FIRMS, BIASED TECHNOLOGICAL CHANGE AND JOB POLARISATION *

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– PRELIMINARY AND INCOMPLETE –
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Abstract

Job polarization is a widely-documented phenomenon in industrialized countries. However, the role of firms in accounting for this process has received less attention. In this paper, I try to understand how firms have shaped the process of job polarization. Using a combination of administrative data and Labor Force Surveys in France, I first document the phenomenon of job polarization in France between 1994 and 2015. Using a simple decomposition exercise, I show that within-firm, between-firm and net-entry components are important channels in explaining job polarization. I construct a general equilibrium model to explain the underlying mechanisms behind the decomposition exercise. In particular, I quantify the role of technological change, change in labor market institution and supply shifts in explaining the accounting decomposition. Preliminary results show that technological change accounts for approximately 23% of the total decline in routine occupations. This result shows that other factors such as labor market institutions and labor supply changes play an important role in explaining job polarisation that have not received sufficient attention in the literature.

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1 Introduction

Labor markets in many industrialised countries have seen a rising trend towards job polarisation: the relative decline in the employment share of middle-skilled routine workers at the expense of an increase in the employment share of high and low-skilled abstract and manual workers, respectively. The current literature has focused on the role of employment within occupations but have not explicitly accounted for the role of firms in driving the observed phenomenon. The main goal of this paper is to fill this gap by highlighting the role of the firms in driving this process. For instance, is job polarisation only a phenomenon arising due to changes in occupations structure within-firms? Or, is it due to changes in between-firm reallocation of workers from routine-intensive firms to abstract and manual-intensive firms? Do new firms entering the markets create as many routine jobs as firms exiting the market or is there a structural decline in the creation of routine jobs? Do these patterns differ by firm size? What is the role of technological change in driving these outcome at the aggregate and micro-level?

I address these questions in two ways: empirically and theoretically. First, I decompose the aggregate phenomenon of job polarisation into within-firm, between-firm and entry and exit components. Second, I try to construct a general equilibrium model and estimate it using micro-data from France to match the observed facts not only at the aggregate but also at the micro-level. Models explaining job polarisation should be consistent with both micro and macro-level evidence. The main hypothesis put forward to explain job polarisation is the so-called Routine-Biased Technological change (RBTC): improvements in ICT technology and automation is complementary to workers performing skill-intensive, cognitive tasks while it substitutes workers performing routine tasks, with no direct impact on workers performing low-skilled manual tasks. As a result, it increases the labour demand for high skilled workers at the expense of workers performing routine tasks. In this paper, I structurally estimate my model to quantify the relative importance of technology-driven explanations in explaining job polarisation. Given I rely on French administrative data between 1994 and 2015 to estimate my model, I also explore the role labour market institution such as the change in labour cost policies (the employers social security contribution) and the minimum wage implemented in late 1990s and in 2000s to study their effect on shaping job polarisation.

The key ingredient of the model is firm heterogeneity à la Melitz (2003) with occupational choice by workers à la Heckman and Honore (1990). The key innovation of this paper is that I allow for differences between firm in occupation-augmenting, non-neutral technological change. Using the structure of the model, I estimate these "shocks" directly from the micro-data. I study the joint distribution of these shocks and its change over time to get insights into how the production process and the occupational structure at the level of the firms has evolved between 1994 and 2015 to shape aggregate polarisation. Moreover,

contrary to other studies in the literature I do not need to proxy RBTC by constructing a Routine Task Intensity index using DOT and/or O*NET data. Given important differences in definition and task content of these occupations between Europe and the US, relying on these measures may lead to mismeasurement of the true routine intensity of occupations in Europe. Previous work in the literature adopt a representative firm approach by focusing on changes taking place at the level of industries.

There are two mechanisms explaining polarisation in the model: a) the evolution of the non-neutral technological change and b) the elasticity of substitution between the three occupations. Combination of these two components, explains not only within-firm polarisation (due to biased technological change) but also between-firm changes. Intuitively, between-firm changes in the model occur since firms intense in routine labour will see a larger decline in relative costs and output prices leading to a shift in product demand towards these firms.

The main findings of this paper are as follow: aggregate polarization in France follows broadly the same pattern as observed in the US. Between 1994 and 2015, the routine occupations declined by approximately 12%. Contrary to the US, the decline in routine occupation is mostly compensated by a sharp increase in manual and low-skilled service occupations. Next, I use a shift-share decomposition to decompose the aggregate job polarisation into within-firm, between-firm and net-entry components. This exercise reveals that majority of the decline in routine occupations is explained due to within-firm and net entry components. This suggests that within-firms the share of routine occupations has decreased. However, I do not observe a pattern of within-firm polarisation. I see that most of the decline in routine occupation is compensated for by the increase in abstract occupations. A new evidence revealed by exercise is that decline in routine occupation due to entry and exit dynamics is not solely concentrated during economic recessions. I observe a more secular decline: low productive firms that had a high initial share of routine occupations are exiting the market, while new firms do not create sufficient new jobs. Finally, the key reason for the increase in the share of manual occupations is due to between-firm changes: workers have moved low manual-intensive firms to high manual-intensive firms over the sample period.

The estimation of the model with only routine-occupation augmenting technological change explains about 22% decline in routine occupation over time. While this simplest model can capture the broad trend in abstract, routine and manual occupations, technology-related explanations can explain only about a quarter of the entire polarisation observed in the data. Moreover, these results also indicate that there exists substantial heterogeneity in technology between firms even within narrowly defined industries. Hence, abstracting from these differences between firm is not innocuous. For instance, if I collapse all the heterogeneity from the model, it can only explain less than 6% of the total de-

cline in routine occupation. Hence, heterogeneity in technology between firms is an important component in explaining the aggregate job polarisation. Given the simplicity of the model with one technology shock, it does not do a very good job in matching the micro level evidence presented below. While it does a fairly good job in capturing the within-firm changes, the simulations predict opposite directions for between and net-entry components compared to what is observed in the data. To rectify this shortcoming of the model, I am currently estimating the model with non-neutral technological shocks pertaining to abstract, routine and manual occupations.

RELATED LITERATURE. This project is related to three strands of the literature. The first strand of literature has focused on aggregate job polarisation by focusing on outcomes at the occupations. Most of these papers in this strand of the literature by D. H. Autor, Levy, and Murnane (2003), Goos, Manning, and Salomons (2009), Acemoglu and D. Autor (2011),David and Dorn (2013) document the decline in the aggregate employment share of routine jobs but do not account for the role played by the firms. Most of this analysis is based on labor force surveys in the aggregate. Given that labor demand decisions are taken at the level of the firm, it is important to look within and between firms and account for these changes at this level.

A separate strand of the literature by Böckerman, Laaksonen, and Vainiomäki (2016), Heyman (2016), Harrigan, Reshef, and Toubal (2016) have addressed the aforementioned issue by highlighting the role of firms but no mechanism to explain what mechanisms drives these changes: is it due to technological change, labor supply shifts or changes in labor market institution. In this paper, I will decompose what fraction of within and between firm changes are accounted by each of these factors. Finally, this paper is also related to the empirical IO literature of production function estimation. This literature has two main solutions to address the endogeneity issue in estimation: a control function approach and using dynamic panel data method. The first of these approaches is highlighted in a the following Olley and Pakes (1996), Ackerberg, Caves, and Frazer (2015), De Loecker (2011) while the latter is by highlighted in Blundell and Bond (2000). In this paper, I use the structure of the model and estimate it differently using Simulated Method of Moments.

2 Data

In this section, I provide additional details about the data that we use in this article. Broadly speaking, I use two administrative data sources from France for the period 1994 and 2015 in this paper: the DADS and FICUS/FARE. In what follows, I provide more details about the data and how I merge these dataset.

2.1 Data description

As mentioned above, I merge two dataset in this article: the French administrative data called DADS Postes [1] and FICUS/FARE. DADS Postes is based on mandatory annual reports filed by all firms with employees, hence, our data includes all private sector French workers except the self-employed. For each worker, the DADS reports gross and net wages, hours paid, occupation, gender and age. There is no information about workers' education or overall labor market experience. The data do not include worker identifiers, however it tells us the worker's employment status, wage and occupation title in period $T-1$. For each individual in the labor force, we are able to identify the firm at which the individual is working. Hence, we are able to observe the entire French workforce of a given firm. Each firm in France is assigned a unique identifier ("SIREN" code) which facilitates keeping track of them over time and matching firm-level dataset. We have access to DADS Postes between 1994 and 2017.[2]

Our second data source is FICUS/FARE which contains the balance sheet data for firms. From the firm-level FICUS/FARE data, I extract measures of total employment, sales, capital, revenues, intermediate inputs, wage bill and industry affiliation. Given that FICUS/FARE also contains the firm identifier "SIREN", it allows me to merge the FICUS/FARE with the DADS. As a result, I can observe entire universe of firms in the data between 1994 and 2015. The information on revenue, intermediate inputs and capital are used in structurally estimating the model. For the current analysis, I restrict my sample to firms with more than 10 workers. The merge between the two dataset is very poor for firms less than 10 workers as many of these firms are not observed in FICUS/FARE. On an average, I observe 1,232,520 firms per year. Additional descriptive statistics concerning the data can be found in Table 1.

