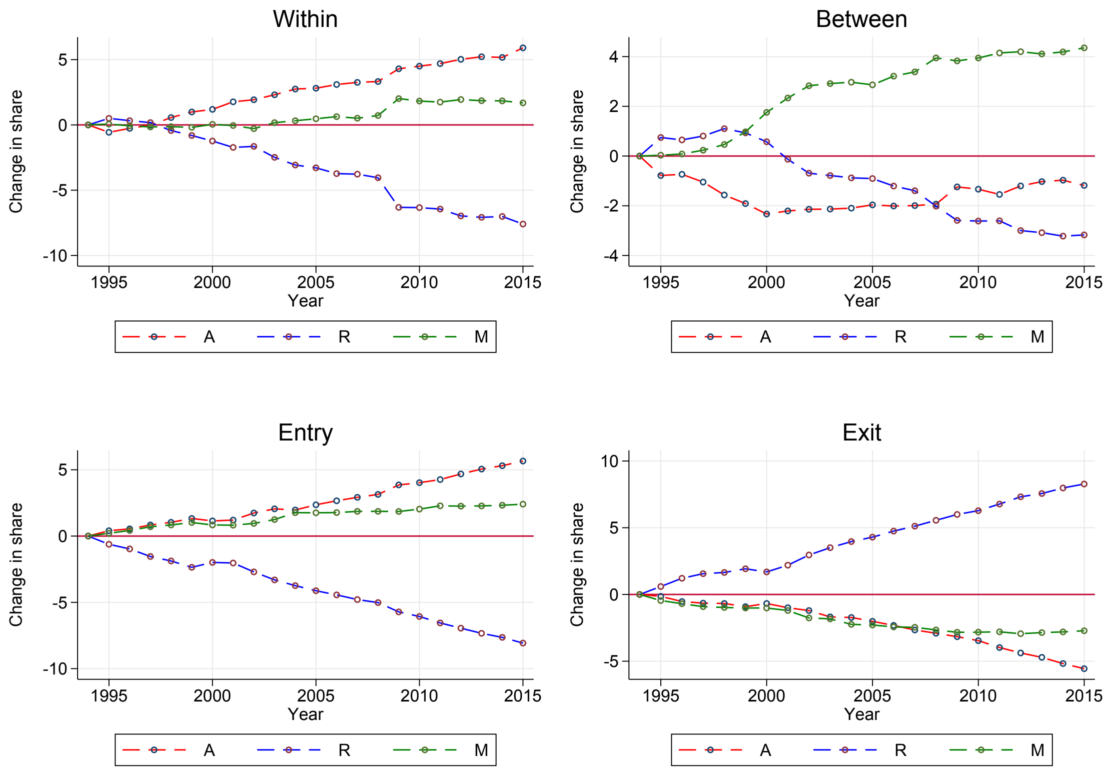
to abstract and manual occupations). On the other hand, firms that exited the labor market had a higher share of manual occupations and a lower share of abstract and routine occupations compared to continuing firms. Consequently, exit contributes positively to the change in the aggregate share of abstract and routine occupations and negatively to the share of manual occupations. The net entry component, which is the sum of entry and exit, explains less than 11% percent of the change in share of each of the three occupations.

The within and between components in Eq. 1 are computed using the set of surviving firms between 1994 and 2015. Since less than 10% of firms survive over this time period, the result of my decomposition exercise in Table 2 might be sensitive to my choice of starting and ending year. To demonstrate that this is not the case, I perform a series of counterfactual exercises to see the effect of each of the four components of Eq. 1 individually over time. I set the initial level of the share of occupation o to its level in 1994 and then cumulatively add the changes of each component in Eq. 1 over time.[9] The result of this exercise is documented in Figure 2. It is evident from the figure that within-firm substitution of routine occupations by abstract occupations and increase in the employment share of manual-intensive firms are both secular trends over time.

Summary of facts. In summary, I document the following facts in the data. First, I find that the employment share of routine occupations in France has declined. Second, the firm-level decomposition highlights that the decline in routine occupations is driven by within-firm substitution of routine occupations (primarily) by abstract occupations. Third, the employment share of abstract and routine-intensive firms declined and that of manual-intensive firms increased. To the best of my knowledge, facts 2 and 3 have not been documented for France before and are new to the literature. These equilibrium dynamics of employment that I have documented can be driving partly due to technology shocks or labor supply shocks to educational composition and preferences. In what follows, I provide a general equilibrium framework to disentangle the effect of each of these shocks on driving the observed facts.

[9] A similar exercise is performed in De Loecker et al. (2020), see figure 4.

Figure 2: **Decomposition of aggregate job polarization at the firm level**



Notes: Author's own calculations using DADS Postes. I set the initial level of the share of occupation o to its level in 1994 and then cumulatively add the changes of each component in Eq. 1 over time. Notice, the set of surviving firms between period $t-1$ and t will be different from those in period t and $t+1$. As a result, the total cumulative change of each of the component will not be same as the numbers in Table 2.

3 Model

Motivated by the facts, I construct a static model to quantify the importance of RBTC and labor supply shocks in explaining job polarization and the split into within-firm and between-firm components. I begin by outlining the setup of the model, followed by the model solution.

3.1 Setup

Environment. There are two types of agents in the economy: firms and workers. There is a continuum of heterogeneous firms in the economy indexed by j. The measure of firms is J and it is assumed exogenous. I abstract from entry and exit decision of firms given that net entry is quantitatively less important in explaining aggregate job polarization in the data.[10] Firms hire abstract,

[10] I can endogenize entry and exit in the model by assuming a fixed entry cost like in Melitz (2003)

routine and manual occupations to produce output. I assume that there is a continuum of workers, indexed by i, who are organized into a stand-in household. The measure of workers in the economy is N and it is assumed to be exogenous. The household consumes goods produced by the firms, and maximizes utility subject to a budget constraint. There are two types of workers in the economy: high- and low-skilled. Each worker supplies its unit of labor inelastically. Conditional on being employed workers optimally self-select into one of three occupations. High- and low-skilled workers compete in the same market which implies that in equilibrium there is a single wage rate in each occupation which is common to both skills. The economy is in a decentralized equilibrium, firms operate under perfectly competitive output and input markets, and prices and wages are such that markets clear.

Technology. Firms produce output using three occupational labor inputs.[11] I specify the production function for a firm j as the following nested-CES specification:[12]

$$Q_j = \left[(\phi_{Mj} N_{Mj})^{\frac{\gamma_M - 1}{\gamma_M}} + \left\{ (\phi_{Rj} N_{Rj})^{\frac{\gamma_A - 1}{\gamma_A}} + (\phi_{Aj} N_{Aj})^{\frac{\gamma_A - 1}{\gamma_A}} \right\}^{\frac{\gamma_A}{\gamma_M} \frac{(\gamma_M - 1)}{(\gamma_A - 1)}} \right]^{\kappa \frac{\gamma_M}{\gamma_M - 1}} \tag{2}$$

where N_{oj} is the number of workers hired by firm j in occupation $o \in \{A, R, M\}$, $\phi_{oj} \in [0, \infty)$ is firm *and* occupation specific factor augmenting technological change, $\gamma_A \in [0, \infty)$ is the elasticity of substitution of abstract and routine occupations, $\gamma_M \in [0, \infty)$ is the elasticity of substitution between the manual occupations and the composite of abstract and routine occupations and κ measures the returns-to-scale.[13] Since the output market is perfectly competitive, I restrict $\kappa < 1$ (decreasing returns-to-scale) to ensure profit maximization provides a unique solution.[14]

I do not impose any parametric restriction on the joint distribution $G(\phi_{Aj}, \phi_{Rj}, \phi_{Mj})$. A key implication of having ϕ_{oj} differ across firms is that in equilibrium the ratios $\frac{N_{Aj}}{N_{Rj}}$, $\frac{N_{Mj}}{N_{Rj}}$ and $\frac{N_{Aj}}{N_{Mj}}$ will also differ across firms. In contrast, if technological change was modelled either as Hicks'-neutral or occupation-augmenting, the relative ratio of occupations would be identical across firms. Finally, each firm produces an identical good and sells it in the output market at price P which I normalize to 1 without loss of generality.

[11]Not modelling capital as a distinct input to labor-augmenting technologies is consistent with the view that technological change is embodied into capital.

[12]An alternative, isomorphic representation of the production function in Eq. 2 is the following:

$$Q_j = \left[\beta_M (\tilde{\phi}_{Mj} N_{Mj})^{\frac{\gamma_M - 1}{\gamma_M}} + (1 - \beta_M) \left\{ (1 - \beta_A)(\tilde{\phi}_{Rj} N_{Rj})^{\frac{\gamma_A - 1}{\gamma_A}} + \beta_A (\tilde{\phi}_{Aj} N_{Aj})^{\frac{\gamma_A - 1}{\gamma_A}} \right\}^{\frac{\gamma_A}{\gamma_M} \frac{(\gamma_M - 1)}{(\gamma_A - 1)}} \right]^{\kappa \frac{\gamma_M}{\gamma_M - 1}}$$

The two formulations are the same since one can rewrite $\phi_{oj} = \beta_M^{\frac{\gamma_M}{\gamma_M - 1}} \tilde{\phi}_{oj}$. One can do a similar manipulation for ϕ_{Aj} and ϕ_{Mj}

[13]In principle, I can allow for a different nest than the one specified in Eq. 2. However, this is the specification that tends to get used most often in the literature on aggregate polarization. For instance, vom Lehn (2020) uses a similar specification in his work on aggregate labor market polarization in the US.

[14]In the estimation, I will test the validity of this restriction.

Occupational choice. I assume that there are two types of workers: high- and low-skilled.[15] Fraction θ_H, assumed exogenous, of the total labor force is high-skilled.[16] Worker's can either choose to be employed or remain unemployed. Conditional on being employed in the labor market, they self-select into abstract, routine or manual occupations. They receive a net wage $(1-\tau_o^W)W_o$, $o \in \{A, R, M\}$, for every hour worked. τ_o^W denotes the tax rate paid by workers to the government while W_o is the gross wage, both of which differ by occupation. Unemployed workers receive unemployment benefits b_K, financed by the government's tax collection.

High- and low-skilled workers are identical in terms of their productivity but differ in terms of the disutility cost they pay, denoted χ_{os}, $s \in \{H, L\}$. I assume that disutility differs by skill and occupation.[17] This allows me to capture the empirical fact the workers with the same level of education work in different occupations. The utility associated with working in abstract (A), routine (R), manual (M) occupations or being unemployed (K) is specified as follows:

$$u_{ixs} = \begin{cases} \ln[(1-\tau_x^W)W_x] - \chi_{xs} + \frac{\epsilon_{ixs}}{\sigma_s}, \quad x \in \{A, R, M\}, \quad s \in \{H, L\} \\ \ln b_K + \frac{\epsilon_{iKs}}{\sigma_s}, \quad \text{if } x = K,\ s \in \{H, L\} \end{cases} \tag{3}$$

where σ_s is a parameter that pins down the scale of utility and ϵ_{ios} (ϵ_{iKs}) denotes the idiosyncratic non-pecuniary benefits of working in occupation o (being unemployed). Eq. 3 implies that, conditional on skill, there exists a distribution of utility across individuals for the same occupation. I assume that ϵ_{ios} (ϵ_{iKs}) is independent and identically distributed type 1 extreme value. Given this assumption, χ_{os} pins down the mean of the utility distribution and σ_s pins down its scale. If χ_{os} is equal to zero and σ_s is equal to one, then the share of workers entering occupation o will be independent of skill. See Eq.16 below for more details.

Government. The government collects taxes from employed workers and firms to finance the unemployment benefits of workers not participating in the labor force.

$$T = \sum_o W_o N_o [\tau_o^W + \tau_o^F] \tag{4}$$

where τ_o^W denotes the tax rate paid by workers in occupation o, τ_o^F denotes payroll tax rate paid

[15] In the empirical application of my model, I will refer to workers with a college-degree as high-skilled and workers with educational qualification less than college as low-skilled.

