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Transatlantic Employment Performances and Job Polarization

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Introduction

Technological change has deeply shaped the economies of developed countries and their labor market over the past four decades. Those changes are usually generating both enthusiasm and fear in the public debate as they affect the growth and the distribution of wealth. On the one hand, technological change is a key determinant of long-run economic growth as argued by Solow (1956). It allows to uplift collectively the income of individuals by increasing the productive capacity of the economy. This benefits consumers by increasing their standard of living. On the other hand, technological change greatly affects the distribution of wealth. It generates inequalities that produce losers and winners by affecting both wage inequalities and the employment prospects of workers.

The reallocation of labor induced by technological change often rose concerns for employment performances. History provides us with several examples where technological progress led to detrimental outcomes for workers. For instance, there was the Luddite movement in the nineteenth century in England. The textile sector underwent important technological and organizational changes induced by the introduction of machines able to perform tasks previously performed by skilled craftpersons. Those workers protested against the mechanization of textile making by destroying the machines causing the disappearance of their employment prospects. Similarly, in 1830, there was an uprising of agricultural workers named the Swing riots. They were protesting against agricultural mechanization and the ever-harsher working conditions in Southern and Eastern England.

The detrimental effect of technological progress on employment outcomes was not solely a popular fear. It has entered the field of economics. For instance, despite praising the collective benefits of technological progress, David Ricardo shared some concerns on the adverse effects of technological change on workers' welfare. He considered the possibility that the diffusion of machines in the production process could generate a deterioration of employment outcomes. In that respect, Ricardo (1821) stated that:

> *"There will necessarily be a diminution in the demand for labor, population will become redundant, and the situation of the laboring classes will be that of distress and poverty."*
>
> *On the Principles of Political Economy and Taxation*, Third Edition (1821)

In the twentieth century, Keynes (1930) also stressed the potential detrimental effects of technological change but he highlights the transitional nature of those effects. The author views them as short-term challenges as he stated that

> *"We are being afflicted with a new disease of which some readers may not yet have heard the name, but of which they will hear a great deal in the years to come -namely, technological unemployment. This means unemployment due to our discovery of means of economizing the use of labor outrunning the pace at which we can find new uses for labor. [...] But this is only a temporary phase of maladjustment."*
>
> *Economic Possibilities for our Grand-children (1930)*

A century later, the challenges described by Keynes are still of contemporary relevance. Recent technological progress induced a massive reallocation process of labor implying both employment gains and losses. Indeed, technological change has deeply shaped the occupational structure of developed economies, such as France and the U.S. over the last four decades. The diffusion of new technologies ignited a reallocation process of labor that led to job polarization. This reallocation process occurred because technological change has been biased towards replacing routine tasks. Middle-paid workers are performing repetitive and codified routine tasks that can be achieved by new technologies to some extent. On the contrary, low-paid jobs usually involve manual tasks requiring face to face interactions or manual dexterity that are not yet easily substitutable with those technologies. Similarly, high-paid jobs usually entail abstract tasks such as cognitive and decisional tasks usually complementary with new technologies. Hence, employment shares of both low- and high-paid occupations increased simultaneously, while the share of middle-paid occupations decreased significantly, shrinking the middle class and ultimately leading to social distress. In that respect, Frey and Osborne (2017) highlight that approximately half of the current U.S. employment has a high probability of disappearing due to computerization.

This thesis goes further in highlighting the implications of technological change on the French and U.S. economies. It also provides explanatory models that take into account the specificities of the labor market. There is no consensus on how the polarization of occupational employment translates into employment performances. Nothing guarantees that the employment gains arising from this reallocation process offset the employment losses. For instance, despite experiencing similar shifts in their occupational employment structure, France and the U.S. depict stark differences in terms of wage inequalities and employment performances between 1982 and 2017. Furthermore, little is known on the short-run effects of task-biased technological shocks and their relevance over the business cycle; yet they massively shifted the occupational employment structure over the last four decades.

Related literature

The nature of technological change

A wide strand of literature studies the implications of the nature of technological change on wage inequalities and the employment structure in the long run. Although it focuses on the U.S. and provides some factual analysis on other countries such as France, it does not usually explain observed differences in employment outcomes. Indeed, Acemoglu and Autor (2011) argue that the nature of technological change is a key determinant of wage inequalities and employment as it does not affect all the workers in the same manner in the U.S. It has been biased towards complementing skilled labor in the late twentieth century. The demand for skilled labor increased significantly with respect to that of unskilled labor. As a consequence, it led to an increase in the skill premium, i.e. the relative wage of skilled labor, generating a substantial rise in wage inequalities and favorable employment prospects for skilled workers. Autor, Levy, and Murnane (2003) further claim that the recent diffusion of new technologies such as computerization depicts a subtler process. The rise in skill premium stems mainly from the development of computerization which enables to execute specific tasks previously performed by workers. Technological change is task-biased rather than skilled-biased. In that respect, Autor and Dorn (2013) demonstrate that the recent waves of technological innovations led to the polarization of occupational employment in the U.S. Furthermore, Goos, Manning, and Salomons (2009) also document job polarization for most European countries and argue that routine-biased technological change is the underlying force driving such shifts in the occupational employment structure.

Transatlantic employment outcomes and labor taxation

Despite experiencing similar changes in their employment structure, France and the U.S. display stark differences in their employment performances in the last four decades. Yet, little is known on why countries display different employment outcomes arising from the occupational reallocation of labor. For instance, Piketty (1998) documents that France has an employment deficit compared to the U.S. The author argues that the service sector in France did not develop as in the U.S. He underlines that if France had had the same employment propensities in the sales and hospitality sectors as in the U.S., there would be an additional 2.8 million employed workers in 1996. A key explanation for the French employment deficit is that the labor cost is high compared to the U.S. especially for low-paid workers. This is in line with Prescott (2004) findings that European countries feature lower levels of labor supply with respect to the U.S. because of the high labor tax rates they implemented in European countries. Rogerson (2008) claims that employment outcomes of European countries deteriorated over time. The reallocation of labor across sectors did not occur to the same extent as in the U.S. leading to weaker employment performances. The author argues that the high European labor tax rates create an incentive to perform many economic activities in the non-market sector rather than in the market service sector. Non-market services are of overwhelming relevance as they are estimated to represent between 15% and 70% of GDP in France depending on how they are valued and the frame of activities considered as indicated by Roy (2012). Those services are mainly produced through performing manual tasks. Yet, little is known on how job polarization relates to changes in employment outcomes. Even less is known on the repercussion of economic policies on employment outcomes resulting from this reallocation process.

Technological shocks and the business cycle

The long-run implications of technological change have been widely studied. In contrast, little is known on the short-run effects of biased technological shocks on employment and the relevance of those shocks over the business cycle. Nevertheless, it is crucial to determine the business cycle properties of technological change in order to understand the effects of monetary policy. For instance, Galí (1999) estimates that hours worked decline after an aggregate technological shock. He argues that this is line with the New-Keynesian theory stating that prices adjust sluggishly allowing monetary policy to have a real impact on the economy. He then finds that technological shocks do not generate recognizable business cycles and that demand shocks appear to be key drivers of aggregate fluctuations justifying the pertinence and need for monetary policy. Yet, most of the literature ignores the nature of technological change while it might be crucial to properly grasp an understanding of aggregate fluctuations. For instance, Balleer and van Rens (2013) analyze the effects of skill-biased and investment-biased technological change on hours worked over the business cycle. They find that hours worked decline after a skill-biased technological shock. However, the authors do not investigate whether these shocks are relevant in accounting for aggregate fluctuations. Yet, Jaimovich and Siu (2018) have shown that routine jobs tend to disappear sharply during short recessionary events rather than smoothly as a trend phenomenon. Though they do not explicitly identify the shocks accounting for those changes, this finding suggests that task-biased technological change might be relevant to explain aggregate fluctuations.

Overview

This thesis is composed of three chapters. They aim to grasp the implications of technological change on the French and U.S. economies and to provide explanatory models that take into account labor market specificities. The three chapters can be read independently from one another.