Table 1: 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

[1] 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)

[2] The same dataset has been used in studying Job Polarisation in France by Reshef et. al (2018). For more information about the data please refer to the appendix of their paper.

3 Descriptive Statistics

In what follows, I present facts on aggregate job polarisation in France and the results from the shift-share decompositions performed on the French micro data. The goal of this section is to highlight three key facts as observed in the data that my model needs to replicate. Given that I observe consistent occupational code between 1994 and 2015, I assign occupations into three groups of occupations: abstract, routine and manual. Here, I follow the works of Charnoz and Orand (2015) and Hairault et al. (2018) to do the assignment. More details concerning the assignment process can be found in the appendix. These papers use the following definitions of abstract, routine and manual tasks, broadly accepted in the literature to underpin their assignment process.

- Abstract: Problem-solving and managerial tasks. These are not well-structured and require non-routine cognitive skills
- Routine: Cognitive or physical tasks that follow closely prescribed sets of rules and procedures and are executed in a well-controlled environment
- Manual: Do not require abstract problem-solving or managerial skills but are nevertheless difficult to automate because they require some flexibility in a less than fully predictable environment

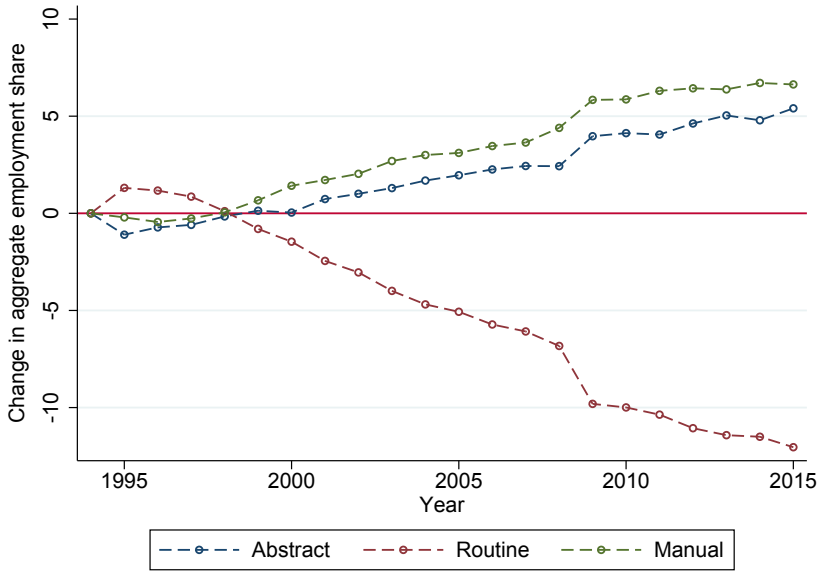
Table 2: Job Polarisation in France vs. US,

	Levels (in %)		Δ Employment Share (in %)	
	France (in 1994)	US (in 1982)	France (1994-2015)	US (1982-2017)
Abstract	17	29	5.40	11.00
Routine	64	56	-12.03	-14.00
Manual	19	15	6.63	3.00

3.1 Aggregate Level

We observe in France a similar decline in routine occupations as observed in the US. As seen in Table 2, between 1994 and 2015, routine occupations declined by approximately 12%. In the US, over a longer period between 1982 and 2017, routine occupations decline approximately 14%. However, there is one key difference between aggregate polarisation in France and the US: in the US, a bulk of the decline in routine occupations is compensated by an increase in employment share of abstract occupations. For instance, abstract employment increased in the US by 11% compared to 5% in France. In fact, in France the decline in routine occupation is equally compensated by an increase in manual and abstract occupations. In Figure 1, I plot the evolution of occupational share

Figure 1: Job Polarisation in France between 1994 and 2015



over time to show that the decline in routine occupations is indeed secular.

In the appendix, I show that majority of the decline in routine workers in France is due to a decline in industrial worker. These workers often tend to be construction workers, heavy and electrical machinery operators. Most of the increase in abstract occupations is driven by engineers, managers and executives. Like the US, the sub-occupation category most responsible for driving the increase in manual occupation are personal service workers. These workers tend to be restaurant servers, food preparation workers, hotel employees, barbers, hair-stylists, beauty-shop managers, child-care specialist, residential building janitors etc.

3.2 Micro-Level

Given that I observe the universe of firms in my sample, I decompose aggregate job polarisation into a within, between and net entry component. For expositional clarity, I introduce the following notation. Let N_{ojt} be the number of hours worked by individuals in occupation $o \in \{A, R, M\}$. A denotes, R denotes routine, M denotes manual. Using the standard shift-share decomposition technique, I decompose the change in aggregate share of occupation o into a component due to change in the share within firms, a component that explains the change in share between components and a change in share due to entry and exit.

$$s_{ojt} = \frac{N_{ojt}}{\sum_o N_{ojt}} \quad : \text{Share of occupation } o \text{ in firm } j\text{'s hours}$$

$$\tau_{jt} = \frac{N_{jt}}{\sum_j N_{jt}} \quad : \text{Share of firm } j \text{ in aggregate hours}$$

$$s_{ot} = \sum_j \tau_{jt} s_{ojt} \quad : \text{Share of occupation } o \text{ in aggregate hours}$$

$$\Delta s_{ot} = \underbrace{\sum_{j \in \mathcal{S}} \overline{\tau}_j \Delta s_{ojt}}_{\text{Within}} + \underbrace{\sum_{j \in \mathcal{S}} \Delta \tau_{jt} \bar{s}_{oj}}_{\text{Between}} + \underbrace{\sum_{j \in \mathcal{N}} \tau_{jt} s_{ojt} - \sum_{j \in \mathcal{X}} \tau_{jt-1} s_{ojt-1}}_{\text{Net Entry}}$$

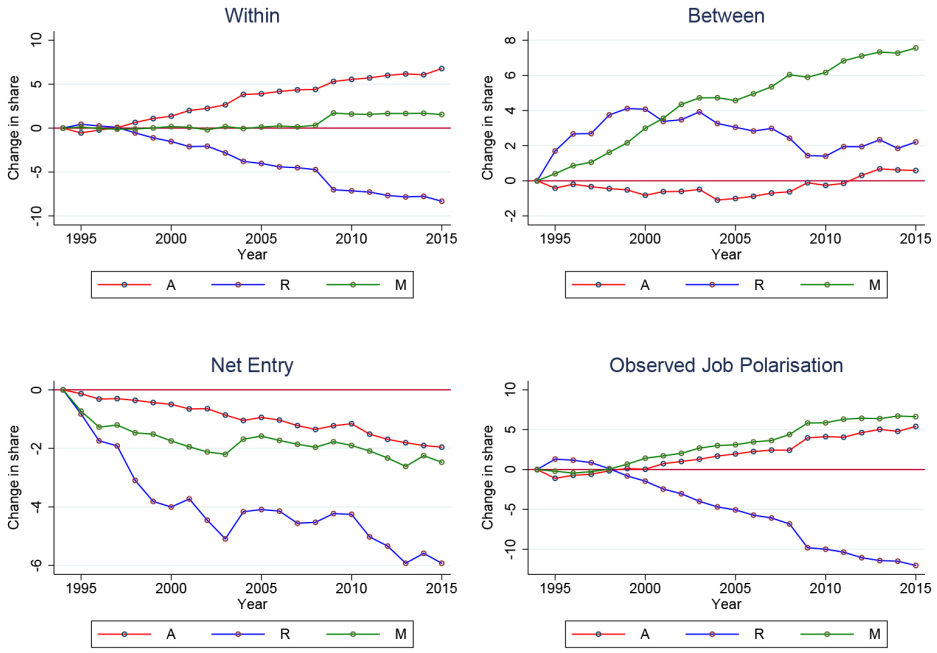
An overbar indicates average over time and Δ's indicate change over time. $\mathcal{S}$ denotes the set of surviving firms, $\mathcal{N}$ denotes entering firms, $\mathcal{X}$ denotes exiting firm.