[16] It is straightforward to endogenize choice of education in this model. I could assume a setup with sequential decisions. Worker's first chose their education level and then decide if they want to work or stay out-of-the labor force. If they want to work they can self-select into one of the three occupations. Conditional on the draw of their expected idiosyncratic cost, worker's can then choose whether to attain a college-degree or not. A similar sequential setup is used in Cortes et al. (2017)

[17] I do not explicitly model heterogeneity in labor efficiency across individuals. This is similar to the assumption in Bárány and Siegel (2020). I do this for two reasons. First, if I allowed occupational sorting conditional on efficiency then I could not separately identify the efficiency of a worker in the model from the number of worker a firm hires. I could only do so in the aggregate. Second, it allows me to take wages directly from the data.

by firms for occupation o, N_o denotes total employment in occupation o and T denotes the total tax collected by the government. The unemployment benefits (b_K) is financed from government tax receipts

$$b_K \underbrace{(N_{KH} + N_{KL})}_{N_K} = \rho T, \quad \rho \in (0, 1)$$

where ρ denotes the fraction of the total tax receipts used to finance unemployment benefits. I assume that the rest of the tax receipts are returned back to the household as a public good.

Household Preferences. Household members derive utility from consuming the output produced by firms. The household collects the income earned by its members and allocates it to maximize the following utility function:

$$\max_{C_j \forall j} U = U(C) \tag{5}$$

$$\text{s.t.} \underbrace{\int_{j=0}^{J} C_j dj}_{=C} = (1 - \tau_A^W) W_A N_A + (1 - \tau_R^W) W_R N_R + (1 - \tau_M^W) W_M N_M + b_K N_K + (1 - \rho) T + \Pi$$

where C_j denotes consumption of output produced by firm j and Π denotes aggregate profits. The preference for the representative household is a limiting case of Constant Elasticity of Substitution (CES) preferences. Since household can perfectly substitute one good for another - the implied elasticity of substitution is infinity - the price of every good must be the same: $P_j = P_q$, for all $j, q \in [0, J], j \neq q$. I assume that the aggregate output is the numéraire and normalize its price to unity.

3.2 Model solution

Firm's problem. Firms are price-takers in the input and output markets. Thus, the firm's problem is to choose their optimal labor demand conditional on market prices:

$$\Pi_j = \max_{N_{Aj}, N_{Rj}, N_{Mj}} Q_j - (1 + \tau_A^F) W_A N_A - (1 + \tau_R^F) W_R N_R - (1 + \tau_M^F) W_M N_M \tag{6}$$

where $(1 + \tau_o^F) W_o$ denotes the total labor cost of hiring a worker in occupation o. Profit maximization implies that the relative demand for abstract and routine occupations is

$$\ln \frac{N_{Aj}}{N_{Rj}} = \gamma_A \ln \frac{(1 + \tau_R^F) W_R}{(1 + \tau_A^F) W_A} + (1 - \gamma_A) \ln \frac{\phi_{Rj}}{\phi_{Aj}}. \tag{7}$$

The relative ratio of abstract and routine occupations is determined in equilibrium by relative wages and relative efficiencies. Their effects on relative demand is mediated by γ_A, the elasticity of substitution. As relative wages of routine occupations increase, a firm would find it optimal to use less of routine occupations in its production. Higher the value of γ_A, higher the relative demand for abstract occupations due to increase in relative wages of routine occupations. Moreover, as routine occupations become more productive (i.e. $\frac{\phi_{Rj}}{\phi_{Aj}}$ increases), its effect on relative demand depends will depend on whether γ_A is less than or greater than 1. If $\gamma_A < 1$, then occupational inputs are *gross complements*. In this case, an increase in relative productivity of routine workers would imply an increase in the relative demand for abstract occupations. Intuitively, as routine workers become more productive, firms require less routine workers to produce the same output. If, instead, $\gamma_A > 1$, then occupations are *gross substitutes* and an increase in the relative productivity of routine occupations will increase the relative demand for routine occupations.

Similarly, the relative demand for manual occupations relative to routine occupations is as follows:

$$\ln \frac{N_{Mj}}{N_{Rj}} = \gamma_M \ln \frac{\tilde{W}_R}{\tilde{W}_M} + (1-\gamma_M) \ln \frac{\phi_{Rj}}{\phi_{Mj}} + \frac{\gamma_M - \gamma_A}{1-\gamma_A} \ln \left[\left(\frac{\phi_{Rj}}{\phi_{Aj}} \frac{\tilde{W}_A}{\tilde{W}_R} \right)^{1-\gamma_A} + 1 \right] \tag{8}$$

where $\tilde{W}_o = (1+\tau_o^F)W_o$. There are two key features of the expression above. First, if $\gamma_A = \gamma_M = \gamma$, implying that the elasticity of substitution is the same for the three occupations, then the third term in Eq. 8 disappears. In this case, Eq. 8 will be similar to Eq. 7, except that abstract occupation will be replaced by manual occupations. I need to account for the third term given that I assume a nested-CES specification.

Second, the effect of an improvement in the productivity of routine workers on relative demand for manual and routine occupations will be mediated by γ_M, the elasticity of substitution between manual occupations and the composite of abstract and routine occupations, *and* γ_A.

$$\frac{\partial \ln \frac{N_{Mj}}{N_{Rj}}}{\partial \phi_{Rj}} = \underbrace{(1-\gamma_M)\frac{1}{\phi_{Rj}}}_{\text{Direct effect}} + \underbrace{\frac{\gamma_M - \gamma_A}{\phi_{Aj}} \left(\frac{\phi_{Aj}}{\phi_{Rj}} \right)^{\gamma_A} \left(\frac{\tilde{W}_A}{\tilde{W}_R} \right)^{\gamma_A - 1}}_{\text{Indirect effect}} > 0 \quad \text{if} \quad \gamma_A < \gamma_M < 1 \tag{9}$$

Note again that, if $\gamma_A = \gamma_M = \gamma$, then the indirect effect (i.e., the second term of Eq. 9) disappears. Eq. 9 states that if occupations are *gross complements*, i.e. $\gamma_A < \gamma_M < 1$, then improvements in productivity of routine occupations will increase the relative demand for manual occupations.[18]

If occupations are gross complements then routine-biased technological change, the replacement of workers in routine occupations by ICT technology, will be captured by an increase in $\frac{\phi_{Rj}}{\phi_{Aj}}$ and $\frac{\phi_{Rj}}{\phi_{Mj}}$. Given I observe wages and quantities in the data, conditional on γ_A and γ_M, I can measure technological change for the universe of firms in the economy. This indirect approach to measuring technological change is akin to Katz and Murphy (1992). We can see this more explicitly by re-arranging Eq. 7 and expressing relative wages on the left-hand side instead of the relative

[18] If $\gamma_M < 1 < \gamma_A$, then an increase in ϕ_{Rj} will increase $\frac{N_{Mj}}{N_{Rj}}$ if the direct effect dominates the indirect effect. If $\gamma_A < 1 < \gamma_M$, then an increase in ϕ_{Rj} will increase $\frac{N_{Mj}}{N_{Rj}}$ if the indirect effect dominates the direct effect.

quantities. The resulting equation is reminiscent of the equation used by Katz and Murphy (1992) to estimate skill-biased technological change, except that this relationship emerges directly from the profit maximizing behaviour of firms in the model.

The key advantage of my approach is that I can measure technological change for the universe of firms in the economy. This is often difficult if one relies on direct physical measures of technology, investments in R&D or innovation, as it is difficult to find estimates of these measures directly in the data outside manufacturing. Doms et al. (1997) use a direct measure by counting the usage of advanced technology in production, however, their study is focused only on the manufacturing industry in the US. I documented in the empirical section that the share of routine occupations has declined even in non-manufacturing in France.[19] Robots, on the other hand, are primarily used in the auto industry and their use might have little to say about the rest of the economy.

The optimal labor demand for the three occupations are as follows:

$$N_{Aj} = \kappa^{\frac{1}{1-\kappa}} \tilde{W}_A^{-\gamma_A} v_j^{\frac{\gamma_M(1-\kappa)-1}{1-\kappa}} \lambda_{\Omega_j}^{\gamma_A-\gamma_M} \phi_{Aj}^{\gamma_A-1} \tag{10}$$

$$N_{Rj} = \kappa^{\frac{1}{1-\kappa}} \tilde{W}_R^{-\gamma_A} v_j^{\frac{\gamma_M(1-\kappa)-1}{1-\kappa}} \lambda_{\Omega_j}^{\gamma_A-\gamma_M} \phi_{Rj}^{\gamma_A-1} \tag{11}$$

$$N_{Mj} = \kappa^{\frac{1}{1-\kappa}} \tilde{W}_M^{-\gamma_M} v_j^{\frac{\gamma_M(1-\kappa)-1}{1-\kappa}} \phi_{Mj}^{\gamma_M-1} \tag{12}$$

where $\lambda_{\Omega j}$ and v_j are defined as follows:

$$v_j = \left[\left(\frac{\tilde{W}_M}{\phi_{Mj}} \right)^{1-\gamma_M} + \lambda_{\Omega j}^{1-\gamma_M} \right]^{\frac{1}{1-\gamma_M}}, \qquad \lambda_{\Omega j} = \left[\left(\frac{\tilde{W}_A}{\phi_{Aj}} \right)^{1-\gamma_A} + \left(\frac{\tilde{W}_R}{\phi_{Rj}} \right)^{1-\gamma_A} \right]^{\frac{1}{1-\gamma_A}}$$

$\lambda_{\Omega j}$ denotes the cost of hiring one unit of the composite of abstract and routine occupations and v_j is the marginal cost of the firm to produce an additional unit of output. For notational simplicity, I suppress the dependence of $\lambda_{\Omega j}$ and v_j on equilibrium wages, the productivity shocks (ϕ's) and structural parameters except when necessary. Labor demand equations describe the standard downward-sloping relationship between wages and quantities for each occupation. To pin down a unique firm-size distribution, I need to ensure that $\kappa < 1$.

The equilibrium quantity and profits of the firms are as follows:

$$Q_j = \left(\frac{\kappa}{v_j} \right)^{\frac{\kappa}{1-\kappa}}, \quad \Pi_j = (1-\kappa) Q_j \tag{13}$$

Expressions in Eq. 13 state that a more productive firms will produce a higher quantity and earn a higher profit in equilibrium. Firms earn a fraction of their output as profits. If the production

[19] Autor et al. (1998) make use of computer equipment in their analysis to study the effect of computers on the labor market. Difficulty with this approach is that computers today are ubiquitous and therefore leave very little variation to exploit.

technology exhibits constant returns-to-scale, i.e. κ is equal to 1, firms earn zero profit in equilibrium.

Finally, the assumption of a perfectly competitive output market is strong, especially given the evidence presented by De Loecker et al. (2020) showing that aggregate markups in the US rose from 21% above marginal cost in 1980 to 61% in 2020. In Deb et al. (2020), we explicitly account for the possibility that output and input markets are both imperfectly competitive. We find that changes in the output market power has a significant effect on the *level* of labor demand but little effects on *relative* labor demand. We model imperfectly competitive markets by allowing firms to compete with a few competitors in the goods and the labor market. These modifications give rise to endogenous markups and markdowns which, in equilibrium, depend jointly on the market structure, i.e. the number of competitors in a market, as well as the distribution of firm-specific technology. In the counterfactual exercise, we shift the number of competitors in the goods market, our measure of output market power that we estimate for the US data, and find that it decreases labor demand proportionally. Consequently, its quantitative effect on relative quantities is negligible. Based on these insights, I abstract from incorporating output market power explicitly in this framework at this point.