Chapter 1 - Transatlantic Employment Outcomes

Chapter 1 studies U.S. and France employment performances between 1982 and 2017. It reassesses the long-run structural analysis initiated by Piketty (1998). It starts with an assessment of the French employment deficit over time. In order to do so, I proceed by constructing long period time series for both France and the U.S. between 1982 and 2017 based on the French Labor Force and the U.S. Current Population Surveys. Then, I rely on those data to assess how much employment could be created and in which types of occupations. This question is crucial given the fact that technological progress has dramatically molded occupational employment prospects over the last four decades in both countries. On the basis of a detailed decomposition of the transatlantic employment gap, I investigate the extent to which cross-country discrepancies in the socio-demographic composition and occupational prospects account for the transatlantic employment gap. I find that the French employment deficit reflects first and foremost a deficit in specific occupational groups that are at the core of the reallocation process of labor induced by technological change. It is accounted for by specific socio-demographic groups that tend to face significant labor market participation decisions. Yet, the transatlantic employment gap changes significantly over time due to employment gains and losses in both countries. The transatlantic employment gap does not only reflect a disfunctioning labor market but also the occupational reallocation of labor that affects the employment prospects and participation decisions of specific socio-demographic groups. Those findings have several implications in terms of economic policies. French labor market policies should jointly support the labor demand of specific occupational groups and the labor market participation of specific socio-demographic groups, as well as occupational mobility in order to dampen the transatlantic employment gap.

Chapter 2 - Job Polarization and Unskilled Employment Losses in France

Chapter 2 examines how taxation policies interact with technological change and it assesses the extent to which these trends shape unskilled employment outcomes in France between 1982 and 2008. It deepens our understanding of the effects of technological change and labor taxation policies on employment performances by considering the task-biased nature of technological change and the distributive aspect of labor taxation policies. In particular, I argue that technological change reallocates unskilled workers from routine jobs towards manual jobs. However, this process is partly obstructed by the presence of a non-market sector producing services that are close substitutes to the manual services produced on the market. Labor taxation policies alter this reallocation process by distorting the relative value of market and non-market work. The French case is especially relevant as France experienced job polarization, deteriorating unskilled employment outcomes and significant changes in labor taxation policies, and as it displays a massive non-market sector. I rely on a parsimonious general equilibrium model with endogenous occupational choice in order to grasp how unskilled employment outcomes are molded by technological change and labor taxation policies. The model is calibrated and used to conduct a counterfactual analysis to investigate how labor taxation policies affect employment outcomes as technological change occurs. I then measure the extent to which technological and labor taxation trends account for the decline in unskilled employment in France between 1982 and 2008. I find that technological change induced significant unskilled employment losses in France between 1982 and 2008 by displacing unskilled workers from routine jobs toward manual jobs and non-market work. Those losses were enhanced by the high and increasing labor tax rates between 1982 and the mid-1990s while they have been mitigated since then by the implementation of payroll tax reduction policies targeted on low-paid workers. These policies have been especially effective in a context of job polarization.

Chapter 3 - Routine-Biased Technological Change and Hours Worked over the Business Cycle

Finally, chapter 3, which is co-authored with Idriss Fontaine, deals with the business cycle properties of routine-biased technological change in the U.S. between 1989 and 2017. We investigate how employment reacts to biased-technology shocks over the business cycle and we measure the extent to which those shocks are relevant in accounting for aggregate fluctuations. In that respect, we reassess Galí (1999)'s findings by investigating whether shifts in the composition of labor demand induced by routine-biased technology shocks can account for the recessionary effect of technology shocks on hours worked. We also reevaluate the relevance of technology shocks in driving aggregate fluctuations. We proceed by constructing quarterly time series of hours worked and task premiums by using the Outgoing Rotation Groups from the Current Population Survey between 1989 and 2017. We then estimate a SVAR model to capture the effects of task-biased technology shocks. We identify those disturbances by deriving long-run exclusion and sign restrictions from a general equilibrium model. We find that routine-biased technology shocks account for most of the decline in total hours worked through a strong fall in routine hours worked. We also argue that business cycles seem driven by non-technology shocks when technology shocks are aggregated as in Galí (1999) while they are driven by task-biased technological shocks when they are disentangled. This stresses the importance of taking into account the biased nature of technological change when studying aggregate fluctuations and designing monetary policy.

Chapter 1

Transatlantic Employment Outcomes

1.1 Introduction

Over the past four decades, the French economy has been characterized by lower employment performances than in the U.S. Economists argue that these differences in employment highlight possible malfunctioning of the French labour market. In that respect, Piketty (1998) proposes a long-run structural analysis to identify which sectors lack employment in France with respect to the U.S. Despite the fact that both countries experienced a decline in agricultural and manufacturing employment, he argues that France has not developed its service sector to the same extent as the U.S. The high labor cost appears to have obstructed the reallocation of labor across sectors.

Despite those differences, both countries experienced similar changes in their occupational structure. They both underwent job polarization as documented by Autor, Katz, and Kearney (2006) and Goos, Manning, and Salomons (2009). The occupational employment structure shifted from middle-paid jobs that perform routine tasks towards high- and low-paid jobs that perform abstract and manual tasks, respectively. This process reflects first and foremost the effects of technological change and globalization. Nevertheless, the employment gains and losses arising from this reallocation process appear to occur at different times for each country. As a consequence, omitting the occupational aspect of labor reallocation provides only a partial understanding of the transatlantic employment gap.

This chapter reassesses the long-run structural analysis initiated by Piketty (1998) by investigating the extent to which occupational and socio-demographic changes shape the transatlantic employment gap. I show that the process of job polarization is at the core of the employment dynamics in both countries and that specific socio-demographic groups account for the relative scarcity of French employment. Hence, the transatlantic employment gap does not solely reflect a disfunctioning labor market. It also reflects the occupational reallocation of labor that has been ongoing over the last four decades and which affects the employment prospects and participation decisions of specific socio-demographic groups.

I first proceed by constructing long period time series for both France and the U.S. between 1982 and 2017 based on the French Labor Force and the U.S. Current Population Surveys. Those time series include information on aggregate employment, occupational employment, the socio-demographic composition and propensities, as well as worker transitions across labor market states for both countries. Two main challenges encountered are the treatment of cross-country and time inconsistencies inherent to survey data. First, surveys are subject to important redesigns over the 1982-2017 period bringing significant discontinuities in the resulting time series. Second, countries collect survey data following different rules and methodologies making cross-country comparisons even more challenging. I tackle data discontinuities by relying on correction procedures, and cross-country inconsistencies by relying on crosswalks and finding compatibilities in variable definitions.

The resulting time series are used to produce three sets of exercises describing thoroughly transatlantic employment outcomes in light of occupational and socio-demographic trends. The first set of results describes the transatlantic employment gap. I identify whether it is accounted for by cross-country discrepancies in employment propensities or in socio-demographic compositions, which then allows to determine the occupational and socio-demographic content of the French employment deficit. In that sense, this comparative analysis builds on Piketty (1998), Cahuc and Debonneuil (2004), Passet (2015) and Catherine, Landier, and Thesmar (2015) who all have conducted similar counterfactual analyses to document the relative scarcity of French employment. This study distinguishes itself by disaggregating the transatlantic employment gap into occupational and socio-demographic groups shedding new implications in terms of economic policies. It also closely relates to Cohen, Lefranc, and Saint-paul (1997) who compare the French and U.S. labor markets. Nevertheless, the authors focus on unemployment as they consider that it is a relevant indicator to capture labor market inefficiencies. In contrast, I focus on occupational employment since the transatlantic employment gap is accounted for by both unemployment and non-participation discrepancies. Furthermore, while employment dynamics reflect unemployment changes in France, they appear to reflect non-participation in the U.S. Thus, unemployment provides only a fragmented picture of the labor market that fails to capture the deterioration of U.S. labor market outcomes. Nevertheless, the finding that a large part of the transatlantic employment gap originates from differences in the timing of employment gain and losses resonates with the authors' point that unemployment differences do not originate from the behavior of the unemployed or the institutions underlying their decisions.

The second set of results describes the employment dynamics of each country over time. I determine the extent to which the transatlantic employment gap is determined by the improvement or the deterioration of employment outcomes in each country. I quantify the extent to which those changes are due to compositional shifts or to changes in employment propensities. I also investigate the aggregate relevance of socio-demographic groups in order to identify those in the midst of this occupational reallocation process. In that respect, I rely on a decomposition method as in Cortes, Jaimovich, and Siu (2017). The latter paper focuses on routine employment changes in the U.S. The authors provide a precise description as well as explanations for those trends through a standard neoclassical model of the labor market. In that spirit, Albertini, Hairault, Langot, and Sopraseuth (2017) provide a search and matching model to quantify the employment gains and losses arising from task-biased technological change, labor market institutions, and the rising educational attainment in France, Germany and the U.S. In contrast, I do not determine the causes of those employment gains and losses. I provide an empirical assessment of transatlantic employment performances by determining the occupational and socio-demographic content of transatlantic employment discrepancies.