In Figure 2, I plot the decomposition for annual changes. In all these figures, I set the initial level to 1994 and then cumulatively add the changes of each of the component terms in equation. In Figure 2, I plot all the three components along with the actual change observed in the data. For exposition clarity, in Figure 3 I only focus on those components that are the most important in explaining the observed phenomenon. These figures highlight what micro-level changes underpin the aggregate job polarisation seen in the data. It became clear from these figures that most the decline in routine occupations is due to within firm substitution of routine workers by abstract workers and due to job destruction of routine jobs by those firms exiting the market. In other words, new firms entering the market are not creating sufficient employment to compensate for the routine jobs lost due to exiting firms. These highlights that these routine jobs tend to be highly fragile and easily destroyed by firms.

The second observation is pertaining to abstract occupations. Most of the increase in abstract occupations is within firms. In fact, around 90% of the total change in the share of abstract workers can be explained by changes within-firms. My data does not allow me to explore the fact if this change in abstract occupations within firm is directly related to the adoption of ICT technology and computerization at the firm-level. The third interesting observation revealed by this exercise is that most of increase in the share of manual workers is due to an increase in the between-firm changes, this suggests that workers have reallocated from firms that were intensive in abstract and routine occupations towards manual occupations. This reallocation of workers towards these firms can be an important source of between firm inequality if these firms also tend to be the ones that pay low wages to workers. Additionally, we do not see any changes within firms in the occupation structure of manual workers.

In summary, the firm-level decomposition highlights that the decline in routine occupations is due to within-firm substitution of routine workers by abstract workers, rise in abstract occupation is purely a within-firm phenomenon and the increase in the share of manual occupations is due to between-firm changes. Next, I try to sketch a model to match these observed trends in the data and then try to isolate the role played by technology in driving these patterns.

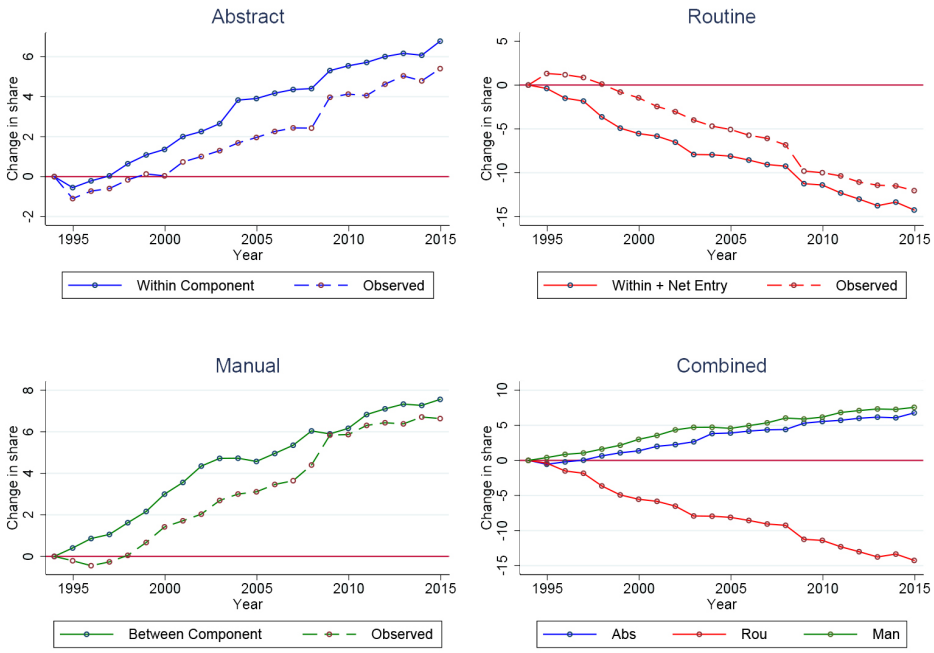
Figure 2: Contribution of within, between and net entry components over time



4 Model

In the following section, I construct a general equilibrium model with firm heterogeneity and occupational choice by workers to explain the observed aggregate job polarisation along with the firm-level decomposition. I use the model to quantify the importance of technological change in explaining the observed decline in routine occupation as compared to changes in the supply of workers. In the model firms are heterogeneous in terms of their technology. The setup is similar to Melitz (2003) with one important difference: technological change in the model is non-neutral. The key innovation is that I allow for techno-

Figure 3: Firm-level Job Polarisation: Most Important Components



logical that firm-occupation specific. There is a representative household that consumes a basket of goods and supplies labor. Workers in the household are endowed with efficiency units which they supply inelastically at the market wage. Based on their endowed efficiency, they select between three occupations: abstract, routine and manual. In what follows, I provide further details about the theoretical structure of the model. To convey all the necessary intuition concerning the model, I develop a model with only routine-augmenting technological shock. I extend the model further to allow for shocks that are multidimensional in the complete model.

4.1 Uni-dimensional case [3]

4.1.1 Preferences

I assume a representative household. They consume a basket of goods which is produced by a continuum of horizontally differentiated varieties, and I as-

[3]This section follows closely the presentation by Melitz and Redding (2014). I am including it here for the purpose of completeness.

sume that preferences over this basket take a Constant Elasticity of Substitution (CES) Dixit and Stiglitz (1977) form:

$$Q = \left(\int_{j \in \Omega} Q_j^{\frac{\eta-1}{\eta}} dj \right)^{\frac{\eta}{\eta-1}}, \quad \eta > 1$$

The household maximizes its utility subject to the following budget constraint

$$\int_j P_j Q_j dj \leq W_A N_A + W_R N_R + W_M N_M \equiv X$$

where W_o is the unit wage earned in occupation $o \in \{A, R, M\}$ where A denotes abstract, R denotes routine and M denotes manual. The demand for each differentiated variety is given by

$$Q_j = D P_j^{-\eta}, \; D = X P^{\eta-1}$$

where the price index of the economy is

$$P = \left(\int_{j \in \Omega} P_j^{1-\eta} dj \right)^{\frac{1}{1-\eta}}.$$

D is an index of market demand that proportionally scales every firm's residual demand. As in Melitz and Redding (2014), this market demand index, in turn, is determined by sector spending and a statistic of the price distribution (the CES price index). Given that I assume a continuum of firms, each firm is of measure zero relative to the market as a whole, and hence take D as given.

4.1.2 Technology

Each variety is produced using labor from three occupations: abstract, routine and manual. For simplicity, I abstract from capital and intermediate inputs in my model. Each firm chooses to supply a distinct horizontally-differentiated variety. The variety is produced via the following CES production function.

$$Q_j = \left[\beta_A (N_{Aj})^{\frac{\sigma-1}{\sigma}} + (\phi_{Rj} N_{Rj})^{\frac{\sigma-1}{\sigma}} + \beta_M (N_{Mj})^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}$$

where ϕ_{Rj} is the firm-occupation specific technological shock. I will use the model to calculate from the data the distribution of ϕ_{Rj} and study its evolution over time in explaining job polarisation. Furthermore, σ is the elasticity of substitution between different occupation input in the firm. Admittedly, the current specification of the production function is restrictive since it does not allow for the elasticity of substitution to vary between different inputs. I am currently developing an extension that allows for this possibility in firm technology.

How do relative improvements in occupation-augmenting productivity affects the labor demand depends crucially on the elasticity of substitution. From the expression above it is easy to see that if $\sigma < 1$, the occupational inputs are gross complements, and an increase in routine occupation augmenting productivity (ϕ_R) will lead to an increase in demand for abstract and manual occupations. If $\sigma > 1$, the factors are gross substitutes, and an increase in ϕ_R will lead to a relative decline in the demand for abstract and manual occupations.

I assume that firms are price-takers in this model. Given the production function, I derive the optimal labor demand of the firm by first calculating the cost-minimizing labor demand for a given level of output Q_j. Next, I pin down the optimal quantity that a firm produces by solving the firm's profit maximization problem. The closed-form solution to a firm's cost-minimizing labor demand is as follows

$$N_{oj} = Q_j \left(\frac{v_j}{W_o} \right)^{\sigma} \beta_o^{\sigma}, \quad o \in \{A, M\}$$
$$N_{Rj} = Q_j \left(\frac{v_j}{W_R} \right)^{\sigma} \phi_{Rj}^{(\sigma-1)}$$

where v_j is the marginal cost

$$v_j = \left[\beta_A \left(\frac{W_A}{\beta_A} \right)^{1-\sigma} + \left(\frac{W_R}{\phi_R} \right)^{1-\sigma} + \beta_M \left(\frac{W_M}{\beta_M} \right)^{1-\sigma} \right]^{\frac{1}{1-\sigma}}$$

This the standard downward-sloping demand curve. For a given level of output, more production firms, i.e, firms with a higher ϕ_{Rj} will hire a lower quantity of labor. Moreover, for a given set of prices, a more productive firm will have a lower marginal cost. Production of each variety involves a fixed cost of f units of routine labor and a constant marginal cost (given that I assume that the production function is constant returns to scale). Given that in the simple model there is only routine occupation augmenting technological shock, the marginal cost is inversely proportion to the firm productivity.