Worker's problem. The problem of a worker i is to decide whether to participate in the labor force or not, and conditional on participation to choose which occupation to enter. This is a standard discrete choice problem.[20] The probability of a worker i of skill s entering into state $x \in \{A, R, M, K\}$ is defined as follows

$$\begin{aligned} \mathrm{Pr}_{ixs} &= \mathrm{Prob}\ [\ u_{ixs} \geq u_{iws}, \quad \text{all } w \neq x] \\ &= \mathrm{Prob}\ [\ \epsilon_{iws} \leq \epsilon_{ixs} + \sigma_s(V_{xs} - V_{ws}), \quad \text{all } w \neq x] \end{aligned} \tag{14}$$

where for notational simplicity, I define V_{xs} as follow

$$V_{xs} = \begin{cases} \ln[(1-\tau_x^W)W_x] - \chi_{xs}, & \text{if } x \in \{A, R, M\}, \quad s \in \{H, L\} \\ \ln b_K, & \text{if } x = K, \ s \in \{H, L\} \end{cases} \tag{15}$$

If ϵ_{ixs} is given, then the last expression of Eq. 14 is the cumulative distribution for each ϵ_{ixs} evaluated at $\epsilon_{ixs} + \sigma_s(V_{xs} - V_{ws})$, which, under the assumption that ϵ_{ixs} is i.i.d. type 1 extreme value equates to $\exp(-\exp(-(\epsilon_{ixs} + \sigma_s(V_{xs} - V_{ws}))))$. Since the ϵ's are independent, the cumulative distribution over all $w \neq x$ is the product of the individual CDFs. Of course, ϵ_{ixs} is not given, and so the probability is the integral of $\mathrm{Pr}_{ixs}|\epsilon_{ixs}$ over all values of ϵ_{ixs} weighted by its density:

[20] Much of the exposition of this sub-section is borrowed from Train (2009) for completeness sake. Interested readers can read further details in Chapter 3.

$$\text{Pr}_{ixs} = \int \underbrace{\left(\prod_{k \neq o} e^{-e^{-(\epsilon_{ixs} + \sigma_s (V_{xs} - V_{ws}))}} \right)}_{= \text{Pr}_{ios} | \epsilon_{ixs}} e^{-\epsilon_{ixs}} e^{-e^{-\epsilon_{ixs}}} d\epsilon_{ios} = \frac{e^{V_{xs}}}{\sum_{x'} e^{V_{x's}}} \tag{16}$$

The solution to the integral in Eq. 16 is a well-known logit choice probability. There are two key features of this probability. First, Pr_{ixs} is necessarily between zero and one. Second, when V_{xs} rises, reflecting an improvement in the observed attributes of alternative (wages in a given occupation increase or disutility cost of working in that occupation declines), with $V_{ws} \;\; \forall w \neq x$ held constant, Pr_{ixs} approaches one. As V_{xs} decreases, Pr_{ixs} approaches zero.

Aggregation. Given the solution to the firm's and the worker's problem, I can now close the model by aggregating the labor demand and supply functions of all the firms and workers, respectively, in the economy. Once the aggregate labor demand and supply equations are derived, I can solve for factor price to pin down the equilibrium of the economy. I start by aggregating labor demand which will be characterized by the distribution of productivity and the measure of firms in the economy.

Let $\overline{\boldsymbol{\phi}} = (\phi_A, \phi_R)^T$ and $\boldsymbol{\phi} = (\phi_A, \phi_R, \phi_M)^T$, we have that,[21]

$$N_A^D = J\kappa^{\frac{1}{1-\kappa}} \tilde{W}_A^{-\gamma_A} \int_0^\infty \int_0^\infty \int_0^\infty v(\boldsymbol{\phi})^{\frac{\gamma_M(1-\kappa)-1}{1-\kappa}} \lambda_\Omega(\overline{\boldsymbol{\phi}})^{\gamma_A - \gamma_M} \phi_A^{\gamma_A - 1} g(\boldsymbol{\phi}) \; d\phi_A d\phi_R d\phi_M \tag{17}$$

$$N_R^D = J\kappa^{\frac{1}{1-\kappa}} \tilde{W}_R^{-\gamma_A} \int_0^\infty \int_0^\infty \int_0^\infty v(\boldsymbol{\phi})^{\frac{\gamma_M(1-\kappa)-1}{1-\kappa}} \lambda_\Omega(\overline{\boldsymbol{\phi}})^{\gamma_A - \gamma_M} \phi_R^{\gamma_A - 1} g(\boldsymbol{\phi}) \; d\phi_A d\phi_R d\phi_M \tag{18}$$

$$N_M^D = J\kappa^{\frac{1}{1-\kappa}} \tilde{W}_M^{-\gamma_M} \int_0^\infty \int_0^\infty \int_0^\infty v(\boldsymbol{\phi})^{\frac{\gamma_M(1-\kappa)-1}{1-\kappa}} \phi_M^{\gamma_M - 1} g(\boldsymbol{\phi}) \; d\phi_A d\phi_R d\phi_M \tag{19}$$

where N_o^D denotes aggregate labor demand for occupation o and $g(\boldsymbol{\phi})$ denotes the joint pdf of technology shocks. In a similar vein, I can aggregate total output and profits produced by firms in the economy as follows:[22]

$$Q = J\kappa^{\frac{\kappa}{1-\kappa}} \int_0^\infty \int_0^\infty \int_0^\infty v(\boldsymbol{\phi})^{\frac{\kappa}{\kappa-1}} g(\boldsymbol{\phi}) \; d\phi_A d\phi_R d\phi_M, \quad \Pi = (1-\kappa)Q. \tag{20}$$

I turn now to aggregate labor supply of workers across different occupations. To do so, I start by replacing V_{xs} in Eq. 16 by its definition from Eq. 15 and dividing both the numerator and the denominator by $\sigma_s W_K$. Eq. 16 gives the share of workers in occupation o conditional on skill s.

[21] To derive Eq. 17 equation, I start from Eq. 10 and aggregate the demand for all firms in the economy:

$$N_o^D = \int_{j=0}^J N_{oj} dj, \quad o \in \{A, R, M\}$$

Then, I commute the integration to ϕ's rather than j to get Eq. 17.

[22] I assume that profits Π are distributed back to workers who supply their labor in a lump-sum manner. Given there is no free entry of firms in the model, aggregate profit will be non-negative in the equilibrium.

From this information, I can calculate the occupational labor supply conditional on skill $s \in \{H, L\}$ as follows:[23]

$$N_{os}^S = \frac{\theta_s N \times \exp\left[\sigma_s[\ln\{(1-\tau_o^W)W_o\} - \ln b_K] - \sigma_s \chi_{os})\right]}{1+\Xi}, \quad \text{if } o \in \{A, R, M\} \tag{21}$$

Ξ is defined as follows

$$\Xi = \sum_{o' \in \{A,R,M\}} \exp\left[\sigma_s[\ln\{(1-\tau_{o'}^W)W_{o'}\} - \ln b_K] - \sigma_s \chi_{o's})\right].$$

N_{os}^S denotes (with a slight abuse of notation) aggregate labor supply in occupation o conditional on skill s.

Finally, using Eq. 21, I can define the aggregate occupation labor supply, N_o^S, as follows:

$$N_A^S = \sum_{s \in \{H,L\}} N_{As}^S \tag{22}$$

$$N_R^S = \sum_{s \in \{H,L\}} N_{Rs}^S \tag{23}$$

$$N_M^S = \sum_{s \in \{H,L\}} N_{Ms}^S \tag{24}$$

Equilibrium. There are four markets in the economy: three labor markets for abstract, routine and manual occupations and one market for aggregate output. As a result, there are four corresponding prices, out of which the price of the aggregate good is normalized to unity.

Definition 1. *The equilibrium is defined as a set of prices $\{W_A, W_R, W_M\}$ such that given prices:*

1. *the three occupational labor markets clear, i.e., the aggregate demand for labor equates aggregate supply*
2. *the aggregate output market clears, i.e. $C = Q$*
3. *the firm-specific quantities maximize profits*
4. *the aggregate quantities maximize household utility*
5. *government budget constraint holds*

[23] The total number of workers staying out-of-the labor force, conditional on skill s, is given as follows:

$$N_{Ks} = \frac{s}{1+\Xi}$$

The computation of the equilibrium is straightforward. To pin down the three unknowns, W_A, W_R and W_M, I use the three occupational labor market clearing conditions to solve a system of three equations in three unknowns. Conditional on the knowledge of these prices, all other model objects can be calculated.

4 Estimation

In this section, I give details about the parameters I directly observe in the data and the ones that I need to estimate. I specify the key identifying conditions to estimate the unobserved parameters and the intuition behind my identification strategy. Once the model is estimated, I will use it to conduct counterfactual exercises in the next section to quantify the role of RBTC and labor supply shocks in explaining job polarization.

4.1 Observed parameters

Share of high-skill. The list of parameters directly observed in the data and their values are described in Table 3. The share of high-skilled workers is calculated from the French Labor Force Survey. Following Verdugo (2014), I define high-skilled workers as those who have at least two years of education after completing their high-school diplomas. All other workers are categorized as low-skilled. I find that the share of high-skilled workers increased from 23% of the total labor force to 40% between 1994 and 2015. As documented by Verdugo (2014), this increase in college-attainment in France is linked to education reforms implemented by the French government in the mid-1990's. The government created new technological and professional baccalaureates with less stringent requirement to obtain the diploma compared to the previous high-school diploma that spurred the access to university education in France.

Tax rate. The occupation-specific firm and worker tax rates are calculated using the work of Bozio et al. (2016). The authors observe gross wages in the DADS and explicitly account for employer's payroll contribution to create a measure of the total labor cost. They separately calculate the evolution of employer's and employee's payroll tax rate by each deciles of the wage distribution. I use this information to construct firm's and worker's tax rates in Table 3.[24]

Equilibrium wages, quantities and unemployment benefit. I use DADS Postes to calculate the number of workers hired (or the total number of hours employed) by each firm in the three occupations. I use two separate definitions for occupational wage rates. The first definition calculates

[24] I define τ_M^F as the average of the employer's payroll tax rate for the bottom two decile of the wage distribution. τ_R^F is defined as the average of the employer's payroll tax rate for deciles 3 to 8. Finally, τ_A^F is defined as the average of the top two deciles. I use the same deciles to calculate τ_o^W, $o \in \{A, R, M\}$. In the data, I observe that the share of manual occupations is very high in the bottom two deciles of the wage distribution and the share of abstract occupations is equally high in the top two deciles. The share of routine occupations is high in the middle of the wage distribution. This provides the rationale to calculate the tax rates for firms and workers as documented in Table 3

Table 3: **Parameters directly observed in the data**

Parameter	**Description**	**1994**	**2015**
θ_H	Share of high-skilled	0.23	0.40
$\tau_A^F, \tau_R^F, \tau_M^F$	Employer's SSC tax rates	0.44, 0.43, 0.38	0.47, 0.38, 0.18
$\tau_A^W, \tau_R^W, \tau_M^W$	Employee's SSC tax rates	0.19, 0.21, 0.21	0.21, 0.22, 0.22
b_K	Unemployment benefits	13990	16470

Notes: The share of high-skilled workers is calculated from the French Labor Force Survey (*Enquête Emploi*). I define high-skilled workers as the ones with at least two years of education after completing high-school (i.e. the workers with *Diplome superieure* or *Bac+2*). The rest of the labor force is categorized as low-skilled. The firm and worker tax rate by occupation is calculated using information from Bozio et al. (2016). The total number of firms in the economy is calculated from DADS Postes.

the occupational wage rate as the average annual wages earned by workers employed in a given occupation o. The second definition calculates it as the average annual wage of a narrowly defined group - 25 to 35 year old men - to limit the influence of compositional changes. For the baseline results presented in the next section, I use the first definition. However, the results are robust to using the second definition. I calibrate the value of b_K as follows:

$$b_K = \theta_{RR} \frac{\sum_o (1 - \tau_o^W) W_o N_o}{N - N_K}$$

where θ_{RR} is the replacement ratio, which is multiplied by the average (net) wages in the economy. Using OECD, I set $\theta_{RR} \in (0.6, 0.7)$. Pinning down b_K, also pins down ρ through the government budget constraint.

4.2 Estimation strategy

In total, I have 5 parameters to estimate: $\kappa, \gamma_A, \gamma_M, \sigma_H, \sigma_L$. The first three parameters pertain to the production function and the latter two pertain to worker's occupational choice. Once I estimate these parameters, I can recover the joint distribution of technology $G(\phi_{Aj}, \phi_{Rj}, \phi_{Mj})$ non-parametrically and estimates of the 6 disutility costs χ_{os}, one for each skill and occupation. I estimate these parameters in three steps, as follows:

Step 1. Estimate $\kappa, \gamma_A, \gamma_M$ using relative first order conditions in Eq. 7 and Eq. 8

Step 2. Given $\{\hat{\kappa}, \hat{\gamma}_A, \hat{\gamma}_M\}$, back-out $\phi_{Aj}, \phi_{Rj}, \phi_{Mj}$ using the structure of the model

Step 3. Estimate σ_H and σ_L and infer disutility costs as structural residuals

I describe each of these steps in detail below.