The final set of results analyses transatlantic employment dynamics from a transitional perspective. It relies on annual transition rate data and a series of counterfactual experiments to identify the key transitions accounting for the occupational employment dynamics. I determine whether job polarization arises from occupational mobility or non-employment adjustments in the long run. Cortes, Jaimovich, Nekarda, and Siu (2014) also study worker flows and occupational employment but they mainly focus on the disappearance of routine jobs in the U.S. They also quantify the extent to which demographic factors explain changes in key transition rates accounting for the decline in routine employment. Charlot, Fontaine, and Sopraseuth (2019) provide a more thorough comparative study on worker flows in France and the U.S. However, they focus on quantifying the contribution of labor market transitions to unemployment fluctuations, as well as the role played by job polarization in affecting labor market dualism. In contrast, I focus on long-run occupational employment trends. I determine whether workers adjust to those changes through occupational mobility or non-employment transitions.

Those findings have several implications in terms of labor market policies. First, low-skilled employment should be further supported as France started since the mid 1990s to implement of labor cost reduction policies targeted on low-paid workers. Nevertheless, the sustainability of the employment gains arising from those policies remains partly threatened by further technological and trade developments. Second, labor market policies should also provide incentives to labor market participation as most of the transatlantic employment gap is accounted for by socio-demographic groups that face important participation decisions and deteriorating employment prospects. Finally, policies should promote occupational mobility as they could dampen aggregate employment losses by allowing displaced workers to transit towards in-demand occupations.

The chapter is organized as followed. Section 1.2 provides a description of the data and correction procedures used to produce time-consistent time series comparable across countries between 1982 and 2017. Section 1.3 documents employment trends as well as job polarization for both France and the U.S. Section 1.4 analyses the transatlantic employment gap and targets the employment deficit. Section 1.5 decomposes employment dynamics in order to determine whether those dynamics are due to socio-demographic factors or changes in employment propensities. Section 1.6 determines the most important flows explaining occupational employment dynamics. Finally, section 1.7 concludes.

1.2 Data

In this section, I describe the data used and the construction of cross-country and time-consistent time series on labor market outcomes for France and U.S. between 1982 and 2017.

1.2.1 Labor force surveys and samples

France. This paper uses data from the 1982 to 2017 French Labor Force Survey (LFS) collected by the French National Institute for Statistics and Economic Studies. The French LFS is a representative sample of the French labor force. This database offers information on individuals' socio-demographic characteristics as well as their labor market and occupational status over a long period of time. The French LFS is a rotative panel. From 1982 to 2002, households were followed for at most three consecutive years. Since 2003, the French LFS became a quarterly survey in which households are followed for at most six consecutive quarters. I use this configuration to match respondents across two subsequent interviews. This allows to monitor individual transitions across labor market states and across occupations between two successive years prior to 2003 and two successive quarters since then.

United-States. For the U.S., I rely on micro data from the IPUMS Current Population Survey (CPS).[1] As for France, this survey is a representative sample of the U.S. labor force. Raw data are collected by the United-States Census Bureau allowing the Bureau of Labor Statistics to monitor U.S. labor market outcomes. The survey covers the 1982 to 2017 period as for France. The survey is a monthly rotative panel in which households are followed for at most a total of eight months. Respondents are included in the CPS for four subsequent months, they are not interviewed for the next eight months. They are then comprised again for the next four months. As for France, the longitudinal aspect of the survey enables me to identify workers' transitions across labor market states and occupations.

Samples. This chapter relies on both the French LFS and the U.S. CPS to study the evolution of aggregate employment and its occupational structure from 1982 to 2017. The study starts in 1982 because the French LFS lacks in precision about some variables prior to 1982 especially about occupational variables. It uses two samples for each country. Both of them focus on the 15 to 64 year-old working age population; military and farming occupations are excluded. The first sample contains all the observations and is used to compute aggregate labor market stocks per capita, propensities to be in a given labor market state as well as the composition of the working-age population. The second sample only keeps observations for which individuals are matched across two subsequent surveys. It is used to study individuals' transitions across labor market states and occupations.

[1] Flood, King, Rodgers, Ruggles, and Warren (2018): `https://cps.ipums.org/cps/`.

1.2.2 Variables and measurement

Occupational groups. In order to study transatlantic employment outcomes in light of job polarization, I aggregate occupations into three task groups: manual, routine and abstract jobs. For the U.S., I rely on the classification proposed by Cortes, Jaimovich, Nekarda, and Siu (2014). In this chapter, one of the main challenges is to provide cross-country comparable time series. Since occupational codes are not consistent across time and countries, I produce a handmade crosswalk for occupational codes for France. It is close to the one proposed by Albertini, Hairault, Langot, and Sopraseuth (2017) and Charlot, Fontaine, and Sopraseuth (2019). Table B.3 displays the crosswalk between occupational codes and task groups. In this study, manual occupations refer to non-routine manual occupations. Those jobs require mostly social interactions and manual dexterity. This definition of manual jobs captures the bulk of the employment growth at the bottom of the occupational mean wage distribution. Thus, manual occupations include mostly personal service workers (CSE56), some specific public service civil servants (CSE52) as well as some protective services (CES53). Routine jobs are located in the middle of the occupational mean wage distribution. They include occupations such as intermediate health and social work personnel (CSE45), intermediate business administration and commerce personnel (CSE46), foremen (CSE48), business administrative personnel (CSE54), salespeople (CSE55), drivers (CSE64), maintenance, storage and transportation workers (CSE65), skilled industry and artisan laborers (CSE62 and 63), and unskilled industry and in construction finishing laborers (CSE67 and 68). A substantial portion of those jobs has been subject to either automation or computerization since the last three decades, which explains why the middle class has been shrinking ever since. Abstract jobs include occupations that often require a relatively high diploma because of the complexity of cognitive tasks accomplished. They include occupations such as wholesalers (CSE22), heads of company (CSE23), liberal professions (CSE31), public service professionals (CSE33), professors and scientific professions (CSE34), business administration and commerce jobs (CSE37), business engineers and technicians (CSE38), intermediate health and social work personnel (CSE43), technicians (CSE47).

Stocks and socio-demographic factors. In order to study the role played by socio-demographic factors in grasping differences in transatlantic labor market outcomes, I rely on time series on aggregate employment, unemployment and non-participation per capita, as well as population shares and propensities to be in abstract, routine, manual employment, unemployment and non-participation for 12 socio-demographic groups depending on

- Gender: men, women;
- Age: 15-25 (young), 26-54 (prime-aged) and 55-64 (old);
- Education: at most a high school degree and more than a high school degree.

Since surveys have been subject to significant modifications in both countries, I build those variables by proceeding as followed. First, I construct aggregate time series on employment, unemployment and non-participation per capita as the fraction of individuals in the considered state over the 15-64 year-old working age population. Then, I construct employment shares for 36 gender $\times$ age $\times$ education $\times$ task groups, as well as unemployment and non-participation shares for 12 gender $\times$ age $\times$ education groups. I correct them for breaks as described in subsection 1.2.3. I use the resulting time series to obtain cross-country and time-consistent time series for aggregate stocks, population shares and propensities to be in a given labor market state for each of the 12 gender $\times$ age $\times$ education groups between 1982 and 2017.

Labor market transitions. I use information on the labor market status and occupational categories of individuals to construct transition rates across five labor market states: abstract, routine, manual employment, unemployment and non-participation for both France and the U.S. In that respect, I closely relate to Charlot, Fontaine, and Sopraseuth (2019). The evolution of stocks is described by the following law of motion

$$S_t = P_{t-1} S_{t-1} \tag{1.1}$$

with $S_t = [A_t\, R_t\, M_t\, U_t\, N_t]'$ the fraction of the working age population in each state. The transition matrix P_{t-1} gives transition rates $P_{ij,t-1}$ from state i in $t-1$ to state j in t. I choose to construct annual transition probabilities to produce consistent time series covering the 1982 to 2017 period.[2] Low-frequency transition rates omit within-year transitions but they nevertheless capture long-run labor market trends which is the aim of this paper.

[2]While CPS data are collected at a monthly frequency, French data were collected annually prior to 2003 and quarterly since then.

I build those transition rates by relying on the longitudinal aspect of U.S. and French labor force surveys. For the U.S., I first match monthly CPS files at annual intervals. I obtain yearly transition rates at a monthly frequency.[3] Then, I average over each year to obtain annual rates observed at a yearly frequency. The resulting time series are corrected for breaks as described in subsection 1.2.3 and then for margin errors as in Elsby, Hobijn, and Şahin (2015).[4] In the case of France, I match annual surveys before 2003 which gives annual transition rates at an annual frequency.[5] Since 2003, the survey became quarterly. I match individuals across quarters at annual intervals which yields yearly transition rates observed at a quarterly frequency. Similarly to the U.S., I then average the resulting transition rates over each year to obtain annual transition rates observed at a yearly frequency. I also correct the resulting time series for breaks and margin errors. Transition rates are displayed in Figures A.2 to A.11.