$$\text{TC}_j = W_R f + Q_j v_j$$

The market structure is monopolistic competition. As a result, each firm chooses its price to maximize its profits subject to a downward-sloping residual demand curve with constant elasticity η. Using the first order condition for profit maximization, the equilibrium price for each variety is a constant mark-up over marginal cost rule.

$$P_j = \frac{\eta}{\eta - 1} v_j$$

which implies that an equilibrium quantity given as follows. The equation simply states that more productive firms have a lower marginal cost and in equilibrium produce a higher quantity.

$$Q_j = D\left(\frac{\eta - 1}{\eta}\right)^{\eta} \frac{1}{v_j^{\eta}}$$

The equilibrium firm revenue of a firm is given as follows

$$R_j = D\left(\frac{\eta - 1}{\eta}\right)^{\eta - 1} v_j^{1-\eta}$$

and equilibrium firm profits are

$$\Pi_j = D v_j^{1-\eta} \frac{(\eta - 1)^{\eta - 1}}{\eta^{\eta}} - f = B v(\phi_R)^{1-\eta} - W_R f$$

where $B = D\frac{(\eta-1)^{\eta-1}}{\eta^{\eta}}$

$$\Pi_j = \frac{R_j}{\eta} - W_R f \implies R_j = \eta(\Pi_j + W_R f)$$

As noted in Melitz and Redding (2014), the constant mark-up rule is an implication of CES preferences and monopolistic competition. These assumptions further ensures that higher firm productivity is passed on fully to consumers in the form of lower prices. Since demand is elastic, this lower price implies a higher revenue for more productive firm. The assumption of CES production technology with constant returns to scale implies that the ratio of average to marginal cost will depend solely on firm output. Together with constant markups, this further implies that "variable" or "gross" profits are a constant proportion of firm revenue. As a result, the aggregate demand indice D will proportionally scale both revenues and gross profits.

4.1.3 Firm Entry and Exit

There is a competitive fringe of potential firms that can enter the market by paying a sunk entry cost of f_E. Potential entrants face uncertainty about their productivity in the sector. Once the sunk entry cost is paid, a firm draws its productivity ϕ_R from a fixed distribution $g(\phi_R)$, with cumulative distribution $G(\phi_R)$. After observing its productivity, a firm decides whether to exit the sector or to produce. The decision yields a survival cutoff productivity ϕ_R^* at which a firm makes zero profits. Since firms differ only by their productivity, I suppress the j subscript for simplicity

$$\Pi(\phi_R^*) = 0$$

The survival cut-off is equal to

$$\phi_R^* = \frac{W_R}{\left[\left(\frac{f}{B}\right)^{\frac{1-\sigma}{1-\eta}} - \beta_A\left(\frac{W_A}{\beta_A}\right)^{1-\sigma} - \beta_M\left(\frac{W_M}{\beta_M}\right)^{1-\sigma}\right]^{\frac{1}{1-\sigma}}}$$

Firms drawing a productivity $\phi_R < \phi_R^*$ would incur losses if they produced. As a result, these firms will exit the market immediately, receiving zero profits and will not be able to cover any portion of their sunk entry cost. Free entry implies that in equilibrium, the expected measure of ex-ante profits (inclusive of entry cost) must be equal to zero

$$\int_0^\infty \Pi(\phi_R) dG(\phi) = \int_{\phi_R^*}^\infty \Big[Bv(\phi_R)^{1-\eta} - W_R f\Big] dG(\phi_R) = W_R f_E$$

Heterogeneity in firm productivity will generate systematic differences in firm employment and occupational structure. The key goal of this paper is to see how this productivity distribution has evolved over time to give rise to observed polarisation in the data. By doing so, it will help us understand which firms are the key drivers of this process and construct counterfactuals to study the effect of change in technology on the decline of routine employment. Finally, to pin down the equilibrium mass of firms, denoted M_A, I start by calculating average profits for an active firm

$$\overline{\Pi} = \frac{W_R f_E}{1 - G(\phi_R^*)}$$

Next, I define the productivity of those firms earning average profits

$$\overline{\phi}_R = \frac{W_R}{\left[\left(\int_{\phi_R^*}^\infty v(\phi_R)^{1-\eta} \frac{dG(\phi_R)}{1-G(\phi_R^*)}\right)^{\frac{1-\sigma}{1-\eta}} - \beta_A\left(\frac{W_A}{\beta_A}\right)^{1-\sigma} - \beta_M\left(\frac{W_M}{\beta_M}\right)^{1-\sigma}\right]^{\frac{1}{1-\sigma}}}$$

The productivity average also references productivity for the aggregate sector consumption index Q and the price index P in the following sense: a hypothetical monopolistic competition equilibrium with M_A representative firms sharing a common productivity $\overline{\phi}_R$ would induce the same consumption index Q (defined below) and price index P (defined below) as M_A heterogeneous firms with equilibrium distribution $G(\phi_R)/[1 - G(\phi^*)]$.

$$Q = M_A^{\frac{\eta}{\eta-1}} Q(\overline{\phi}_R)$$
$$P = M_A^{\frac{1}{1-\eta}} \left(\frac{\eta}{\eta-1}\right) \left[\int_{\phi_R^*}^\infty v(\phi_R)^{1-\eta} \frac{dG(\phi_R)}{1-G(\phi_R^*)}\right]^{\frac{1}{1-\eta}}$$

In the current setup, the mass M_A of active firms represents the portion of the mass M_E of entrants that survive. This portion depends on the survival cutoff $\phi_R^* : M_A = [1 - G(\phi^*)]M_E$. Finally, the aggregate demand for labor is given as follows. Given that routine labor is used both for production by the M_A active firms and to cover the entry cost f_E incurred by all M_E entrants, it is included in the demand for aggregate routine labor.

$$N_o^d = \frac{A}{W_o^\sigma}\left(\frac{\eta-1}{\eta}\right)^\eta \int_{\phi_R^*}^\infty v(\phi_o)^{\sigma-\eta}\phi_o^{\sigma-1}\frac{M_A g(\phi_R)}{1-G(\phi_R^*)}d(\phi_R), \quad o \in \{A, M\}$$

$$N_R^d = \frac{A}{W_R^\sigma}\left(\frac{\eta-1}{\eta}\right)^\eta \int_{\phi_R^*}^\infty v(\phi_R)^{\sigma-\eta}\phi_R^{\sigma-1}\frac{M_A g(\phi_R)}{1-G(\phi_R^*)}d(\phi_R) + M_A f + M_E f_E$$

Note that the free entry condition ensures that aggregate profits exactly cover the aggregate entry and therefore the aggregate sector revenues is determined by the input supply. Given the fact that we have a closed economy, it must be equal to the sector aggregate expenditure. As in Melitz (2003), the aggregate labor supply affects neither firm selection nor average firm sales. As a result, changes in this measure of market size must be reflected one-for-one in the mass of both active firms and entrants. This results is completely specific to this model and is due to our assumption of CES preferences.

4.1.4 Labor Supply

Following Barany and Siegel (2015), I assume that individuals are heterogeneous in their endowment of efficiency units of labor, $\mathbf{e} \in \mathbf{R}_+^3$, which is drawn from a time invariant distribution $f(\mathbf{e})$. The endowment, $\mathbf{a}$, determines each individual's productivity in occupations A, R and M. We assume that each individual ability corresponds to one occupation, such that $e_A \equiv \mathbf{e}(1)$ denotes the individual's efficiency units of labor in abstract occupations, $e_R \equiv \mathbf{e}(2)$ in routine occupation, while $e_M \equiv \mathbf{e}(3)$ denotes his efficiency units in manual occupations. Therefore the wage of an individual with $\mathbf{e} = (e_A, e_R, e_M)$ efficiency units of labor if working in occupation o is $e_o W_o$. It is optimal for an individual with (e_A, e_R, e_M) efficiency units of labor to work in.