Step 1. While the production function contains information on the three technology parameters κ, γ_A and γ_M, the only parameter identified from it is κ. To see this, let us re-write the production function as follows[25]

$$\ln Q_j = \kappa \frac{\gamma_M}{\gamma_M - 1} \ln \frac{E_{Aj} + E_{Rj} + E_{Mj}}{E_{Aj} + E_{Rj}} + \kappa \frac{\gamma_A}{\gamma_A - 1} \ln \frac{E_{Aj} + E_{Rj}}{E_{Rj}} + \kappa \ln N_{Rj} + \kappa \ln \phi_{Rj} \tag{25}$$

where $E_{oj} = (1 + \tau_o^F) W_o N_{oj}$. The key advantage of Eq. 25 is that it is log-linear and I have reduced the original equation with three productivity shocks to only one. Running an OLS on Eq. 25 will not allow me to recover the structural parameters since firms choose their optimal labor demand conditional on knowledge of ϕ_{Rj}, which is unobserved by the econometrician. Theory provides a link between what is unobserved (the ϕ's) and the equilibrium objects that I observe directly in the data (i.e. wages and workers hired by firms in each occupation). Hence, I can write

$$\phi_{Rj} = h\left(N_{Aj}, N_{Rj}, N_{Mj}, W_A, W_R, W_M, \tau_A^F, \tau_R^F, \tau_M^F\right) \tag{26}$$

where $h(\cdot)$ is known. Replacing ϕ_{Rj} in Eq. 25 by $h(\cdot)$ from Eq. 26, simplifies it as follows:

$$\ln Q_j = \frac{1}{\kappa} + \ln(E_{Aj} + E_{Rj} + E_{Mj}) + \omega_j \tag{27}$$

where ω_j is an i.i.d. measurement error introduced to keep the expression stochastic. As can be seen from Eq. 27, I cannot identify the parameters pertaining to the elasticity of substitution (γ_A and γ_M) from the production once I fully control for unobserved heterogeneity in ϕ_{Rj}. This is reminiscent of the functional dependence problem highlighted by Ackerberg et al. (2015): conditional on fully controlling for ϕ_{Rj}, there is no independent variation in N_{Rj}, $\frac{E_{Aj}+E_{Rj}}{E_{Rj}}$ and $\frac{E_{Aj}+E_{Rj}+E_{Mj}}{E_{Aj}+E_{Rj}}$ to identify γ_A and γ_M. However, κ is identified from Eq. 27 and I estimate it using OLS.[26]

To identify γ_A, I use the relative FOC first presented in Eq. 7. I re-write the expression by taking expectations on both sides and including a time sub-script t as follows:

$$\mathbb{E} \ln \frac{N_{Ajt}}{N_{Rjt}} = \gamma_A \mathbb{E} \ln \frac{(1 + \tau_{Rt}^F) W_{Rt}}{(1 + \tau_{At}^F) W_{At}} + (1 - \gamma_A) \mathbb{E} \ln \frac{\phi_{Rjt}}{\phi_{Ajt}}. \tag{28}$$

where the expectation is over j. Running an OLS on the above expression will not allow me to recover an unbiased and consistent estimate of γ_A since the relative wages will be correlated with the aggregate component of the relative technology shocks (which is unobserved).

I will rely on the time-series variation in the tax rate in my estimation of γ_A. Specially, I will

[25] To derive this equation, start by rewriting the production function as follows.

$$Q_j = (\phi_{Rj} N_{Rj})^{\kappa} \left[\left(\frac{\phi_{Mj} N_{Mj}}{\phi_{Rj} N_{Rj}} \right)^{\frac{\gamma_M - 1}{\gamma_M}} + \left[1 + \left(\frac{\phi_{Aj} N_{Aj}}{\phi_{Rj} N_{Rj}} \right)^{\frac{\gamma_A - 1}{\gamma_A}} \right]^{\frac{\gamma_A(\gamma_M - 1)}{\gamma_M(\gamma_A - 1)}} \right]^{\kappa \frac{\gamma_M}{\gamma_M - 1}}$$

Next, invert the relative FOC's of $\frac{N_{Aj}}{N_{Rj}}$ and $\frac{N_{Mj}}{N_{Rj}}$ to express the relative ratio of ϕ's as a function of observables (relative wages and relative quantities). Finally, take logs on both sides to get Eq. 25.

[26] I replace the left hand side of Eq. 27 by value-added observed in the balance-sheet data.

instrument the relative labor cost, $\ln \frac{(1+\tau^F_{Rt})W_{Rt}}{(1+\tau^F_{At})W_{At}}$, in Eq. 28 by the employers payroll contribution $\frac{(1+\tau^F_{Rt})}{(1+\tau^F_{At})}$. Payroll taxes are either used to finance future benefits for workers (e.g., pensions) or the French public health system and are a plausible source of exogenous variation. As has been documented by Bozio et al. (2016), for many countries the difference between gross wages and total labor cost paid by the employer is small and this wedge has remained stable. The picture is very different for France where payroll taxes are substantial (around 17% of GDP) and have dramatically changed over the period starting the mid-1990's.[27] France has the highest payroll tax rate among OECD countries, with marginal rates close to 40% of gross earnings. Employer payroll taxes have been reduced on low-wage earners and increased on high-wage earners.[28] Hence, it can be argued that the payroll taxes evolve independently of the aggregate technology shocks in the economy and constitute a valid instrument in this setting.[29] Thus, the key identifying assumption in estimating γ_A is the following:

$$\frac{(1+\tau^F_{Rt})}{(1+\tau^F_{At})} \perp\!\!\!\perp \mathbb{E} \ln \frac{\phi_{Rjt}}{\phi_{Ajt}} \tag{29}$$

Finally, to estimate γ_M, I use the relative FOC between manual and routine occupations. I follow the same steps as outlined in the estimation of γ_A. The key identifying assumption in estimating γ_M is the following

$$\frac{(1+\tau^F_{Rt})}{(1+\tau^F_{Mt})} \perp\!\!\!\perp \mathbb{E} \ln \frac{\phi_{Rjt}}{\phi_{Mjt}} \tag{30}$$

Step 2. Once the three technology parameters are estimated, I can proceed to recover the technology shocks. To do so, I invert the firm-level FOCs in Eq. 7 and Eq. 8. After taking exponents on both sides, this inversion gives me the $\frac{\phi_{Aj}}{\phi_{Rj}}$ and $\frac{\phi_{Mj}}{\phi_{Rj}}$ in Eq. 31 and Eq. 32 respectively. Once I know the ratios of these shocks, I separately identify their levels by inverting the labor demand equation for routine occupations in Eq. 11. This gives me the level of ϕ_{Rj} and I can use Eq. 31 and Eq. 32 to calculate ϕ_{Aj} and ϕ_{Rj}, respectively.

$$\frac{\hat{\phi}_{Ajt}}{\hat{\phi}_{Rjt}} = \left[\frac{N_{Ajt}}{N_{Rjt}} \times \left(\frac{\tilde{W}_{At}}{\tilde{W}_{Rt}}\right)^{\hat{\gamma}_A}\right]^{\frac{1}{\hat{\gamma}_A - 1}} \tag{31}$$

$$\frac{\hat{\phi}_{Mjt}}{\hat{\phi}_{Rjt}} = \left[\frac{N_{Mjt}}{N_{Rjt}} \times \frac{\tilde{W}_{Mt}^{\hat{\gamma}_M}}{\tilde{W}_{Rt}^{\hat{\gamma}_A}} \times \overline{\lambda}_{\Omega jt}^{\hat{\gamma}_A - \hat{\gamma}_M}\right]^{\frac{1}{\hat{\gamma}_M - 1}} \tag{32}$$

[27] Starting from the mid-1990s to the present day, average payroll tax rates stabilized at aroung 46% of labor cost for the top half of the wage distribution while it decline for the lower percentiles. The rationale behind this was to reduce unemployment among low skilled workers by declining the labor cost for employers. Those payroll tax cuts initially affected workers whose wage was below 1.1 times the national minimum wage but has been progressively extended to 1.6 times the national minimum wage.

[28] See Bozio et al. (2016) for information on the two important reforms pertaining to employers payroll taxes in mid-1960's and mid-1990's.

[29] For instance, these payroll taxes can evolve as a function of the labor force composition which is exogenous to the change in technology.

$$\hat{\phi}_{Rjt} = \left[\frac{N_{Rjt} \times \tilde{W}_{Rt}^{\hat{\gamma}_A}}{\hat{\kappa}^{\frac{1}{1-\hat{\kappa}}} \times \overline{v}_j^{\frac{\hat{\gamma}_M(1-\hat{\kappa})-1}{1-\hat{\kappa}}} \times \overline{\lambda}_{\Omega jt}^{\hat{\gamma}_A - \hat{\gamma}_M}} \right]^{\frac{1-\hat{\kappa}}{\hat{\kappa}}} \tag{33}$$

where $\overline{\lambda}_{\Omega_{jt}}$ and $\overline{v}_{jt}$ are defined as follows

$$\overline{\lambda}_{\Omega_{jt}} = \left[\left(\tilde{W}_{At} \frac{\hat{\phi}_{Rjt}}{\hat{\phi}_{Ajt}} \right)^{1-\gamma_A} + \tilde{W}_{Rt}^{1-\gamma_A} \right]^{\frac{1}{1-\gamma_A}}, \quad \overline{v}_{jt} = \left[\left(\tilde{W}_{Mt} \frac{\hat{\phi}_{Rjt}}{\hat{\phi}_{Mjt}} \right)^{1-\gamma_M} + \overline{\lambda}_{\Omega_{jt}}^{1-\gamma_M} \right]^{\frac{1}{1-\gamma_M}}$$

Step 3. To estimate the scale parameters σ_H and σ_L, I rely on an instrumental variable strategy. To formulate the estimation equation that I take to the data, I start by noting that I can re-write Eq. 21 for the three occupations as follows:

$$\ln \frac{N_{ost}}{N_{Kst}} = \sigma_s \ln \frac{(1-\tau_{ot}^W) W_{ot}}{b_K} - \sigma_s \chi_{ost}, \quad o \in \{A, R, M\}, \quad s \in \{H, L\}. \tag{34}$$

I stack the three occupations together and run the system of equations separately for high and low-skilled workers to infer σ_H and σ_L. Notice that the OLS estimate of σ_H and σ_L will be biased as the disutility cost that are unobserved to the econometrician will be correlated with wages. To circumvent this identification problem, I instrument equilibrium wages with employer's payroll tax rate, the same instrument I used to estimate the elasticity of substitution parameters in Step 1. In the case of σ_H and σ_L, these instruments act as standard exclusion restrictions. Once I estimate σ_H and σ_L, I infer disutility costs from Eq. 34 as structural residuals of the labor supply equation.

4.3 Intuition behind the identification strategy

In general, estimating the slope of both the demand the supply curve requires at least two instruments. However, as shown by Zoutman et al. (2018), in specific cases theory provides restrictions such that two elasticities can be identified by a single instrument. Let me demonstrate the key intuition behind the identification strategy via an illustrative example.[30] For simplicity, assume there is no occupational choice on behalf of workers and labor is supplied perfectly inelastically. I observe equilibrium quantity, N_t, and wages before taxes, W_t. There is a tax rate levied on firms denoted τ_t and it is assumed exogenous. Assuming log-linearity, the supply-demand system is given by

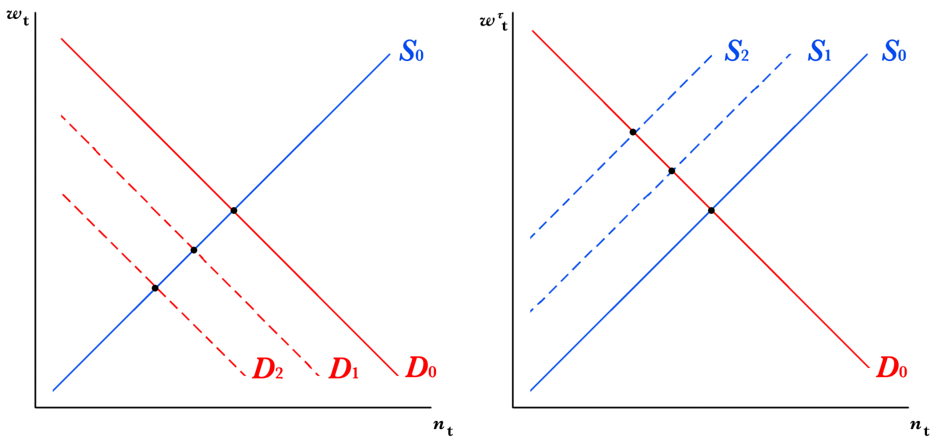
$$n_t = \epsilon^D w_t + \gamma z_t + \nu_t^D \tag{35}$$

$$n_t = \epsilon^S w_t + \eta z_t + \nu_t^S \tag{36}$$

where lower case letters n_t and w_t indicate logged quantities and price, respectively, $z_t \equiv f(\tau_t)$ is a pre-specified function of the tax rate, and ν_t^S and ν_t^D are supply and demand disturbance terms.