1.2.3 Break correction

French and U.S. long period time series are both subject to sharp discontinuities. I first describe why such breaks occur for each country. I then present subsequently the two models used to correct those breaks.[6]

Data discontinuities. Long period time series built from the French LFS are subject to two significant breaks because of two major redesigns and changes in classifications. The first redesign was implemented in 1990 when the sample was renewed. The questionnaire was modified notably concerning the collection of information on education. Moreover, interviews switched to computer-assisted classification of occupations. The second redesign occurred in 2003. The survey shifted from an annual rotating panel to a quarterly one. Additionally, the occupational classification changed from the PCS1982 to the PCS2003.

Long period time series for the U.S. are subject to three important breaks due to survey redesigns and changes in classifications. For instance, the occupational classification changed in 1983 introducing

[3]Transition rates are missing in several months due to changes in sample identifiers and in occupational classifications. I replace those missing data by the observations of the same month of the previous year.

[4]Appendix A.2 provides a description of the margin error correction.

[5]Observations for 1990 and 2002 are missing for the same reason as for U.S. data. I replace those with the previous yearly observations.

[6]The models are similar to those of the French National Statistical Institute (INSEE) to compute long-run time series: `https://www.insee.fr/fr/statistiques/2388195?sommaire=2045174#documentation`.

some discontinuity in aggregate time series.[7] In 1993, a redefinition of education variables introduced breaks in educational-based times series (Jaeger, 1997). In 1994, the survey experienced the most drastic redesign over the time period considered. The aim was to improve the quality of the data by introducing a new questionnaire and modernized data collection methods (R Cohany, Polivka, and M Rothgeb, 1994). Such modifications pose a challenge for constructing long period time series that I tackle by using correction factors.

Additive factor correction. The first model allows to correct time series by an additive factor. This correction procedure is used on sufficiently aggregated time series namely aggregate labor market stocks.[8] It is based on a local estimation of a linear model. It works in four steps. First, I consider a number of sufficiently aggregated variables $\widetilde{y}_{s,t}$ that lie between zero and one, and sum to one $\sum_{s=1}^{S} \widetilde{y}_{s,t} = 1$. I choose a reference category arbitrarily $\widetilde{y}_{S,t}$. Second, I regress raw variables $\widetilde{y}_{s,t}$ (except for the reference category) on a time trend and a dummy variable that is equal to one when observations precede the break date:

$$\tilde{y}_{s,t} = \beta_{0,s} + \beta_{1,s} t + \beta_{2,s} \mathbb{1}\left\{t < Break\right\} + \varepsilon_{s,t}. \tag{1.2}$$

The model is estimated on a restricted sample of five years around the break date representing a number of five observations for yearly data. Third, I treat raw time series $\widetilde{y}_{s,t}$ by subtracting the OLS estimated break coefficient $\hat{\beta}_{2,s}$ to observations that precede the break date in order to obtain a corrected variable $\widetilde{y}_{s,t}$:

$$y_{s,t} \quad = \quad \tilde{y}_{s,t} - \hat{\beta}_{2,s} \mathbb{1}\left\{t < Break\right\}. \tag{1.3}$$

Fourth, I impute the remaining reference time series such that the sum of the variables equals one:

$$y_{S,t} \quad = \quad 1 - \sum_{s=1}^{S-1} y_{s,t}. \tag{1.4}$$

The resulting variables $y_{s,t}$ are considered to be corrected for the considered break.

[7] Changes in occupational classifications also occurred in 1992, 2003 and 2011 but they don't fracture time series especially after aggregating occupational groups as in Cortes, Jaimovich, Nekarda, and Siu (2014).

[8] Aggregate, abstract, routine and manual employment per capita as well as unemployment, non-participation per capita are treated with the additive factor.

Multiplicative factor correction. In some cases, the additive factor correction is not suited. For instance, it can lead to negative numbers while corrected time series should lie within the unit interval. Such occurrences emerge when time series are close to zero and subject to important breaks. This is especially the case when one considers disaggregated variables.[9] In that case, I rely on a multiplicative factor correction model. It is a variant of the additive model. It also works in four steps. First, I consider a number of variables $\widetilde{y}_{s,t}$ that lie between zero and one, and sum to one $\sum_{s=1}^{S} \widetilde{y}_{s,t} = 1$. I choose a reference category arbitrarily $\widetilde{y}_{S,t}$. Second, I estimate a logistic variant of the model described by equation 1.2:

$$\tilde{z}_{s,t} \quad = \quad \beta_{0,s} + \beta_{1,s} t + \beta_{2,s} \mathbb{1}\left\{t < Break\right\} + \varepsilon_{s,t} \tag{1.5}$$

where $\tilde{z}_{s,t} = ln\left(\tilde{y}_{s,t}/\tilde{y}_{S,t}\right)$. The model is estimated on a restricted sample of five years around the break date representing a number of five observations for yearly data. Third, I treat raw time series by subtracting the OLS estimated break coefficient $\hat{\beta}_{2,s}$ to observations preceding the break date:

$$z_{s,t} \quad = \quad \tilde{z}_{s,t} - \hat{\beta}_{2,s} \mathbb{1}\left\{t < Break\right\} \tag{1.6}$$

where $z_{s,t} = ln\left(y_{s,t}/y_{S,t}\right)$. Fourth, I recover the relevant time series by inverting the logistic transform:

$$y_{S,t} \quad = \quad \frac{1}{1 + \sum_{s=1}^{S-1} e^{z_{s,t}}} \tag{1.7}$$

$$y_{s,t} \quad = \quad y_{S,t} e^{z_{s,t}}. \tag{1.8}$$

As previously, the resulting variables $y_{s,t}$ are considered to be corrected for the break.

1.3 Aggregate employment and job polarization

In this section, I first broadly document aggregate employment, unemployment and non-participation dynamics to capture transatlantic employment performances. Second, I decompose aggregate employment by occupational groups to show that both countries underwent job polarization.

[9] Employment, unemployment and non-participation shares by socio-demographic groups and transition probabilities are treated with the multiplicative factor.

1.3.1 Aggregate employment outcomes

Figure 1.1 – Employment, unemployment and non-participation per capita

Notes: the sample includes the 15-64 year-old working age population. Military and farming occupations are excluded.

Transatlantic labor market performances are computed as the fraction of the working age population in employment, unemployment and non-participation. In that respect, Figure 1.1 displays the dynamics of aggregate employment, unemployment and non-participation per capita between 1982 and 2017.

On average, employment performances in France are lower than in the U.S. This is reflected by higher unemployment and also lower labor market participation. Indeed, average employment per capita in France is of 61.89% against 69.29% in the U.S. while average unemployment and non-participation per capita are of 6.63% and 31.49% in France against 4.57% and 26.14% in the U.S.

The two countries exhibit opposite employment dynamics. Their employment performances first diverge from 1982 to 1998 and then converge. In France, employment per capita first declines from 62.85% to 60.33% between 1982 and 1998. It then increases by 4.06 pp to reach 64.39% in 2017. Most of this increase occurs in the late 1990s. On the contrary, U.S. employment per capita first increases from 64.97% to 72.56% between 1982 and 1998. It then decreases by 3.74 pp to reach 68.82% in 2017. It should be noted however that most of the decline occurs during economic recessions and that aggregate employment recently increases.

Long-run employment dynamics appear to be foremost reflected by unemployment dynamics in France and by non-participation dynamics in the U.S. In France, unemployment mirrors the non-monotonous employment dynamics. It first increases from 4.63% to 7.99% between 1982 and 1998 while it falls by 1.14 pp to reach 6.85% in 2017. Most of this decline occurred during the late 1990s and early 2000s. On the contrary, non-participation follows a steady downward trend. It falls steadily from 32.52% to 28.76% over the entire time period. In the U.S., unemployment absorbs the cyclical variations in employment while non-participation mostly mirrors its non-monotonous long-run pattern. For instance, unemployment per capita increases by 3.59 pp between 2007 and 2010 reflecting the effect of the Great recession. On the contrary, non-participation dynamics are smoother. It first decreases from 28.29% to 23.96% between 1982 and 2000 and then increases by 4.03 pp to reach 27.99% in 2017. Thus, employment is the relevant indicator when comparing French and U.S. labor markets. Unemployment does not fully capture the ongoing changes affecting them.