Abstract occupation iff

$$e_A > \frac{1}{\frac{W_A}{W_R}}e_R \quad \text{and} \quad e_A > \frac{\frac{W_M}{W_R}}{\frac{W_A}{W_R}}e_R$$

Routine occupation iff

$$e_R > \frac{W_A}{W_R}e_A \quad \text{and} \quad e_R > \frac{W_M}{W_R}e_M$$

Manual occupation iff

$$e_M > \frac{\frac{W_A}{W_R}}{\frac{W_M}{W_R}} e_A \quad \text{and} \quad e_M > \frac{1}{W_M} W_R e_R$$

The optimal occupational choices of individuals determine the effective labor supplies in the three markets:

$$N_A\left(\frac{W_A}{W_R}, \frac{W_M}{W_R}\right) = \int_0^{\infty} \int_0^{\frac{W_A}{W_R} e_A} \int_0^{\frac{\frac{W_A}{W_R}}{\frac{W_M}{W_R}} e_A} e_A f(e_A, e_R, e_M) de_M de_R de_A$$

$$N_R\left(\frac{W_A}{W_R}, \frac{W_M}{W_R}\right) = \int_0^{\infty} \int_0^{\frac{1}{\frac{W_A}{W_R}} e_R} \int_0^{\frac{1}{\frac{W_M}{W_R}} e_R} e_R f(e_A, e_R, e_M) de_M de_A de_R$$

$$N_M\left(\frac{W_A}{W_R}, \frac{W_M}{W_R}\right) = \int_0^{\infty} \int_0^{\frac{\frac{W_M}{W_R}}{\frac{W_A}{W_R}} e_M} \int_0^{\frac{W_M}{W_R} e_M} e_M f(e_A, e_R, e_M) de_R de_A de_M$$

In the data, the effective labor supply in occupation o is not observed. Instead what we observe is the hours worked, which correspond to the raw labor supply, or employment share in the model.

$$L_A\left(\frac{W_A}{W_R}, \frac{W_M}{W_R}\right) = \int_0^{\infty} \int_0^{\frac{W_A}{W_R} e_A} \int_0^{\frac{\frac{W_A}{W_R}}{\frac{W_M}{W_R}} e_A} f(e_A, e_R, e_M) de_M de_R de_A$$

$$L_R\left(\frac{W_A}{W_R}, \frac{W_M}{W_R}\right) = \int_0^{\infty} \int_0^{\frac{1}{\frac{W_A}{W_R}} e_R} \int_0^{\frac{1}{\frac{W_M}{W_R}} e_R} f(e_A, e_R, e_M) de_M de_A de_R$$

$$L_M\left(\frac{W_A}{W_R}, \frac{W_M}{W_R}\right) = \int_0^{\infty} \int_0^{\frac{\frac{W_M}{W_R}}{\frac{W_A}{W_R}} e_M} \int_0^{\frac{W_M}{W_R} e_M} f(e_A, e_R, e_M) de_R de_A de_M$$

4.1.5 Solving for equilibrium

Contrary to the Melitz (2003) model, factor prices appear in the free entry condition equation. I need to jointly solve for wages and the cut-off condition. I normalise the wages of routine workers to be equal to 1. Hence, the equilibrium boils down to solving for three equations in three unknowns: ϕ^*, W_A, W_M. The three equations are as follows:

$$\frac{f_E}{f} = \int_{\phi_R^*}^{\infty} \left[\left\{ \frac{\beta_A (W_A \beta_A^{-1})^{1-\sigma} + (W_R \phi_R^{-1})^{1-\sigma} + \beta_M (W_M \beta_M^{-1})^{1-\sigma}}{\beta_A (W_A \beta_A^{-1})^{1-\sigma} + (W_R \phi_R^{*-1})^{1-\sigma} + \beta_M (W_M \beta_M^{-1})^{1-\sigma}} \right\}^{\frac{1-\eta}{1-\sigma}} - 1 \right] dG(\phi_R)$$

$$N_A^s = N_A^d$$
$$N_M^s = N_M^d$$

The first of these three equation is the free-entry condition, analogous to Melitz (2003) adjusted for the fact that the production is different between these two model. The last conditions are the market clearing condition for abstract and manual occupations. Given Walrus' law, and the normalisation of routine wages equal to 1, if both these markets clear, the routine occupations market will clear automatically.

4.1.6 Calibration

There are two key distributions in the model that I need to parameterize. The first is the distribution of ϕ_R anf the second is the joint distribution of worker's efficiency units. With regards to routine augmenting technology, I assume that the PDF of $\phi_R \sim \mathbb{LN}(\mu_\phi, \sigma_\phi^2)$ is log-normally distributed, i.e. $\omega_R = \log(\phi_R) \sim \mathbb{N}(\mu_\omega, \sigma_\omega^2)$. The relationship between μ_ω and μ_ϕ and the two variance is specified above.

$$f(\phi_R) = \frac{1}{\phi_R \sigma_\omega \sqrt{2\pi}} \exp\left(- \frac{(\ln \phi_R - \mu_\omega)^2}{2\sigma_\omega^2} \right)$$

Next, I need to parameterize the the distribution of efficiency units. For the baseline calibration, I follow Barany and Siegel (2015) to assume that the worker's occupational efficiencies are drawn from a trivariate log-normal distribution. This assumption is clearly not innocuous. However, the log-normal distribution is particularly important in the selection literature and the empirical wage distribution are skewed to the right typically resemble a log-normal distribution. Assuming that the underlying distribution of abilities is trivariate log-normal does not guarantee that after selection the resulting one dimensional wage distribution is also going to be log-normal. An additional advantage of this assumption is that the assumed distribution allows for a very flexible correlation structure. Further information about the parameter values that chosen to perform the comparative statics and counterfactual exercises are specified in Table 3.

4.1.7 Comparative Statics

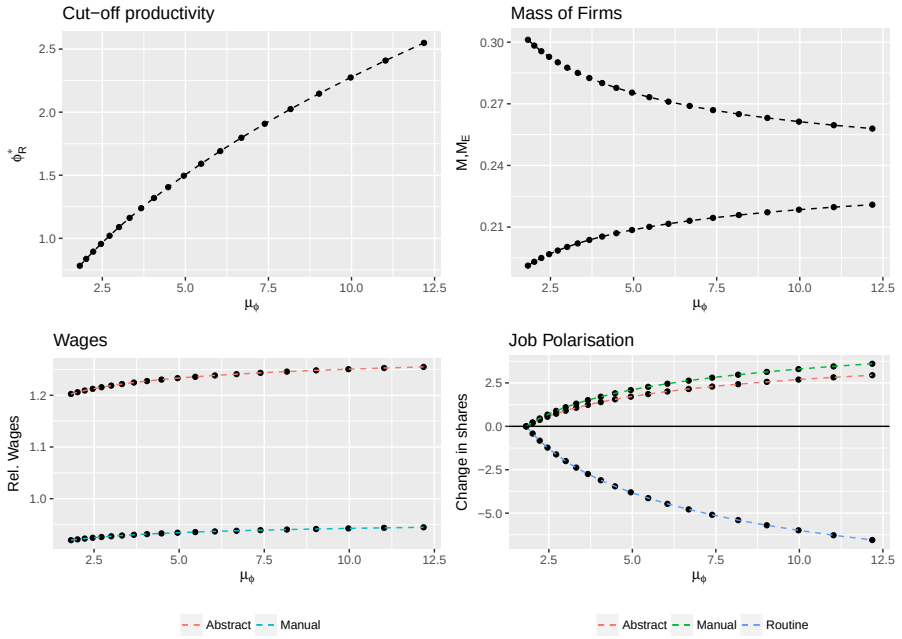
To develop further intuition of the model and highlight the key mechanisms that generate polarisation in the model, I perform a simple comparative statics exercise. In the comparative I change the mean of ϕ_R, the routine-occupation augmenting technological change. As previously mentioned, there are two key ingredients generating polarisation in this model: biased technological change and the elasticity of substitution lower than 1 (implying that labor inputs are

Table 3: Parameter values used for calibration

Parameters	Description	Value	Source
β_A, β_M	Cost share abstract and manual	0.1, 0.3	
η	Elasticity of demand	3	
σ	Elasticity of substitution	0.5	
f	Operating cost	1	Harrigan and Reshef
f_E	Entry cost	0.5	(2015)
$\mu_{\chi 1}, \mu_{\chi 2}$	Mean: cost distribution	-0.03, 0.4	Barany and Siegel
$\sigma^2_{\chi 1}, \sigma^2_{\chi 2}$	Variance: cost distribution	0.08, 0.50	(2018)
ρ	Correlation of cost differences	0.4	

gross complements). As observed in Figure 4, bottom right, these simple assumptions are able to replicate the observed job polarisation.