[30] A similar example is provided in Zoutman et al. (2018)

Figure 3: **The effect of an increase in tax rate in identifying supply and demand elasticities**



I allow the instrument to enter both supply and demand equations initially. The reduced-form equations can be represented as follows:

$$\begin{pmatrix} n_t \\ w_t \end{pmatrix} = \begin{pmatrix} \pi_{zn} \\ \pi_{zw} \end{pmatrix} z_t + \xi_t, \quad \text{where} \quad \begin{pmatrix} \pi_{zn} \\ \pi_{zw} \end{pmatrix} = \begin{pmatrix} \frac{\epsilon^S \gamma - \epsilon^D \eta}{\epsilon_S - \epsilon_D} \\ \frac{\gamma - \eta}{\epsilon_S - \epsilon_D} \end{pmatrix} \tag{37}$$

From Eq. 37, it is clear that I cannot separately identify the demand and supply elasticities given that I have two reduced parameters in the π vector and four structural parameters to estimate. I will impose two restrictions motivated by the theory to show that the structural parameters are indeed identified under these restrictions. The first restriction is the standard exclusion restriction: the instrument z_t, which in my general model is the employer's payroll taxes, only enter Eq. 35 and not the supply equation (Eq. 36), i.e. $\eta = 0$. This (standard) exclusion restriction should help identify ϵ_S. The second restriction relies on the idea that firm's labor demand decision are not based on equilibrium wage but the total labor cost they have to pay. Therefore, an increase in w_t and an increase in gross of tax rate $z_t \equiv \ln(1 + \tau_t)$, affect labor demand in an identical manner. As a result, the coefficient on the instrument in the demand equation equals the demand elasticity $\gamma = \epsilon^D$. Under these two restrictions, it can be shown that

$$\begin{pmatrix} \pi_{zn} \\ \pi_{zw} \end{pmatrix} = \begin{pmatrix} \frac{\epsilon^S \epsilon^D}{\epsilon_S - \epsilon_D} \\ \frac{\epsilon_D}{\epsilon_S - \epsilon_D} \end{pmatrix} \implies \epsilon_S = \frac{\pi_{zn}}{\pi_{zw}}, \quad \epsilon_D = \frac{\pi_{zn}}{1 + \pi_{zw}}$$

This simple example shows that with the tax rate and under the two restrictions outlined earlier, the supply and demand elasticities are indeed identified. The graphical intuition of the idea is given in Figure 3.

5 Results

In this section, I start by discussing the estimation results of the structural parameters. Then, I proceed to document the distribution of technology shocks that I infer through the lens of my model. Finally, I perform a series of counterfactual exercises to quantify the importance of RBTC and labor supply shocks in explaining changes within firms, between firms and aggregate job polarization.

5.1 Estimation results

The estimation results are documented in Table 4, panel A. I find that the value of κ, the parameter measuring returns-to-scale, is 0.931. This value is less than one consistent with the theoretical restriction of decreasing returns-to-scale. The OLS estimate of γ_A, the elasticity of substitution between abstract and routine occupations is 1.75. This estimate can be biased due to endogeneity issues mentioned in the previous section. I address these concerns by using the relative tax-rate of employer's payroll contribution as instruments for relative wages. I find that the IV estimate of γ_A decreases to 1.45. The OLS and IV estimates of γ_M, the elasticity of substitution between manual and the composite of abstract and routine occupations, are 2.64 and 2.76, respectively.

To the best of my knowledge, the only other estimate of the elasticity of substitution (between occupations) in the literature is by Goos et al. (2014), who find a value between 0.854 and 0.899, depending on their specification.[31] The value estimated in this paper is higher compared to their estimate and given that it is above one implies that occupations are *gross substitutes*. There are important differences between the model and the estimation strategy used by Goos et al. (2014) compared to this paper. They assume a partial equilibrium framework and do not explicitly address the endogeneity issues involved in estimating the elasticity parameter since they assume that the wages are exogenous. In contrast, I outline a general equilibrium model and account explicitly for the endogeneity of wages in my estimation.[32]

Other work in the literature calibrates a value of γ_A to be less than one (Duernecker et al. (2016) calibrate a value of 0.56 for two occupations, Lee and Shin (2017) calibrate a value of 0.70, and Aum et al. (2018) a value of 0.81). As a robustness check, I re-run my counterfactual analysis below by assuming $\gamma_A < \gamma_M < 1$. None of the results presented later change qualitatively when I use this alternative calibration for the elasticity parameters. The intuition behind this result stems from the fact that if $\gamma_A < \gamma_M < 1$, then polarization in the model occurs due to increase in $\frac{\phi_{Rj}}{\phi_{Aj}}$ and $\frac{\phi_{Rj}}{\phi_{Mj}}$. However, if $1 > \gamma_A > \gamma_M$, then the model can still capture aggregate job polarization, albeit via an increase in $\frac{\phi_{Aj}}{\phi_{Rj}}$ and $\frac{\phi_{Mj}}{\phi_{Rj}}$ instead.

Finally, I find that the OLS estimates of σ_H and σ_L are downward biased. I find that σ_H is greater than σ_L which implies that variance of the idiosyncratic preferences of high-skilled workers is

[31] See Table 3 in their paper. The coefficient on log industry marginal cost reports the estimate of the elasticity of substitution parameter of their specification.

[32] Moreover, they do not aggregate occupations into three groups while estimating their specification.

Table 4: **Parameter estimates of technology, labor supply and disutlity costs**

A. **Parameter Estimates**					
	κ	γ_A	γ_M	σ_H	σ_L
OLS	0.931***	1.75***	2.64***	2.47***	-0.23
	(0.02)	(0.02)	(0.05)	(0.20)	(0.24)
IV	-	1.45***	2.76***	3.44***	1.20***
		(0.03)	(0.06)	(0.30)	(0.39)
First-stage	-	-0.63***	-0.77***	1.36***	1.36***
		(0.01)	(0.01)	(0.14)	(0.14)
N	22	22	22	66	66

B. **Estimates of disutility cost parameters**						
	χ_{AH}	χ_{RH}	χ_{MH}	χ_{AL}	χ_{RL}	χ_{ML}
1994	0.46	-0.18	0.07	1.72	-0.90	-0.55
2015	0.36	-0.38	-0.24	1.51	-0.81	-0.92

Notes: Standard errors are reported in parenthesis. *** p < 0.01, ** p < 0.5, * p <0.1. κ is estimated by merging DADS Postes with FICUS/FARE. I run OLS on Eq. 27 after taking expectations on both sides. N denotes the total number of observations used in estimation. All other coefficient are estimated using DADS Postes and the French Labor Survey between 1994 and 2015.

lower than that of low-skilled workers. In Table 4, panel B, I present the estimates of the disutility cost of working in occupation o conditional on skill, denoted χ_{os}. The estimates suggest that the disutility cost of entering into abstract occupations is higher for a low-skilled worker compared to a high-skilled worker. On the contrary, the amenity (given the estimate of χ_{os} is negative) of entering into routine and manual occupation is higher for low-skilled workers compared to high-skilled workers. Importantly, these estimates change over time. In particular, there are important changes in these estimates for low-skilled workers: while the estimates of χ_{RL} decreases over time (note that the *chi*'s are preceded by a negative sign in the specification), the estimate of χ_{ML} increases over time. My analysis cannot provide definitive evidence on what underlying factors are driving this shift in the distribution of disutility costs over time for low-skilled workers. Given the evidence on alternative work arrangements seen across many industrialized countries,[33] this

[33]Katz and Krueger (2019) find that the percentage of workers engaged in alternative work arrangements - defined as temporary help agency workers, on-call workers, contract workers, and independent contractors or freelancers - rose from 10% in 1995 to 15.8% in 2015. Using the American Time Use Survey (ATUS), Kaplan and Schulhofer-Wohl (2018), find that there is a substantial heterogeneity in how the non-physical costs and benefits of work have changed over

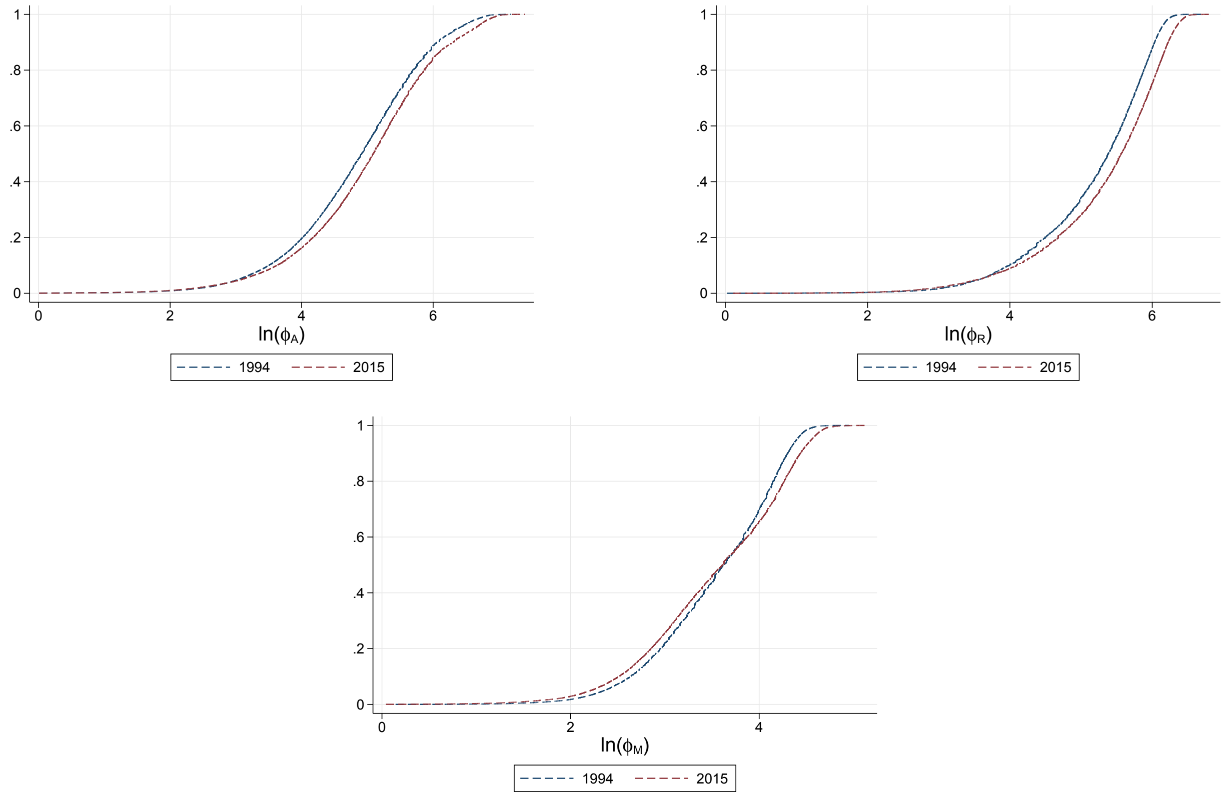
could potentially reflect workers preferences for autonomy and workplace flexibility or changes in the physical and non-physical costs of work in routine occupations. However, these changes could also capture elements that I do not directly incorporate in my theoretical framework such as changes in labor market institutions and the role of labor market power. I will study the implication of these changes in worker preferences over time in my counterfactual exercise that follow this section.

Distribution of technology shocks. Conditional on the estimates of $\kappa, \gamma_A, \gamma_M$, I use Eq. 34-36 to infer the values for $\phi_{Aj}, \phi_{Rj}, \phi_{Mj}$. In Figure 4, I employ kernels to estimate the distribution of the log of these productivity terms for 1994 and 2015. The figure suggests that there is a first-order stochastic dominance (FOSD) of 2015 distribution of $\ln \phi_{Aj}$ and $\ln \phi_{Rj}$ compared to 1994. Meanwhile, I observe a second-order stochastic shift (SOSD) in the 2015 distribution of $\ln \phi_{Mj}$ over 1994. Technological change differs strongly between of firms of different size. To demonstrate this point, in Appendix B Figure A3, I plot the distribution of these shocks separately for firms that employ less than 100 workers, to whom I refer to as small and medium-sized firms, and those that employ more than or equal to 100 workers, the large firms in the economy. I find that 2015 distribution of $\ln \phi_{Aj}$ FOSD the 1994 distribution for small and medium-sized (SMS) firms and the large firms. In the case of routine occupations, the results show there is evidence of FOSD of the 2015 distribution for SMS firms (panel c), while the 2015 distribution SOSD the 1994 distribution for large firms (panel d). Finally, for manual occupations I find there is SOSD of the 2015 distribution of $\ln \phi_{Mj}$ for SMS firms and the large firms in the economy.