1.3.2 Job polarization

Despite differences in their aggregate employment dynamics, France and the U.S. are both subject to routine-biased technological change and globalization which lead to the polarization of their occupational employment structure.

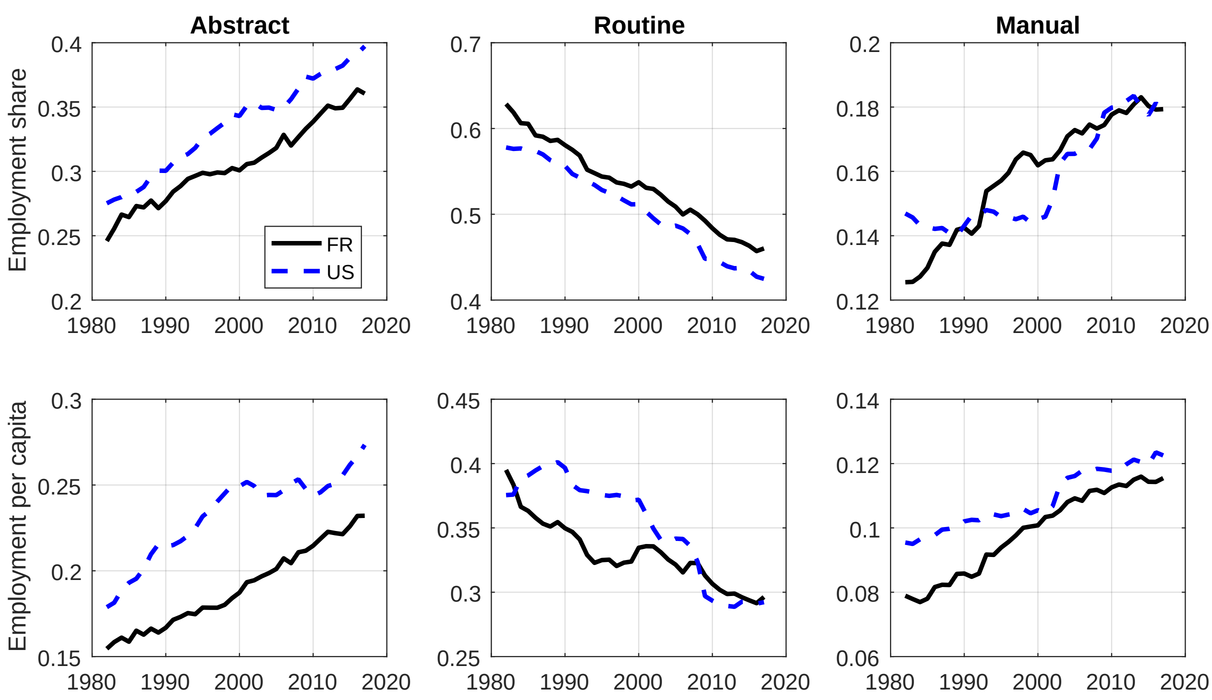

Figure 1.2 – Employment share and per capita by occupational groups
Notes: the sample includes the 15-64 year-old working age population. Military and farming occupations are excluded.

Figure 1.2 depicts the abstract, routine and manual employment shares (first row) and employment per capita for each occupational groups (second row). As documented by Goos, Manning, and Salomons (2009), Albertini, Hairault, Langot, and Sopraseuth (2017) and Charlot, Fontaine, and

Sopraseuth (2019), both France and the U.S. experience job polarization mainly because of the diffusion of new technologies and the rise of import competition. The occupational shifts away from routine jobs towards both abstract and manual jobs over the entire period studied reflect the substitution of capital for routine labor. Those changes in employment shares also reflect changes in employment per capita. Routine employment per capita declines while abstract and manual employment per capita increase significantly over the entire time span in both countries.

1.4 The transatlantic employment gap

In this section, I account for cross-country differences in employment outcomes over time. First, I compare the average socio-demographic composition and employment propensities in France and the U.S. Then, I grasp the extent to which those components account for the employment gap over time. Furthermore, I identify the occupational nature and the socio-demographic structure of the French employment deficit. I further identify the extent to which the French employment deficit translates into unemployment and non-participation.

1.4.1 Socio-demographic composition and propensities

Differences in employment outcomes arise from discrepancies either in the socio-demographic composition of the working age population or in employment propensities. Thus, I document the average propensities and socio-demographic composition to roughly grasp similarities and discrepancies across countries. The demographic composition of a country is captured by the fraction of type g individuals in the total working age population $\theta_{g,t}$. The propensities of type g individuals to be in the state $S_{g,t}$ is defined as the fraction of the type g working age population in the considered state.

Table 1.1 documents the average demographic composition as well as propensities to be employed by task for each aggregate socio-demographic group in both countries.[10] On average, there are significant cross-country differences in the educational composition, as well as in propensities of young and old individuals to be employed. For instance, France is only composed by 19.78% of individuals with at least a high school degree against 30.45% for the U.S. The propensity to be

[10] Table A.3 reports those figures for each of the twelve disaggregated demographic categories.

	France				U.S.			
	θ	E	U	N	θ	E	U	N
Gender								
Men	48.74	68.58	6.54	24.87	48.84	75.92	5.10	18.98
Women	51.26	55.53	6.71	37.76	51.16	62.99	4.06	32.96
Age								
Young	21.02	30.72	8.24	61.05	21.67	50.83	7.25	41.93
Prime-aged	62.58	79.11	7.10	13.79	63.32	78.23	4.13	17.63
Old	16.40	34.93	2.57	62.51	15.01	57.17	2.49	40.34
Diploma								
>HSD	19.78	79.73	4.76	15.51	30.45	83.40	2.68	13.92
≤HSD	80.22	57.42	7.08	35.50	69.55	63.10	5.37	31.53

Table 1.1 – Average composition and propensities by socio-demographic groups

Notes: 15-24 year-olds (Young), 25-54 year-olds (Prime-aged), 55-64 year-olds (Old), with at most a high school degree (≤HSD), with more than a high school degree (>HSD). E, U and N refer respectively to aggregate employment, unemployment and non-participation propensities.

employed for the most qualified group is approximately 20 pp higher than for the less qualified group in both countries. Furthermore, despite a similar age structure, the propensity to be employed across different age groups varies significantly. It is much lower for young and old individuals in France compared to the U.S. with 30.72% and 34.93% in France and 50.83% and 57.17% in the U.S.

On the contrary, employment propensities of prime-aged individuals are slightly higher in France (79.11%) than in the U.S. (78.23%). Moreover, both countries have a similar gender and age composition but different educational structures. The working age population of both countries is composed of approximately 51% of women and 49% of men. It contains roughly 63% of prime-aged workers against around 21% of young and 16% of old individuals. At first sight, transatlantic employment differences are emanating from discrepancies in employment propensities by age and in the skill composition of the working age population.

1.4.2 The transatlantic employment gap

I now describe the transatlantic employment gap. I quantify the importance of socio-demographic and propensity discrepancies in accounting for the employment gap. I proceed by decomposing the employment gap across time, occupational and socio-demographic groups. In doing so, I reassess the long-run structural analysis initiated by Piketty (1998) and determine the occupational nature of the French employment deficit.[11]

Employment per capita in country c at time t (E^c_t) is a by-product of propensities and sizes of socio-demographic groups. Hence, it can be written as

$$E^c_t = \sum_{g=1}^{G} \theta^c_{g,t} E^c_{g,t} \tag{1.9}$$

where $E^c_{g,t}$ is defined as the group g propensity to be employed in country c. The socio-demographic composition of the working age population is captured by $\theta^c_{g,t}$ which is the fraction of type g individuals in the overall working age population of country c. Based on equation (1.9), the transatlantic employment gap $G_{obs,t}$ is defined as

$$G_{obs,t} = \sum_{g=1}^{G} \left(\theta^{us}_{g,t} E^{us}_{g,t} - \theta^{fr}_{g,t} E^{fr}_{g,t}\right). \tag{1.10}$$

A positive employment gap means that there is an employment deficit in France with respect to the U.S. The employment gap is then decomposed into a demographic component ($G_{dem,t}$) and a propensity component ($G_{pro,t}$) such that

$$G_{obs,t} = \underbrace{\sum_{g=1}^{G}(\theta^{us}_{g,t} - \theta^{fr}_{g,t})\frac{E^{us}_{g,t} + E^{fr}_{g,t}}{2}}_{G_{dem,t}} + \underbrace{\sum_{g=1}^{G}(E^{us}_{g,t} - E^{fr}_{g,t})\frac{\theta^{us}_{g,t} + \theta^{fr}_{g,t}}{2}}_{G_{pro,t}}. \tag{1.11}$$

On the one hand, the propensity component measures the employment deficit arising from discrepancies in employment propensities between countries. On the other hand, the demographic component measures the contribution of discrepancies in the socio-demographic composition of the working age population to the transatlantic employment gap.