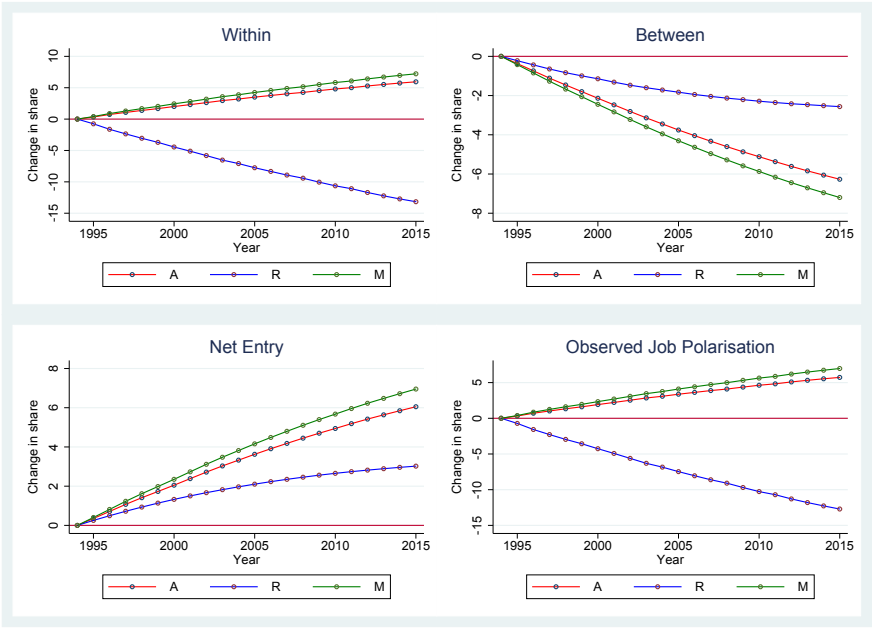
Figure 4: Comparative Statics: Effect of RBTC on key model objects



However, as seen in Figure 5, these assumption cannot really replicate the observed micro-level predictions in the data. Given there is free entry in the model, an increase in the average draw obtained by the firm upon paying the fixed cost f_E encourages entry over time which is opposite to what we see in the real data where the share of routine component is declining due to net entry and remain quite stable between firms. Moreover, within firm we observe

that both abstract and manual occupations increase while in the data we only observe an increase in abstract occupations. This simple exercise highlights that maybe the change in average technology pertaining to routine occupations may not be the true underlying force of observed micro-level causes of polarisation.

Figure 5: Comparative Statics: Effect of RBTC on firm-level decomposition



4.1.8 Backing out shocks

How well can this simple model do to match the observe facts in the data? To answer this question, I take the model directly to micro-data by estimating ϕ_{Rj} by using the structure of the model. Theory suggests that the relative FOCs of any two of the three occupations is as follows

$$\ln \frac{N_{Aj}}{N_{Rj}} = \sigma \ln \frac{\tilde{W}_R}{\tilde{W}_A} + (1-\sigma) \ln \phi_{Rj} + \sigma \ln \beta_A$$
$$\ln \frac{N_{Mj}}{N_{Rj}} = \sigma \ln \frac{\tilde{W}_R}{\tilde{W}_M} + (1-\sigma) \ln \phi_{Rj} + \sigma \ln \beta_M$$

Given the CES production function, these relative FOCs are reminiscent of the classic Katz and Murphy (1992) framework well-known for explaining the rise

in the skill premium due to Skill-Biased Technical Change (SBTC) and labor supply. Given I have two equations to pin down one unobservable, the model is over-identified. This provides a direct test of the model. In principle, if the model is the true data-generating process, ϕ_{Rj} backed out (conditional on σ) should be identical. Furthermore, it also gives a direct test of log-normality assumption that I imposed on the shocks of the model. As can be seen from Figure 6 and Figure 7, the distribution of $\log(\phi_R)$ look normal, but these values of ϕ_R are not the same. This provides another motivation to develop a more flexible model with abstract and manual occupation augmenting technology.

4.1.9 Effect of RBTC on French Job Polarisation

After backing out the shocks, I simulate my model using the distribution of $\omega_R \sim \mathbb{N}(\hat{\mu}, \hat{\sigma}^2)$. I see how well my model is able to fit the data. I plot the fit of my model job polarisation in Figure 8. Clearly, this very simple model explains quite well the shape of the overall job polarisation. However, the model is unable to generate the actual magnitude of the decline in routine occupation. In the data, routine occupations decline by 12%, while in the model they decline by 4%. As mentioned previously, I try to improve the fit of the model by extending it to allow for multidimensional productivity and backing out a joint distribution of (ϕ_A, ϕ_R, ϕ_M).

I also calculate the effect of the change in the mean and the change in both the mean and the variance in explaining the decline in routine occupation. The results of this exercise are summarised in Table 4. The table suggests a surprising result: if I collapse all the heterogeneity in the model and assume that all firms are identical, this representative firm framework explain less than 6% of the total decline in routine occupations. This result is summarised in column 4.

Table 4: Contribution of RBTC in the decline of routine occupation

	Δ	σ^2_ϕ	σ^2_ϕ and μ_ϕ	Rep. firm	% Contribution
Abstract	5.40	0.91	1.23	0.32	23%
Routine	-12.03	-2.02	-2.74	-0.72	22%
Manual	6.63	1.10	1.50	0.40	22%

4.2 Multi-dimensional case

In this section, I extend the simple model with uni-dimensional shock to a case where technological change is multi-dimensional: I allow for both abstract and manual augmenting technology, along with routine-augmenting technology. The main body of the model remains the same apart from this change, so in this section I only focus on key changes made to the model from Section 5.1.

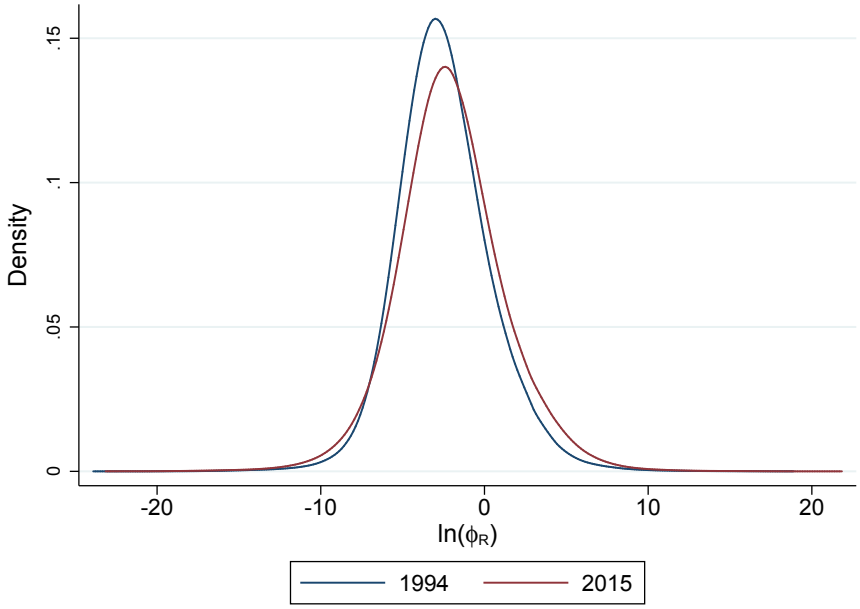


Figure 6: Truncated Distribution of ϕ_R using relative FOC 1, $\ln \frac{N_{Aj}}{N_{Rj}}$

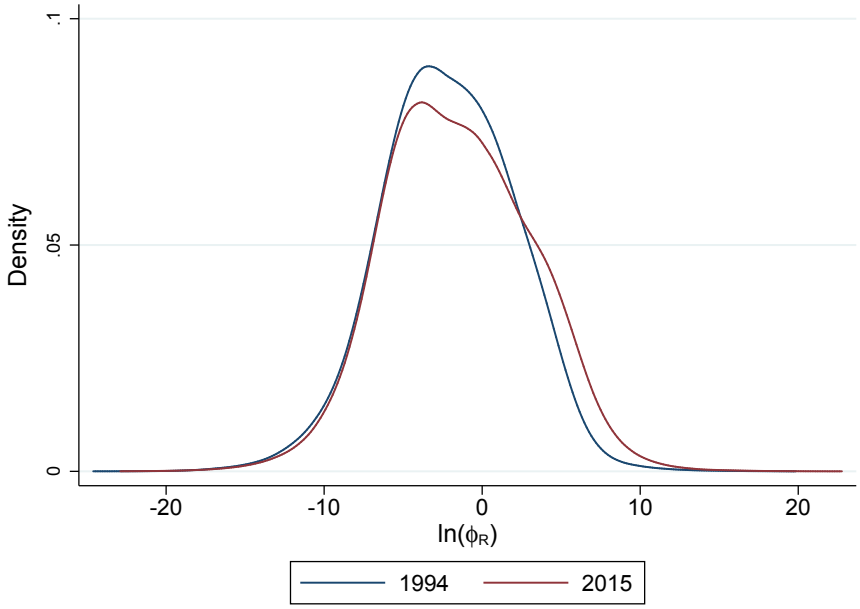
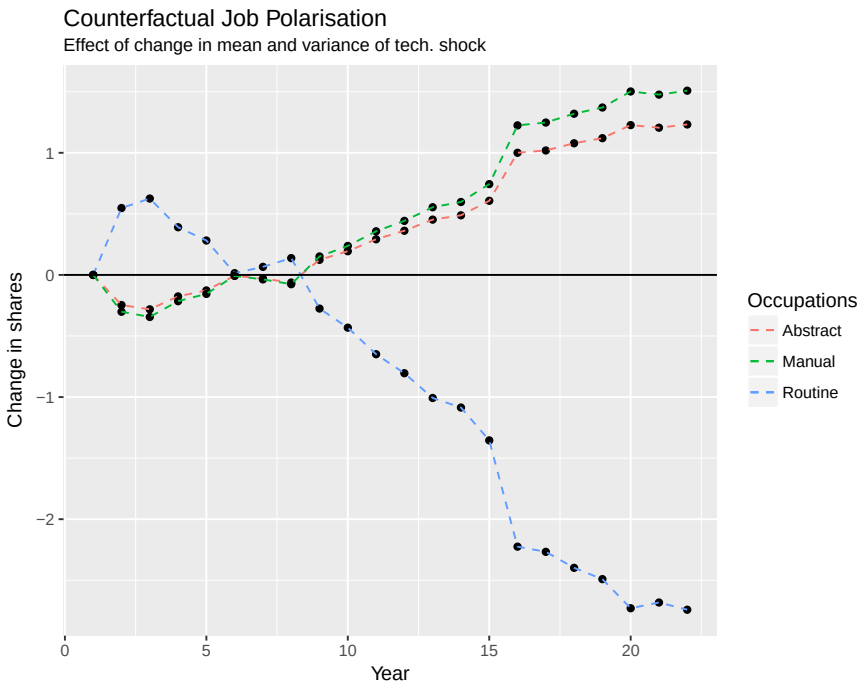