Given that my estimates of γ_A and γ_M are both greater than one, the model predicts routine-biased technological change if $\ln \frac{\phi_{Aj}}{\phi_{Rj}}$ and $\ln \frac{\phi_{Mj}}{\phi_{Rj}}$ both increase over time. In other words, we should see a first-order stochastic dominance of the 2015 distributions compared to 1994. In Figure 5, I plot how these distributions have changed over time, separately for SMS firms and the large firms. With regards to the distribution of $\ln \frac{\phi_{Aj}}{\phi_{Rj}}$, I find that there is a FOSD of the 2015 distribution for both SMS and large firms. On the other hand, there is SOSD of the 2015 distribution of $\ln \frac{\phi_{Mj}}{\phi_{Rj}}$ for SMS firms compared to the 1994 distribution, while there is a shift to the right of the 2015 distribution compared to the 1994 distribution for the large firms. These estimates suggests that routine-biased technological change is not a uniform process affecting all firms equally. Evidence from Figure 5 shows that RBTC is mostly occurring in large firms of the economy where we see clear evidence of a right-ward shift of the both $\ln \frac{\phi_{Aj}}{\phi_{Rj}}$ and $\ln \frac{\phi_{Mj}}{\phi_{Rj}}$ distributions in 2015. In the counterfactual experiments that follow this sub-section, I will quantify to what extent these changes in the firm technology can explain aggregate job polarization and changes within firms and between firms.

time. Women have shifted towards occupations that produce more happiness and meaningfulness while men have shifted towards occupations that less happiness and meaningfulness.

Figure 4: **CDF of the** $\ln(\phi_A), \ln(\phi_R)$ **and** $\ln(\phi_M)$**: 1994 vs. 2015**

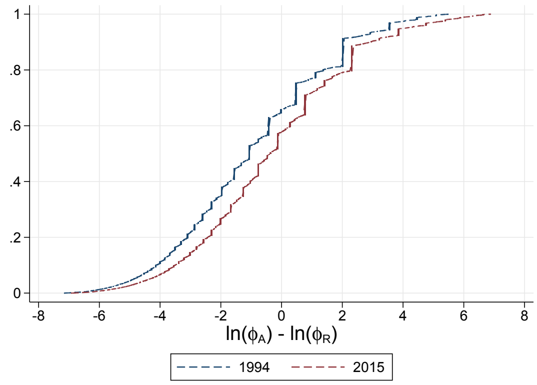


5.2 Counterfactual experiments

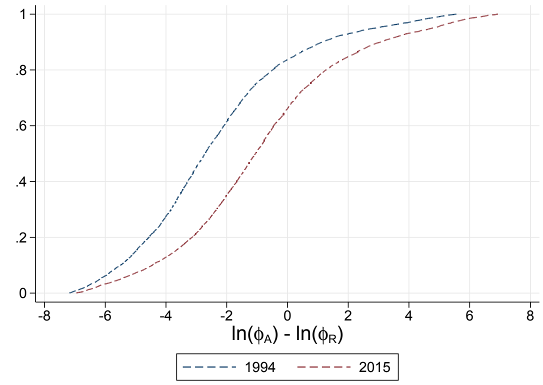
To quantify the effect of RBTC, educational change and change in disutility costs in explaining job polarization, I perform the following counterfactual exercise. Denote $\mathbf{\Phi}_t = (\{\hat{\phi}_{Ajt}, \hat{\phi}_{Rjt}, \hat{\phi}_{Mjt}\}_{j=1}^{J_t})^T$ as the level of technology shocks estimated at time t, $\boldsymbol{\theta}_t = (\theta_{Ht}, N_t)^T$ as the aggregate share of high-skilled workers in the economy at time t, $\boldsymbol{\chi}_t = (\chi_{AHt}, \chi_{RHt}, \chi_{MHt}, \chi_{ALt}, \chi_{RLt}, \chi_{MLt})^T$ denote the disutility cost paid by workers at time t and $\boldsymbol{\tau}_t = (\tau^W_{At}, \tau^W_{Rt}, \tau^W_{Mt}, \tau^F_{At}, \tau^F_{Rt}, \tau^F_{Mt})^T$ as the level of employer and employee tax rates at time t. The time-subscript can take one of two values: 0 or 1, where 0 denotes year 1994 and 1 denotes the year 2015. I can disentangle the contribution of RBTC, educational shift and the cost distribution in explaining the change of the employment share of occupation o as specified in Eq. 38. The first term of the decomposition gives the contribution of technological change in explaining the change in the aggregate employment share of occupation o. In this experiment, I shift the distribution of $\mathbf{\Phi}_t$ from 1994 to 2015 as estimated in the data and hold all other components fixed to their level in 1994. The second component gives us the (conditional) contribution of the change in the educational composition of the labor force in explaining the change in the aggregate share of occupation o. The contribution is conditional since the level of technology is held to its level in 2015 from the previous step. I follow the same step to account for the contribution of disutility costs and changes in the tax-rates over time.Notice that,

Figure 5: **CDF of the** $\ln(\phi_A) - \ln(\phi_R)$ **and** $\ln(\phi_M) - \ln(\phi_R)$ **by firm size: 1994 vs. 2015**

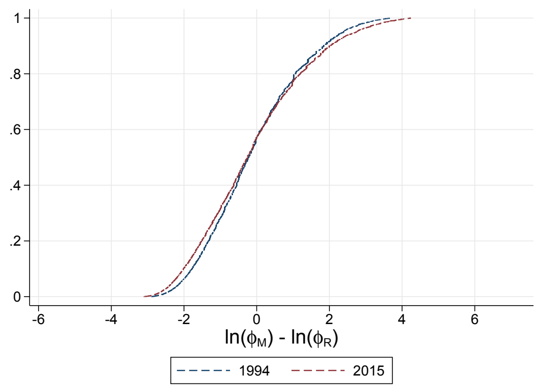
(a) Firms with < 100 workers



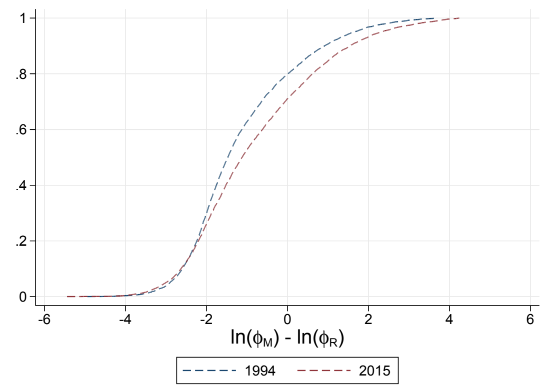
(b) Firms with ≥ 100 workers



(c) Firms with < 100 workers



(d) Firms with ≥ 100 workers



by construction, the contribution of technology, education, cost distribution and payroll taxes sum up to the total change predicted by the model. The results are presented in Table 5.[34]

$$\Delta s_{ot} = s_o(\boldsymbol{\Phi}_1, \boldsymbol{\theta}_1, \chi_1, \boldsymbol{\tau}_1) - s_o(\boldsymbol{\Phi}_0, \boldsymbol{\theta}_0, \chi_0, \boldsymbol{\tau}_0) \tag{38}$$

$$\Delta s_{ot} = \underbrace{s_o(\boldsymbol{\Phi}_1, \boldsymbol{\theta}_0, \chi_0, \boldsymbol{\tau}_0) - s_o(\boldsymbol{\Phi}_0, \boldsymbol{\theta}_0, \chi_0, \boldsymbol{\tau}_0)}_{\text{Contribution of technological change}} + \underbrace{s_o(\boldsymbol{\Phi}_1, \boldsymbol{\theta}_1, \chi_0, \boldsymbol{\tau}_0) - s_o(\boldsymbol{\Phi}_1, \boldsymbol{\theta}_0, \chi_0, \boldsymbol{\tau}_0)}_{\text{Contr. of education composition } | \text{ tech}}$$

$$+ \underbrace{s_o(\boldsymbol{\Phi}_1, \boldsymbol{\theta}_1, \chi_1, \boldsymbol{\tau}_0) - s_o(\boldsymbol{\Phi}_1, \boldsymbol{\theta}_1, \chi_0, \boldsymbol{\tau}_0)}_{\text{Contr.of preference shifts } | \text{ educ, tech}} + \underbrace{s_o(\boldsymbol{\Phi}_1, \boldsymbol{\theta}_1, \chi_1, \boldsymbol{\tau}_1) - s_o(\boldsymbol{\Phi}_1, \boldsymbol{\theta}_1, \chi_1, \boldsymbol{\tau}_0)}_{\text{Contr. of payroll taxes } | \text{ propensity, educ, tech}}$$

[34]The results are robust to a different ordering. Results for different ordering available upon request.

Table 5: **Quantifying the contribution of technology, education, preferences and taxes**

	Δ^{Data}	**Technology**	**Education**^{c}	**Preferences**^{c}	**Taxes**^{c}
Abstract	4.65	3.18	6.14	-1.77	-2.90
Routine	-10.89	-2.37	-3.05	-5.60	0.13
Manual	6.23	-0.81	-3.09	7.37	2.76

Notes: The superscript c denotes the fact that contribution of education is conditional on technology being at the 2015 level, the contribution of preferences is conditional on technology and education being at the 2015 level and so forth.

Contribution of RBTC. I start by considering the contribution of technological change on the aggregate employment share of the three occupations. Given that the occupational choice is endogenous in the model, if technological change is the key driver of aggregate job polarization then this counterfactual should be able to explain the changes in the employment shares as observed in the data. I find that the total contribution of technological change is to decrease the aggregate employment share of routine *and* manual occupations by 2.37 pp and 0.81 pp, respectively, and increase it by 3.18 pp for manual occupations. In the data, I documented that the aggregate employment share of abstract and manual occupations increased by 4.66 pp, and 6.23 pp, respectively, while it declined for routine occupations by 10.89 pp. In percentage terms, technological change explains approximately 21.7% of the total decline in the employment share of routine occupations. As is evident from these results, routine-biased technological change in and by itself can explain less than one-quarter of the decline in the aggregate employment share of routine occupations.

To understand the mechanism through which technological change affects the equilibrium, I decompose its contribution into a within-firm and a between-firm effect.[35] These results are also documented in Table 6. I find that technological change induces firms to substitute routine occupations by abstract occupations within firms. This is the substitution channel conventionally highlighted by the literature. On average, the share of routine and manual occupations decline by 5.75 pp and 0.87 pp, respectively, while the share of abstract occupations increase by 6.62 pp. The contribution of the substitution channel is to account for approximately 52.8% of the decline in the aggregate share of routine occupations. However, this is not the only margin through which changes in $\phi_{Aj}, \phi_{Rj}, \phi_{Mj}$ affect the equilibrium share of routine occupations. I find that the employment share of routine intensive firms *increased* by 3.48 pp. This is explained by the fact that RBTC increases the productivity of routine intensive firms relatively more compared to non-routine intensive firms. As a consequence, employment gets reallocated from non-routine intensive firms to routine intensive firms, which in turn increases the employment share of routine intensive firms.

To provide further evidence that RBTC affects routine and non-routine intensive firms unequally, I compare the (log) firm size distribution in 1994 with the counterfactual (log) firm size distribution in 2015, accounting only for the effect of technological change. As it can be seen from

[35] I apply the decomposition from Eq. 1 on the simulated economies generated from this counterfactual.

Table 6: **Within- and between-firm decomposition: Counterfactual vs. Data**

	Δ	**Within**	**Between**	**Net Entry**
Abstract	3.18	6.62	-3.56	0.13
	4.65	7.12	-3.01	0.54
Routine	-2.37	-5.75	3.48	-0.10
	-10.89	-8.48	-1.59	-0.82
Manual	-0.81	-0.87	0.08	-0.03
	6.23	1.32	4.57	0.34

Figure 6a, there is more mass on the right tail of the counterfactual (log) firm size distribution in 2015 compared to 1994. This implies that big firms become even bigger over time and small firms get smaller. It turns out that those firms getting bigger over time had a high initial share of routine occupations. To show this, in Figure 6b, I plot the occupational composition of firms by their size in 1994. This figure shows that in 1994 the share of abstract and manual occupations is decreasing in the (log) firm size while the share of routine occupations is increasing. I verified that a similar relationship holds for 2015. Combined together these graphs show that firms big firms tend to be intensive in routine occupations, i.e. have a high share of routine occupations, and benefit more from higher productivity compared to non-routine intensive firms due to RBTC.