Table 1.2 reports the transatlantic employment gap decomposition in 1982, 1998 and 2017. The employment gap evolves dramatically over the period studied mostly because of substantial changes in employment propensities. First, it starts at 2.12 pp in 1982 and then increases substantially in 1998 to attain 12.24 pp. It then declines to reach 4.44 pp in 2017. Employment propensities account for only 0.83 pp of the employment gap in 1982. Their contribution rises dramatically to reach

[11] Piketty (1998) uses a slightly different method presented in Appendix A.1. The decomposition that I use delivers similar results as well as an exact decomposition of the transatlantic employment gap.

	1982			1998			2017		
	G_{dem}	G_{pro}	G_{obs}	G_{dem}	G_{pro}	G_{obs}	G_{dem}	G_{pro}	G_{obs}
Abstract	5.59	-3.17	2.42	5.12	1.38	6.50	3.51	0.62	4.13
Routine	-3.58	1.62	-1.96	-2.83	7.99	5.16	-1.66	1.26	-0.40
Manual	-0.72	2.38	1.65	-1.09	1.68	0.58	-1.09	1.80	0.71
Employment	1.29	0.83	2.12	1.19	11.05	12.24	0.76	3.68	4.44

Table 1.2 – Decomposition and occupational content of the transatlantic employment gap
Notes: values are in percentage points. G_{dem} and G_{pro} capture respectively transatlantic employment per capita differences accounted for by discrepancies in the socio-demographic composition and employment propensities. They add up to the observed employment gap G_{obs}.

11.05 pp in 1998 and then declines to 3.68 pp in 2017. This represents an employment deficit of 4.1 million jobs in 1998 and 1.5 million jobs in 2017 against only 0.2 million jobs in 1982.[12] On the contrary, discrepancies in the socio-demographic composition between both countries account for approximately 1 pp of the employment gap across time.

I now determine the occupational nature of the employment deficit induced by propensity discrepancies. The employment deficit translates mostly into a lack in routine and manual occupations. In 1982, the employment deficit induced by propensity discrepancies is relatively small (0.83 pp). Manual occupations account for 2.38 pp of this deficit against 1.62 pp for routine occupations. On the contrary, abstract occupations contributed for -3.17 pp which means that abstract employment propensities are higher in France at that time. In 1998, the employment gap reaches its peak. Routine occupations account for 72.31% of the 11.05 pp employment deficit. On the contrary, manual and abstract occupations account for only 15.20% and 12.49% of the employment deficit, respectively. Hence, 2.9 out of the 4.1 million job deficit is accounted for by a lack in routine occupations in France compared to the U.S. against 0.62 and 0.51 million manual and abstract jobs, respectively. In 2017, the employment deficit induced by propensity discrepancies declined drastically by 3.68 pp. Routine jobs now account for 34.24% of the employment deficit against 48.91% and 16.85% for manual and abstract jobs, respectively. As shown further, this contraction is mainly accounted for by a significant decline in U.S. routine employment and a stabilization of French routine employment leading to a convergence in routine employment per capita of both countries.

The employment gap arising from compositional discrepancies of the working age population is

[12] There are 28,421,272 individuals aged between 15 and 64 years old in 1982 against 36,635,560 in 1998 and 40,400,668 in 2017. Hence, for example, the employment gap induced by discrepancies in employment propensities measured in number of jobs is equal to $36,635,560 \times 11.05\% = 4,048,229$ in 1998.

entirely accounted for by lack in abstract employment for any period considered. For instance, it accounts for 5.59 pp in 1982, 5.12 pp in 1998 and 3.51 pp in 2017. The U.S. socio-demographic composition is more intensive in groups usually holding abstract jobs which are located at the top of the wage distribution. Those groups are characterized by higher employment propensities.

Hence, the transatlantic employment gap does not solely reflect a disfunctioning labor market but also the occupational reallocation of labor that has been ongoing over the last four decades. France is characterized by a relatively high labor cost on low-skilled labor but also by technological and trade developments which all affect low-skilled employment prospects. The high labor cost in France is due to the high level of labor taxation and minimum wage. It interacts with the occupational reallocation of labor. On the one hand, it obstructs the reallocation of low-skilled workers which leads to low manual employment gains. On the other hand, it deepens the disappearance of routine jobs by accelerating the substitution of automation devices for routine labor.[13]

Those findings shed a new light on the conclusion drawn by Piketty (1998), Cahuc and Debonneuil (2004) and Catherine, Landier, and Thesmar (2015). The authors argue that the high labor cost in France prevents the reallocation of labor from the manufacturing sector towards service sectors which rely intensively on low-paid workers. In that respect, labor cost reduction policies targeted on low-paid workers implemented in France since the mid 1990s are especially effective to diminish the French employment deficit. However, by disregarding the occupational nature of jobs, those studies omit that a significant amount of the French employment deficit is composed of routine jobs which are jeopardized by technological change and globalization. Hence, reducing the labor cost of low-skilled workers might generate important manual and routine employment gains. However, part of those gains might not be sustainable as they will remain threatened by further technological and trade developments.

1.4.3 Decomposition by socio-demographic groups

I now describe how these composition and propensity discrepancies are distributed across socio-demographic groups. I show that they are concentrated in some key groups.

Figure 1.3 displays the contribution of each socio-demographic group to the employment gap for discrepancies in both composition (left panels) and employment propensities (right panels) over time. In 1982, the employment deficit induced by employment propensity discrepancies (G_{pro}) is negligible. It is mainly accounted for by a lack in manual employment from young low-skilled individuals. They account for 3.41 pp of the propensity component (0.83 pp), from which 62.80% arise from manual occupations against 27.61% and 9.59% from routine and abstract occupations, respectively. The lower employment outcomes of French young low-skilled individuals are partly offset by the higher employment outcomes of prime-aged workers. They account for -4.16 pp of the propensity component, from which 81.47% arise from an excess in French abstract employment propensities.

In 1998, all socio-demographic groups contribute to the deterioration of French employment outcomes relatively to the U.S. Nevertheless, it originates primarily from a deficit in routine jobs for low-skilled young and senior individuals. Their contribution adds up to a total of 8.04 pp. This represents 72.78% of the employment deficit from which 63.70% stem from a deficit in routine jobs against 22.34% and 13.66% from manual and abstract jobs, respectively. Thus, out of the 4.1 million job deficit in 1998, 3.0 million concern low-skilled young and senior individuals out of which 1.9 million stem from a lack in routine occupations. In 2017, the employment deficit is still significant but falls sharply. French low-skilled young and senior individuals still suffer from lower employment prospects with respect to the U.S. They contribute for 4.37 pp to the employment deficit from which 56.84% arise from routine occupations against 24.29% and 18.87% from manual and abstract occupations, respectively.

[13] Acemoglu, Manera, and Restrepo (2020) argue that the U.S. tax system favors excessive automation leading to a suboptimal employment level. France has a much higher labor tax burden than the U.S. In that respect, one would expect a higher degree of automation and a lower level of employment than in the U.S. In that respect, Piketty (1998) suggests that automation is more intense in the hospitality sector in France and that large commercial stores usually employ more workers in the U.S. because of its low labor cost relative to France. Thus, the French employment deficit reflects the deteriorating effect of its high labor cost and the excessive use of automation technologies even in some service sectors.

The composition component (G_{dem}) is accounted for by discrepancies in the educational composition of the working age population at all time. For instance, discrepancies in the share of high-skilled workers in the working age population account for 9.29 pp against -8.00 pp for low-skilled workers in 1982. Despite the fact that those differences are persistent, they slowly diminish across time. Discrepancies in the share of high-skilled workers account for 6.72 pp against -5.96 pp for low-skilled workers in 2017.

Hence, the lower employment outcomes in France are first and foremost accounted for by low-skilled young and senior individuals in routine and manual occupations to a lesser extent. Those agents are facing two major challenges. First, they lie at both edges of the labor market. On the one hand, youth employment depends on the ability to acquire skills and adapt those skills to the firms' need. Furthermore, those individuals suffer from unstable job prospects due to the segmentation of work contracts. On the other hand, senior employment depends on the retirement option value. Second, the employment prospects of low-skilled workers are the most affected by technological change and the rise in trade exposure since they tend to hold routine occupations. The employment gap is also partly accounted for by the lower skill intensity of the working age population in France. This means that there are still potential employment gains to be made by increasing the education level in France.