Figure 7: Truncated Distribution of ϕ_R using relative FOC 2, $\ln \frac{N_{Mj}}{N_{Rj}}$

Figure 8: Model Predicted Job Polarisation



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

The first key difference between the technology from this Section to the Section 5.1 is that the relative first order condition change and now I will not be able to back-out ϕ_R directly from the relative FOCs. I explain in the next section, how I will back out the shocks in this case.

$$\ln \frac{N_{Aj}}{N_{Rj}} = \sigma \ln \frac{W_R}{W_A} + (1-\sigma) \ln \frac{\phi_{Rj}}{\phi_{Aj}}$$
$$\ln \frac{N_{Mj}}{N_{Rj}} = \sigma \ln \frac{W_R}{W_M} + (1-\sigma) \ln \frac{\phi_{Rj}}{\phi_{Mj}}$$

The cost-minimizing labor demand for occupations is modified to be the following

$$N_{oj} = Q_j \left(\frac{v_j}{W_o} \right)^{\sigma} \phi_{oj}^{(\sigma-1)}$$

where v_j is the marginal cost

$$v_j(\phi_{Aj}, \phi_{Rj}, \phi_{Mj}) = \left[\left(\frac{W_A}{\phi_{Aj}} \right)^{1-\sigma} + \left(\frac{W_R}{\phi_{Rj}} \right)^{1-\sigma} + \left(\frac{W_M}{\phi_{Mj}} \right)^{1-\sigma} \right]^{\frac{1}{1-\sigma}}$$

Total cost:

$$\text{TC} = W_R f + Q_j \times v_j(\phi_A, \phi_R, \phi_M)$$

4.2.1 Firm Entry and Exit

There is a competitive fringe of potential firms that can enter the market by paying a sunk entry cost of f_E. Potential entrants face uncertainty about their productivity in the sector. Once the sunk entry cost is paid, a firm draws its productivity from a (fixed) joint distribution $g(\phi_A, \phi_R, \phi_M)$. After observing its productivity, a firm decides whether to exit the market or to produce. The decision to enter and exit will now yield a survival cutoff "index" v^* at which a firm makes zero profits. Below this index, the firm exits the market.

$$\Pi(v^*) = A(v^*)^{1-\eta} \frac{(\eta - 1)^{\eta - 1}}{\eta^\eta} - W_R f = 0$$

$$\Pi(v^*) = B(v^*)^{1-\eta} - W_R f = 0$$

Following Harrigan and Reshef (2011), the cutoff v^* defines a manifold in the (ϕ_A, ϕ_R, ϕ_M) space such that

$$\text{D}(v^*, W_A, W_R, W_M) = \left\{ (\phi_A, \phi_R, \phi_M) \in \mathbb{R}^1_+ \times \mathbb{R}^1_+ \times \mathbb{R}^1_+ : v^* \leq v \right\}.$$

All firms with $(\phi_A, \phi_R, \phi_M) \in D$ are active in equilibrium. After paying the entry fixed cost and before discovering its technology, the ex-ante probability that a potential firm is active is the probability that it draws a technology (ϕ_A, ϕ_R, ϕ_M) in D

$$\chi_D = \Pr[(\phi_A, \phi_R, \phi_M) \in \text{D}] = \iiint_{(\phi_A, \phi_R, \phi_M) \in \text{D}} g(\phi_A, \phi_R, \phi_M) \text{d}\phi_A \text{d}\phi_R \text{d}\phi_M$$

Hence, combining the zero-profit condition with the free-entry condition, we obtain a single equation that determines the productivity cutoff

$$\iiint_{(\phi_A, \phi_R, \phi_M) \in \text{D}} \left[\left(\frac{v(\phi_A, \phi_R, \phi_M)}{v^*} \right)^{1-\eta} - 1 \right] \text{g}(\phi_A, \phi_R, \phi_M) \text{d}\phi_A \text{d}\phi_R \text{d}\phi_M = \frac{f_E}{f}$$

Alternatively, I can write down the free-entry condition as follows. First define

$$C(v^*) = \left[v^{*1-\sigma} - \left(\frac{W_A}{\phi_A} \right)^{1-\sigma} - \left(\frac{W_R}{\phi_R} \right)^{1-\sigma} \right]^{\frac{1}{1-\sigma}}$$

Hence,

$$\phi_M = \frac{W_M}{C(v^*)}$$

$$\int_0^\infty \int_0^\infty \int_{\frac{W_M}{C(v^*)}}^\infty \left[\left(\frac{v(\phi_A, \phi_R, \phi_M)}{v^*} \right)^{1-\eta} - 1 \right] \mathrm{g}(\phi_A, \phi_R, \phi_M) \mathrm{d}\phi_M \mathrm{d}\phi_R \mathrm{d}\phi_A = \frac{f_E}{f}$$

4.2.2 Average profits, revenues and productivity

The average profit for an active firm

$$\overline{\Pi} = \frac{W_R f_E}{\chi_D}$$

Second, calculate the average revenue for an active firm

$$\overline{R} = \eta[\overline{\Pi} + W_R f] = \eta W_R \left[\frac{f_E}{\chi_D} + f \right]$$

Finally, the weighted average marginal cost/competitiveness of active firms is given by the following expression:

$$\overline{v}(v^*) = \left[\iiint_D v^{1-\eta} \, \frac{\mathrm{g}(\phi_A, \phi_R, \phi_M)}{\chi_D} \mathrm{d}\phi_A \mathrm{d}\phi_R \mathrm{d}\phi_M \right]^{\frac{1}{1-\eta}}$$

4.2.3 Aggregation

The mass of active firms in equilibrium is pinned down as follows

$$M_A = \frac{R}{\overline{R}} = \frac{W_A N_A + W_R N_R + W_M N_M}{\eta W_R \left[\frac{f_E}{\chi_D} + f \right]}$$

and let M_E be the mass of entrants which is pinned down as follows

$$M_E = \frac{M_A}{\chi_D}$$

We need to pin down the dual price index P

$$P = M_A^{\frac{1}{1-\eta}} \left(\frac{\eta}{\eta-1}\right) \underbrace{\left[\iiint_D v^{1-\eta} \frac{g(\phi_A,\phi_R,\phi_M)}{\chi_D} d\phi_A d\phi_R d\phi_M\right]^{\frac{1}{1-\eta}}}_{\overline{v}(v^*)}$$

4.2.4 Labor market clearing

In equilibrium, there is a mass M_A of active firms. Hence the demand for occupation A and M is given by

$$N_o = \int_j Q(j) \left(\frac{v}{W_o}\right)^{\sigma} \phi_o^{(\sigma-1)} dj = \int_j A \left(\frac{\eta-1}{\eta}\right)^{\eta} \frac{1}{v^{\eta}} \left(\frac{v}{W_o}\right)^{\sigma} \phi_o^{\sigma-1} dj$$

$$N_o = \frac{M_A}{\chi_D} \frac{A}{W_o^{\sigma}} \left(\frac{\eta-1}{\eta}\right)^{\eta} \iiint_D v(\phi_A,\phi_R,\phi_M)^{\sigma-\eta} \phi_o^{\sigma-1}\, g(\phi_A,\phi_R,\phi_M) d\phi_A d\phi_R d\phi_M$$

Similarly, the demand for routine occupation is given by

$$N_R = N_R + M_A f + M_E f_E$$
$$N_R = \frac{M_A}{\chi_D} \frac{A}{W_R^{\sigma}} \left(\frac{\eta-1}{\eta}\right)^{\eta} \iiint_D v(\cdot)^{\sigma-\eta} \phi_R^{\sigma-1} g(\phi_A,\phi_R,\phi_M) d\phi_A d\phi_R d\phi_M$$