In summary, the productivity-enhancing channel, which raises the aggregate employment share of routine occupations, partially offsets the substitution channel, which reduces the aggregate employment share of routine occupations. The net effect of these two channels is to decrease the aggregate share of routine occupations by 2.37 pp.

Contribution of educational composition. I quantify the importance of the shift in education in explaining aggregate job polarization. I change the parameter $\boldsymbol{\theta}_t$ from its 1994 level to its 2015 level holding the disutility cost parameters and payroll taxes fixed to their level in 1994. Technology parameters are held fixed at their level in 2015 as outlined in Eq. 38. At the aggregate level, the total contribution of technological change is to increase the share of abstract occupations by 6.14 pp, while the share of routine and manual occupations decline by 3.05 pp and 3.09 pp, respectively. As these results show, the shift in the educational composition of the labor force is responsible for explaining the rise in the aggregate share of abstract occupations.

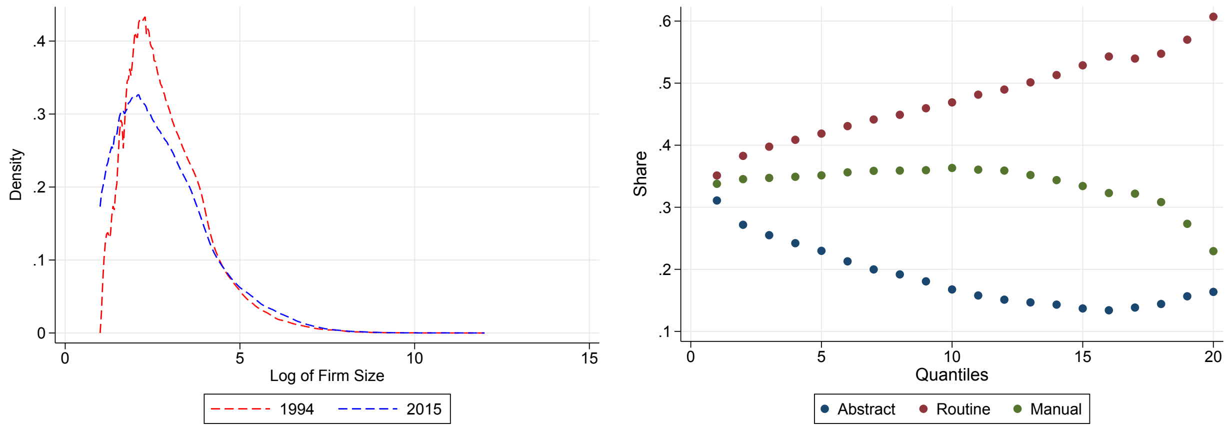
To understand the mechanism through which educational composition affect the aggregate share of abstract occupations, I decompose it into within- and between-firm effects. The results are documented in Table **??**. I find that the share of abstract occupations increases, while it decreases for routine and manual occupations within firms. I find similar patterns for between-firm changes, however, in terms of magnitude, between-firm effects are quantitatively more important.

To grasp the intuition behind these findings, it is informative to start by looking at the relative

Figure 6: **Counterfactual firm size distribution and occupational composition by firm size**

(a) Counterfactual Firm Size Distribution

(b) Occupational Composition vs. Firm Size



first order conditions in Eq. 7 and Eq. 8. Given that there is no change in technology over time, the relative labor demand is only affected through changes in relative wages. Since the share of abstract occupations increases while the share of routine and manual occupations decrease, the wages of abstract occupations relative to routine and manual occupations must have declined (remember, occupations are gross substitutes). The question then remains: why do relative wages decline due to shift in θ_t? Since high-skilled workers face a low disutility cost of entering in abstract occupations relative to routine and manual occupations, as θ_t increase, relatively more workers enter into abstract occupations. This can be seen in Figure 7a, where I simulate the effect of a shift in θ_t on worker's labor supply decision using the 1994 wages from the data. Absent the general equilibrium feedback on wages, it shows that the share of high-skilled workers in abstract occupations increases from 7% to 12%. The share of high-skilled workers in routine occupations increases, but the overall share of routine and manual occupations both decrease.

The net effect of these changes is to shift the labor supply curve of abstract occupations to the right and given no concurrent shift in demand, lowers the wages in equilibrium. Due to lower wages, firms that initially had a high share of abstract occupations benefit from a lower labor cost and improve their productivity compared to non-abstract intensive firms. This leads to reallocation of workers towards these firms raising the share of abstract occupations in the aggregate.

Contribution of disutility costs. I consider the effect of the shift in the disutility costs over time in explaining aggregate job polarization. The total effect of this change is to decline the aggregate share of abstract and routine occupations by 1.77 pp and 5.60 pp, respectively, while it increases the share of manual occupations by 7.37 pp. The within- and between-firm decomposition (Table ??) shows that the share of manual occupations increases, while it decreases for abstract and routine occupations within firms. I find similar patterns for between-firm changes, however, in terms of magnitude, between-firm effects are quantitatively more important.

Table 7: **Quantifying the contribution of other factors**

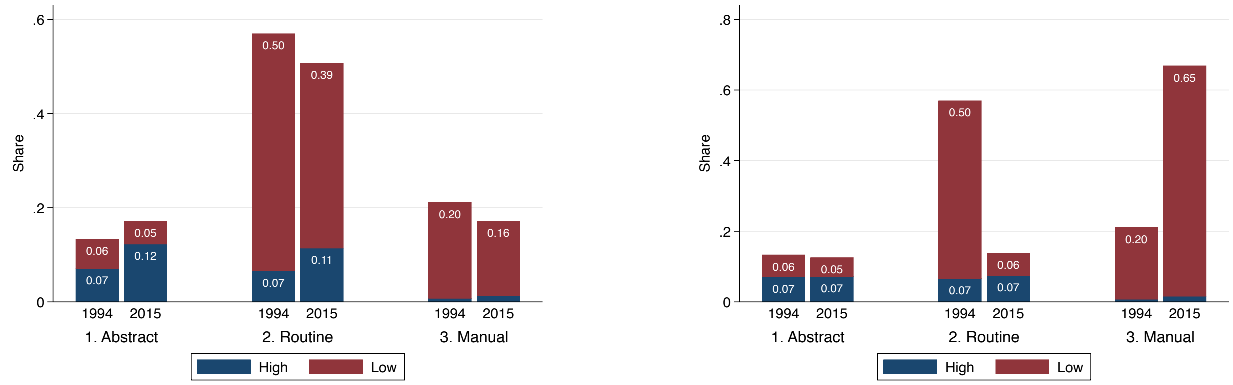
		Δ	**Within**	**Between**
Abstract	Education	6.14	0.93	5.20
	Propensity	-1.77	-0.24	-1.52
	Taxes	-2.90	-0.41	-2.48
	Total	**1.47**	**0.28**	**1.20**
Routine	Education	-3.05	-0.39	-2.65
	Propensity	-5.60	-1.46	-4.14
	Taxes	0.13	-0.02	0.16
	Total	**-8.52**	**-1.09**	**-6.63**
Manual	Education	-3.09	-0.54	-2.54
	Propensity	7.37	1.70	5.67
	Taxes	2.76	0.44	2.37
	Total	**7.04**	**1.60**	**5.50**

Notes: In this decomposition, there will be no role for entry and exit. This is because I also shift the total number of firms from 129321 in 1994 to 114231 in 2015 along with the three technology shocks in the counterfactual pertaining to technology. Hence, in the subsequent counterfactuals, the total number of firms are also held fixed and the net entry component is zero. Results are robust to an alternative specification where I shift N, the total number of firms in the economy, separately from the technology shocks.

The intuition behind this result is similar to the one presented above. Change in disutility cost over time act as a negative supply shock to routine occupations. In Figure 7b, I simulate the effect of a shift in χ_t on worker's labor supply decision using the 1994 wages from the data. As is seen from the graph, change in disutility costs play a substantially important role in driving the decline in the aggregate share of routine occupations. Notice that the aggregate share of abstract occupations is unaffected in this simulation. This is due to the fact that these costs change mostly for low-skilled workers who face a high disutility cost of entering in abstract occupations in 1994 and 2015. The shift in supply for manual occupations lowers the wages for manual occupations and increases the employment share of manual-intensive firms.

Figure 7: **The effect of changes in θ_t and χ_t on labor supply**

(a) Effect of shift in θ_t (b) Effect of shift in χ_t



6 Conclusion

This paper delves further into the drivers of aggregate job polarization. The general consensus in the literature is that routine-biased technological change (RBTC) is a key driver of this phenomenon. In this paper, I show that RBTC has important macroeconomic implications, especially on the firm-size distribution, but it can exclusively explain aggregate job polarization. I show this to be case for France, a country that has rapidly polarized starting the mid-1990's.

Using administrative data for France, I first document that changes in the occupational composition within firms and changes in employment growth between firms are quantitatively important in explaining aggregate job polarization. I rationalize these facts by constructing a general equilibrium model with firm heterogeneity and endogenous occupational choice where job polarization and changes within and between firms are explained by the interaction of two forces: technology shocks that make routine occupations relatively more productive; and supply shocks that change the labor force composition over time. To address the endogeneity issues in estimating demand and supply parameters, I rely on the recent insights by Zoutman et al. (2018), and exploit the variation in payroll tax-rates as instrument to estimate these parameters.

Upon estimation, I find that RBTC affects aggregate employment share of routine occupations through two competing channels. On the one hand, RBTC induces within-firm substitution of routine occupations by non-routine occupations. This substitution channel, conventionally emphasized in the literature, reduces the share of routine occupations in the aggregate by approximately 52.8%. On the other hand, improvement in firm productivity induced by such a technological change increases productivity of routine-intensive firms, and their size over time. This between-firm effect is quantitatively important and partially offsets the decline induced by the substitution channel. The net effect of these two forces is that, in equilibrium, the aggregate share of routine occupations decreases by 2.37 pp despite rapid routine-biased technological change. The model shows that changes in the educational composition of the labor force as well as changes in worker preferences is an important driving force of aggregate job polarization.

There are two key limitations of this project that I would like to address in the future. I assume that the shift in the educational composition of the labor force is exogenous. Clearly, education, in part, may respond to technological change. I would like to endogenize educational choice in the future extensions of my work by allowing individuals to choose between two schooling levels, high school and college as in Heckman et al. (1998). Second, I assume that input markets are perfectly competitive. An important avenue for future research is to account for the role of non-competitive labor markets in explaining job polarization as in Card et al. (2018) and Deb et al. (2020). Introducing monopsony power in the model can also help to better understand the role of minimum wage in affecting job polarization through its effect on the employment of low-skilled workers in the economy.

Appendix

Appendix A: Descriptive Statistics, Occupational Classification and job polarization by industry

Occupational Classification

Every job in DADS Postes is categorized by a two-digit PCS occupational code. Following the occupational classification adopted by Albertini et al. (2017) in their work on job polarization in France, I aggregate these 22 codes into three groups: abstract, routine and manual occupations. The classification into three groups is based on following definitions:

- **Abstract**: These occupations include problem-solving and managerial tasks as primary functions on their job. Examples of occupations included in this group are engineers (PCS 38), executives (PCS 37) and scientists (PCS 34).
- **Routine**: This group includes occupations that perform cognitive or physical tasks that follow closely prescribed sets of rules and procedures and are executed in a well-controlled environment. Example includes occupations such industrial workers (PCS 62 and 67), office workers (PCS 54) and mid-level managers (PCS 46).
- **Manual**: This occupational group do not need to perform abstract problem-solving or managerial tasks but are nevertheless difficult to automate because they require some flexibility in a less than fully predictable environment. Example includes personal service workers (PCS 56), driver and security workers (PCS 53 and 64) among others.

The occupational grouping tries to capture the fact that automation and ICT capital should replace workers performing repetitive tasks. Further details concerning the assignment process, the employment share of each occupational group in 1994, and its change over time is documented in Appendix A, Table A2 (Abstract), Table A3 (Manual), Table A4 (Routine).

Descriptive Statistics

In the following Appendix, I provide additional details on sample selection and descriptive statistics of the sample as well as classification of PCS occupations into Abstract, Routine and Manual occupations. In terms of sample selection, as mentioned in the main text, I keep all workers between the age of 18 and 65 and include all firms that hires at least one worker in each of the three occupations: abstract, routine and manual. Before making this selection, I observe the following distribution of firm size in the data. As shown in Table A1, most firms in the sample have less than 10 workers, however bulk of aggregate employment is concentrated in large firms.