1.4.4 Non-employment

Until now, the transatlantic employment gap was analyzed through the lens of occupational employment. I now depict how employment discrepancies translate into non-employment. It is key to determine whether propensity discrepancies take the form of unemployment or non-participation for at least two reasons. First, high non-participation could reflect labor market exclusion due both to low employment prospects induced by technological change and the low option value of labor. Second, unemployed have more intense job search behavior than non-participants. Hence, they have a greater probability to return to employment than non-participants.

The French employment deficit reflects either higher unemployment propensities or higher non-participation propensities or a mix of both. In that respect, employment per capita expressed in equation (1.9) can be written as a function of unemployment rates $u^c_{g,t}$ and non-participation per capita ratios $N^c_{g,t}$ as follows

$$E^c_t = \sum_{g=1}^{G} \theta^c_{g,t} \left(1 - u^c_{g,t}\right) \left(1 - N^c_{g,t}\right). \tag{1.12}$$

where the unemployment rate $u^c_{g,t}$ is defined as the fraction of unemployed in the labor force ($U^c_{g,t}/(1 - N^c_{g,t})$). The transatlantic employment gap is decomposed as previously except that now the propensity component ($G_{pro,t}$) itself is broken down into two components related to cross-country differences in unemployment rates ($G_{pro,u,t}$) and non-participation per capita ratios ($G_{pro,N,t}$)

$$\begin{aligned} G_{pro,t} = & \underbrace{\sum_{g=1}^{G} \left(u^{fr}_{g,t} - u^{us}_{g,t}\right) \frac{\left(1 - N^{us}_{g,t} + 1 - N^{fr}_{g,t}\right)}{2} \frac{\left(\theta^{us}_{g,t} + \theta^{fr}_{g,t}\right)}{2}}_{G_{pro,u,t}} \\ & + \underbrace{\sum_{g=1}^{G} \left(N^{fr}_{g,t} - N^{us}_{g,t}\right) \frac{\left(1 - u^{us}_{g,t} + 1 - u^{fr}_{g,t}\right)}{2} \frac{\left(\theta^{us}_{g,t} + \theta^{fr}_{g,t}\right)}{2}}_{G_{pro,N,t}}. \end{aligned} \tag{1.13}$$

	$G_{pro,u}$	$G_{pro,N}$	G_{pro}
1982	-1.85	2.68	0.83
1998	5.32	5.72	11.05
2017	3.78	-0.10	3.68

Table 1.3 – Non-employment content of the French employment deficit
Notes: values are in percentage points. $G_{pro,u}$ and $G_{pro,N}$ capture the contribution of unemployment rate and non-participation ratio discrepancies to the propensity component G_{pro}.

Table 1.3 displays the contribution of unemployment rate and non-participation ratio discrepancies to the French employment deficit over time. While high unemployment is a salient feature of the deterioration of French employment outcomes, non-participation is at the core of French lower employment prospects. In 1982, the higher non-participation propensities in France contributed for 2.68 pp to the employment deficit but it is partly dampened by lower unemployment rates which contributed for -1.85 pp. This explains why the employment gap induced by propensity discrepancies is negligible at that time. In 1998, French employment outcomes significantly deteriorate relatively to the U.S. This reflects both into higher unemployment rates (5.32 pp) and higher non-participation (5.72 pp). While the contribution of unemployment rate discrepancies increases more than non-participation discrepancies, the latter explains 51.76% of the 11.05 pp employment deficit against

48.14% for unemployment rates. In 2017, the French employment outcomes are still lower than in the U.S. but they significantly improve. Unemployment rate discrepancies appear to account for all of the employment deficit (3.78 pp) while the excess in non-participation appears to shrink on aggregate (-0.10 pp). However, those figures hide significant heterogeneity across socio-demographic groups.

Figure 1.4 decomposes the propensity component across socio-demographic groups as previously except that now it does so through the lens of non-employment rather than occupational employment. Two main observations arise from this decomposition. First, the French employment deficit is first and foremost due to an excess in non-participation of low-skilled young and senior individuals. As explained previously, those groups are the main contributors to the lower employment outcomes in France at any period considered. They contribute for 72.78% of the French employment deficit in 1998 when the employment gap is at its highest. This contribution is primarily accounted for by lower labor market participation propensities and higher unemployment rates to a much lower extent. For instance, in 1998, non-participation and unemployment discrepancies account for 82.29% and 17.71% of the employment deficit arising from those two groups. Thus, the French employment deficit is first and foremost a labor market participation issue rather than an unemployment issue.

Second, although labor market participation is crucial to explain the employment deficit, the rise in unemployment is a salient feature of the French labor market. Nevertheless, the contribution of unemployment discrepancies to the employment deficit is primarily accounted for by prime-aged individuals who have similar employment prospects than in the U.S. In 1998, this group accounts for only 15.55% of the employment deficit. Unemployment rate discrepancies account for 3.67 pp against -1.95 pp for non-participation discrepancies. In 2017, prime-aged individuals in France have even higher employment propensities than in the U.S. as their contribution to the employment deficit reaches -1.55 pp. Even though they have higher unemployment propensities (2.24 pp), they have significantly higher labor market participation propensities (-3.79 pp). Although the rise of unemployment is a salient feature of the lower French labor market performances, it is only the tip of the iceberg. The lower French employment outcomes translate first and foremost into a lack in labor market participation of socio-demographic groups challenged both by their position on the labor market and by structural changes in the economic environment.

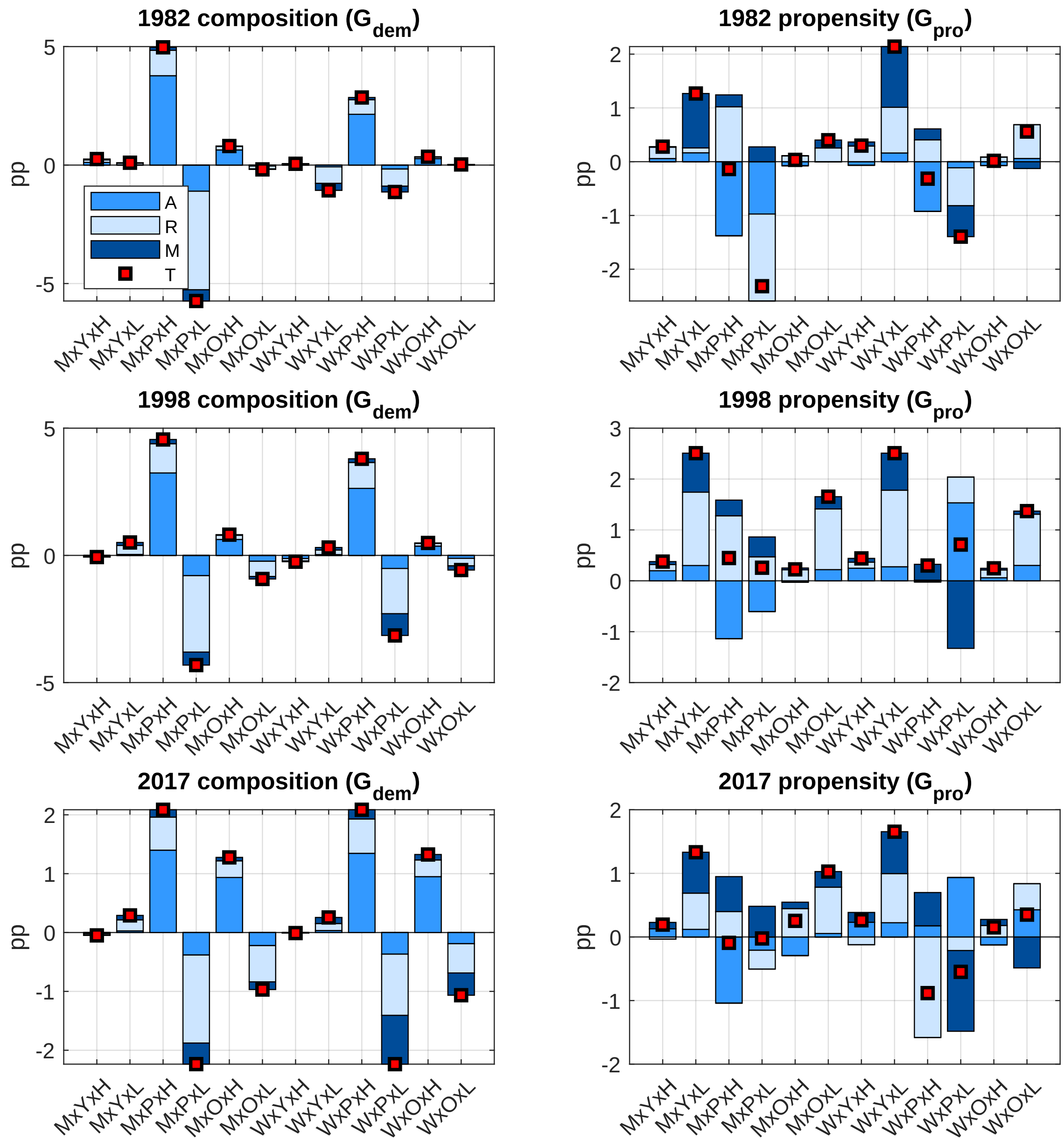

Figure 1.3 – Decomposition and occupational content of the transatlantic employment gap by socio-demographic groups

Notes: men (M), women (W), 15-24 year-olds (Y), 25-54 year-olds (P), 55-64 year-olds (O), with at most a high school degree (L), with more than a high school degree (H). A, R and M refer to abstract, routine, manual components, respectively, where $T = A + R + M$. Values are in percentage points (pp).