5 Structural Estimation

5.1 Backing out unobservables and SMM

I start by backing out the joint distribution of occupation-augmenting technology: (ϕ_A, ϕ_R, ϕ_M). To back out shocks, I can no longer rely on relative FOCs. Instead, given I have a closed form solutions for labor demand, I jointly solve a three-system of equations in three unknown for each firm:

$$N_{Aj} = D \left(\frac{\eta-1}{\eta}\right)^{\eta} \frac{v_j^{\sigma-\eta}}{W_A^{\sigma}} \phi_{Aj}^{\sigma-1}$$
$$N_{Rj} = D \left(\frac{\eta-1}{\eta}\right)^{\eta} \frac{v_j^{\sigma-\eta}}{W_R^{\sigma}} \phi_{Rj}^{\sigma-1}$$
$$N_{Mj} = D \left(\frac{\eta-1}{\eta}\right)^{\eta} \frac{v_j^{\sigma-\eta}}{W_M^{\sigma}} \phi_{Mj}^{\sigma-1}$$

These shocks are estimated for a given set of primitives: σ, η. Given thre is selection in the model, I only observe surviving firms in the data. Hence, I need to estimate the joint distribution of the un-truncated distribution of shocks. I use Simulated Method of Moments to estimate the un-truncated distribution. Given I observe the entire distribution of marginal cost directly in the data, I can pin down v^*. This allows me to then pin down the fixed cost of production f using the following condition

$$f = B(v^*)^{1-\eta}$$

Next, I pin down f_E using the following condition

$$f_E = \chi_D(\overline{R}\eta W_R - f)$$

5.2 Results and Counterfactuals

[TO BE COMPLETED]

The full model is currently being estimated on the full French data.

6 Conclusion

In this paper, I show that the French labor markets is getting polarized in many industrial economies. I found that routine occupations declined by approximately 12% in the employment share. In the US, the decline over a longer time period was 14%. Given access to administrative micro-data, I decompose aggregate job polarisation into three components. I find two key reasons for the decline of routine employment: within-firm substitution of routine workers by abstract workers and declining share of routine-intensive firms as new firms entering the market do not create as many routine jobs as those firms exiting the market. I build a simple general equilibrium model to match both the aggregate and micro-level facts on job polarisation. I find that in the simple model, technological change is able to explain about a quarter of the decline in the routine occupations. While technology plays an important role, the model highlights the important role of other factors such as labor supply and institution. The model is being generalised and estimated via SMM to quantify the importance of these other channels.

References

[1] Daron Acemoglu and David Autor. "Skills, tasks and technologies: Implications for employment and earnings". In: *Handbook of labor economics*. Vol. 4. Elsevier, 2011, pp. 1043–1171.

[2] Daniel A Ackerberg, Kevin Caves, and Garth Frazer. "Identification properties of recent production function estimators". In: *Econometrica* 83.6 (2015), pp. 2411–2451.

[3] David H Autor, Frank Levy, and Richard J Murnane. "The skill content of recent technological change: An empirical exploration". In: *The Quarterly journal of economics* 118.4 (2003), pp. 1279–1333.

[4] Richard Blundell and Stephen Bond. "GMM estimation with persistent panel data: an application to production functions". In: *Econometric reviews* 19.3 (2000), pp. 321–340.

[5] Petri Böckerman, Seppo Laaksonen, and Jari Vainiomäki. "Are jobs more polarized in ICT firms?" In: (2016).

[6] H David and David Dorn. "The growth of low-skill service jobs and the polarization of the US labor market". In: *American Economic Review* 103.5 (2013), pp. 1553–97.

[7] Jan De Loecker. "Product differentiation, multiproduct firms, and estimating the impact of trade liberalization on productivity". In: *Econometrica* 79.5 (2011), pp. 1407–1451.

[8] Avinash K Dixit and Joseph E Stiglitz. "Monopolistic competition and optimum product diversity". In: *The American economic review* 67.3 (1977), pp. 297–308.

[9] Maarten Goos, Alan Manning, and Anna Salomons. "Job polarization in Europe". In: *American economic review* 99.2 (2009), pp. 58–63.

[10] James Harrigan and Ariell Reshef. *Skill biased heterogeneous firms, trade liberalization, and the skill premium*. Tech. rep. National Bureau of Economic Research, 2011.

[11] James Harrigan, Ariell Reshef, and Farid Toubal. *The march of the techies: Technology, trade, and job polarization in France, 1994-2007*. Tech. rep. National Bureau of Economic Research, 2016.

[12] James J Heckman and Bo E Honore. "The empirical content of the Roy model". In: *Econometrica: Journal of the Econometric Society* (1990), pp. 1121–1149.

[13] Fredrik Heyman. "Job polarization, job tasks and the role of firms". In: *Economics letters* 145 (2016), pp. 246–251.

[14] Marc J Melitz. "The impact of trade on intra-industry reallocations and aggregate industry productivity". In: *econometrica* 71.6 (2003), pp. 1695–1725.

[15] Marc J Melitz and Stephen J Redding. "Heterogeneous firms and trade". In: *Handbook of international economics*. Vol. 4. Elsevier, 2014, pp. 1–54.

[16] S Olley and A Pakes. "The dynamics of productivity in the Telecommunications Equipment Industry, in "Econometrica", vol. 64". In: (1996).

7 Appendix

In this Appendix, I provide more details concerning the sub-categories of occupations assigned to Abstract, Routine and Manual occupations. Interested reader should refer to Reshef, Harrigan and Toubal (2015) for further details concerning the PCS occupation codes.

Table 5: Abstract occupation subcategories

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 6: Routine occupation subcategories

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, Heavy and electrical machinery operators, Operators of electrical and electronic equipments, Shipping, moving and warehouse workers, Production workers
Mid-level managers	46	Mid-level professionals in various industries, Supervisors in financial, legal and other services, 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	Designers of electrical, electronic and mechanical equipment, Installation and maintenance of IT and non-IT equipments
Retail workers	55	Retails employees, cashiers

Table 7: Manual occupation subcategories

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

Figure 9: Change in employment share of Abstract occupational subcategories

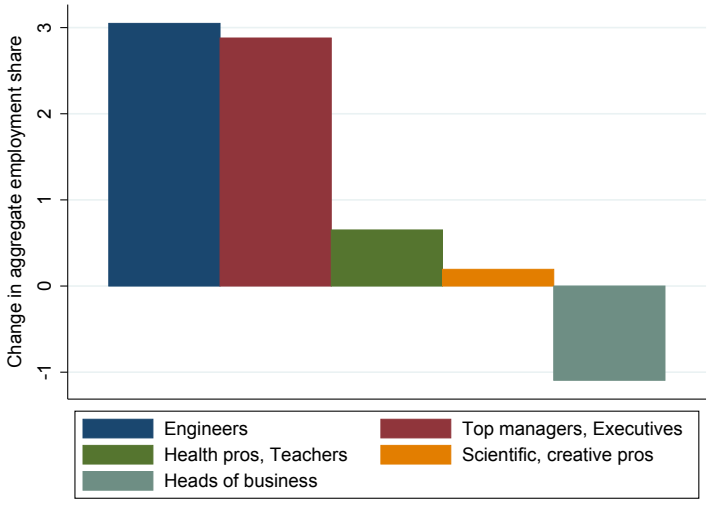


Figure 10: Change in employment share of Routine occupational subcategories

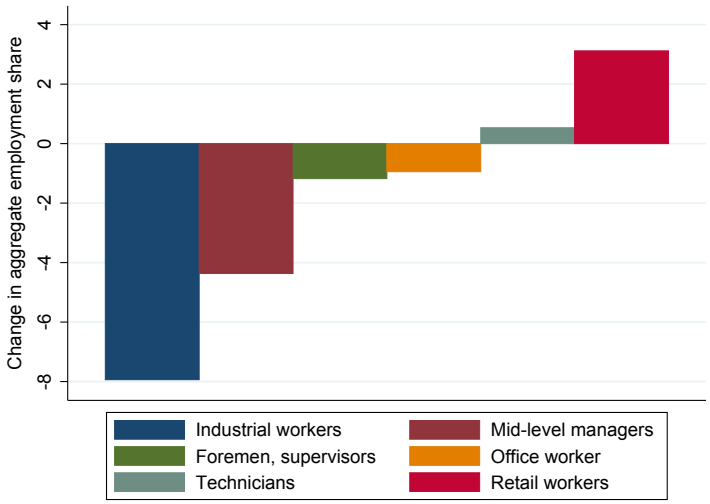


Figure 11: Change in employment share of Manual occupational subcategories