Table A1: **Full Sample: DADS Postes, 1994-2015**

Firms with ... workers	Avg. Number of Firms	Percentage of Firms	Percentage of Hours
Less than 10	1,074,510	87.10	21.0
10-99	143,762	11.70	29.0
100-500	11,868	1.00	18.0
Above 500	2,380	0.20	32.0

Occupational Classification and Job Polarization by Industry

Next, I document the classification of occupations into three groups in Table A2 (Abstract), Table A3 (Manual), Table A4 (Routine). As mentioned in the main text, I follow the classification adopted by Albertini et al. (2017). For completeness, I also describe the representative 4-digit sub-occupations description. The main idea that this classification tries to capture is that routine occupations can be directly substituted by advances in ICT technology while non-routine occupations is only indirectly affected. Non-routine occupations are further classified based on their task content: non-cognitive are abstract occupations and non-routine manual are called manual occupations. In Figure A1, I plot the employment share of selected PCS occupational groups and their change over time. The change in employment share for routine occupations by manufacturing and non-manufacturing industries is plotted in Figure A2.

Table A2: **List of PCS occupations categorized as Abstract**

Title	**2-digit PCS Codes**	**Representative 4-digit sub-occupations**
Engineers	38	Technical managers for large companies, Engineers and R&D manager, Electrical chemical and materials engineers, IT R&D engineers, Purchase, planning, quality control and production managers, Telecommunications engineers and specialists
Top Managers, Executives	37	Managers of large companies, Finance, accounting, sales and advertising managers
Health Professionals, Teachers	42 + 43	High school teachers, Education counsellors, Nurse, Physiotherapist
Scientific, creative professionals	34 + 35	Professors, Public Researchers, Psychology Specialists, Pharmacists
Heads of Business	21 + 23	Heads of businesses (large and small businnes included)

Table A3: **List of PCS occupations categorized as Manual**

Title	**2-digit PCS Codes**	**Representative 4-digit sub-occupations**
Personal Service workers	56	Restaurant servers, food prep workers. Hotel employees, Barbers, Hair Stylists, Beauty shop employees, Child care providers, Home health aids, Residential building janitors, Caretakers
Drivers, Security workers	53 + 64	Truck, taxi and delivery drivers
Manual workers	63 + 68	Includes both skilled and unskilled: Gardener, Master electricians, bricklayers, carpenters, Master cooks, Bakers, butchers
Crane and forklift operator	65	Warehouse truck and forklift drivers, heavy crane and vehicle operators, Other skilled warehouse workers

Table A4: **List of PCS occupations categorized as Routine**

Title	**2-digit PCS Codes**	**Representative 4-digit sub-occupations**
Industrial workers	62 + 67	Includes both low and high-skilled: Construction workers Metalworkers, pipe fitters, wielders, Operators of electrical and electronic equipment, Shipping, moving and warehouse workers, Production workers
Mid-level managers	46	Mid-level professionals in various industries, Store, hotel and food service managers
Foremen, supervisors	48	Foremen and supervisors from manufacturing industries, food service industries
Office workers	54	Receptionist, secretaries
Technicians	47	Installation and maintenance of IT and non-IT equipments
Retail workers	55	Retails employees, cashiers

Figure A1: **Employment share in levels and change for selected PCS occupations**

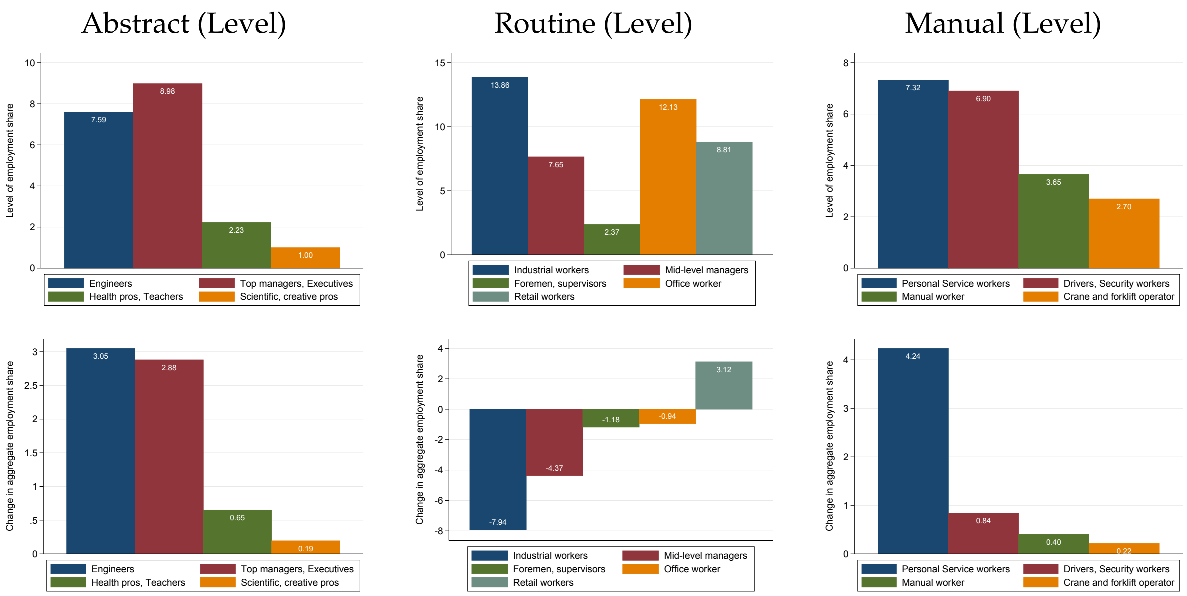
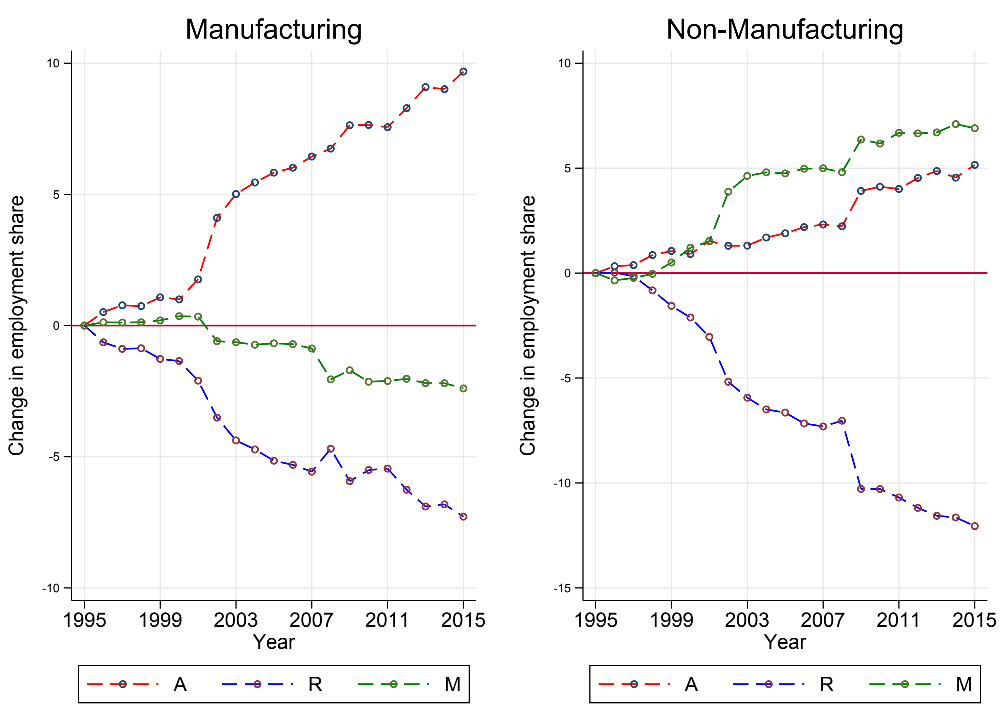


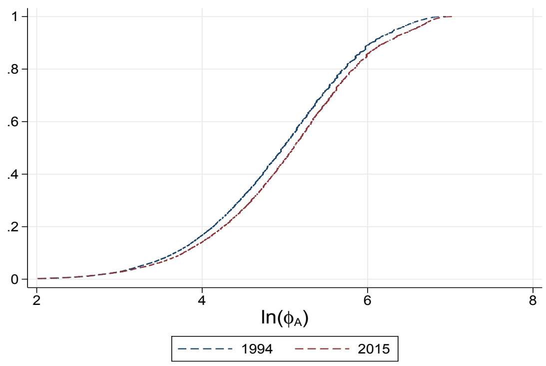
Figure A2: **Job Polarisation by Industry**



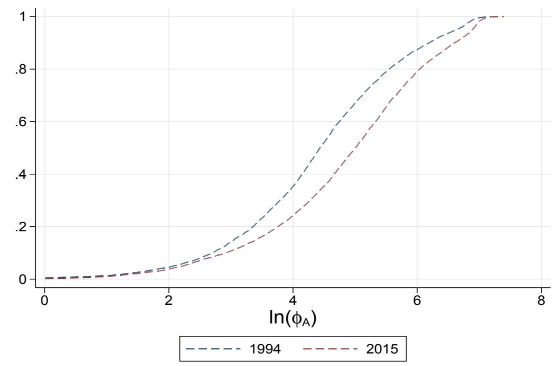
Appendix B: Distribution of technology shocks by firm size

Figure A3: **CDF of the** $\ln(\phi_A), \ln(\phi_R)$ **and** $\ln(\phi_M)$ **by firm size: 1994 vs. 2015**

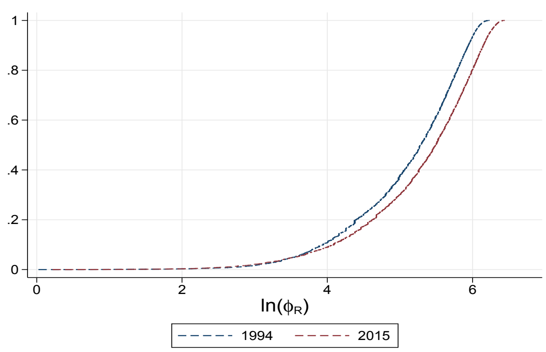
(a) Firms with < 100 workers



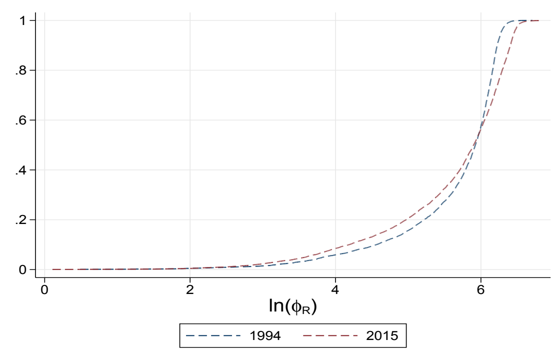
(b) Firms with ≥ 100 workers



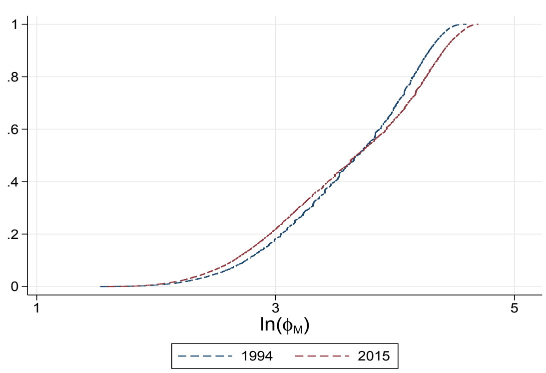
(c) Firms with < 100 workers



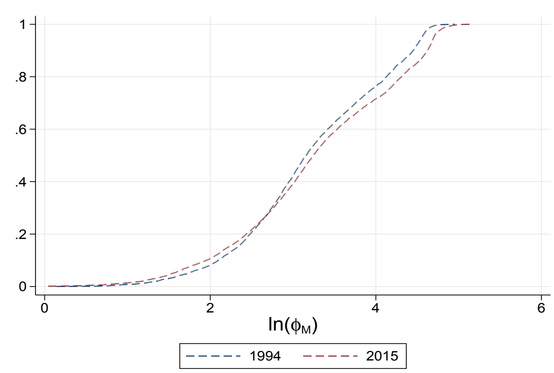
(d) Firms with ≥ 100 workers



(e) Firms with < 100 workers



(f) Firms with ≥ 100 workers



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