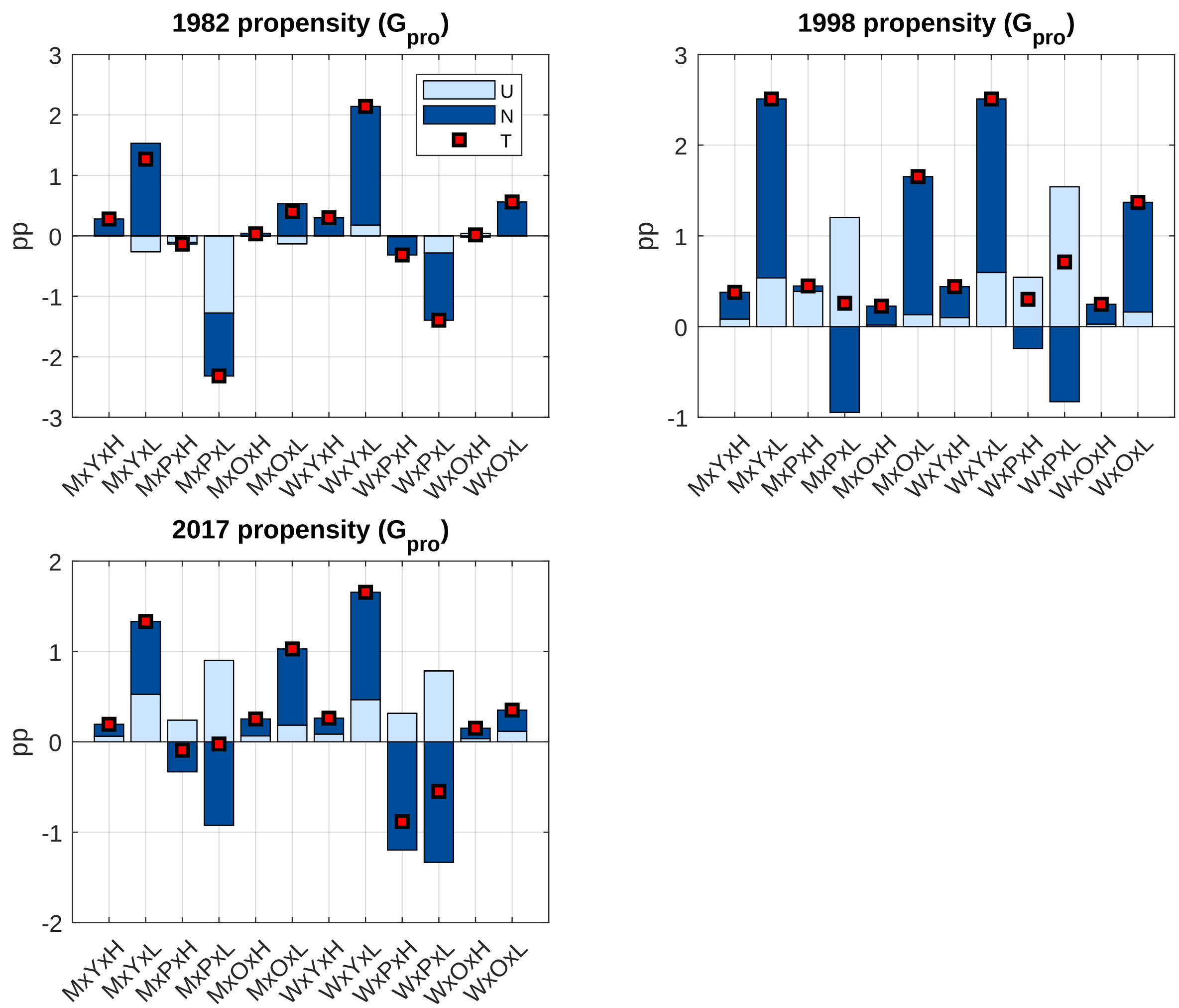

Figure 1.4 – Non-employment content of the French employment deficit by socio-demographic groups
Notes: men (M), women (W), 15-24 year-olds (Y), 25-54 year-olds (P), 55-64 year-olds (O), with at most a high school degree (L), with more than a high school degree (H). u and N refer to unemployment rate and non-participation components, respectively, where $T = u + N$. Values are in percentage points (pp).

1.5 Employment dynamics

This section describes the employment dynamics that shape the transatlantic employment gap over time. It allows to determine whether changes in this gap occur through an improvement in employment performances in one country or through the deterioration in employment performances in the other country. Then, it depicts the aggregate relevance of socio-demographic groups in explaining occupational employment dynamics.

1.5.1 Employment change decomposition

As mentioned previously, the fraction of individuals in a state S_t is a by-product of propensities and sizes of socio-demographic groups. Hence, it can be written as

$$S_t = \sum_{g=1}^{G} \theta_{g,t} S_{g,t} \tag{1.14}$$

where $S_{g,t}$ is defined as the group g propensity to be in the state S. The socio-demographic composition of the working age population is captured by $\theta_{g,t}$ which is the fraction of type g individuals in the overall working age population. Based on equation (1.14), changes in the stock S_t between an initial year t_0 and final year t_1 are defined as

$$\underbrace{\Delta S_{t_1}}_{\text{(C4)}} = \underbrace{\sum_{g=1}^{G} \theta_{g,t_0} \Delta S_{g,t_1}}_{\text{(C1)}} + \underbrace{\sum_{g=1}^{G} \Delta\theta_{g,t_1} S_{g,t_0}}_{\text{(C2)}} + \underbrace{\sum_{g=1}^{G} \Delta\theta_{g,t_1} \Delta S_{g,t_1}}_{\text{(C3)}}. \tag{1.15}$$

Hence, changes in a stock (C4) is decomposed into three aggregate components. The propensity component (C1) reflects changes in the aggregate stock S_t induced by variations in propensities for a given population structure. The composition component (C2) captures changes in the considered stock due to shifts in the socio-demographic composition of the working age population given employment propensities. The interaction component (C3) captures changes in the stock S_t owed to co-movements in propensities and group sizes.

	Level		Difference			
	1982	1998	Propensity (C1)	Composition (C2)	Interaction (C3)	Total (C4)
France						
Employment	62.85	60.32	-7.43	4.05	0.85	-2.53
Abstract	15.46	18.02	-2.40	5.89	-0.93	2.56
Routine	39.51	32.30	-7.52	-1.42	1.73	-7.21
Manual	7.89	10.00	2.48	-0.41	0.04	2.11
Unemployment	4.63	7.99	3.51	-0.39	0.24	3.36
Non-Participation	32.52	31.69	3.92	-3.66	-1.09	-0.82
U.S.						
Employment	64.97	72.56	4.64	2.90	0.04	7.58
Abstract	17.88	24.51	2.29	4.38	-0.03	6.63
Routine	37.55	37.46	0.50	-0.71	0.12	-0.09
Manual	9.55	10.59	1.85	-0.76	-0.04	1.04
Unemployment	6.73	3.48	-3.00	-0.35	0.09	-3.25
Non-Participation	28.29	23.96	-1.64	-2.55	-0.14	-4.33

Table 1.4 – Employment changes between 1982 and 1998

Notes: levels are in percentage while differences are in percentage points. The sum of the propensity (C1), composition (C2) and interaction (C3) components amounts to the total change (C4).

Transatlantic employment outcomes between 1982 and 1998

Table 1.4 reports the decomposition of changes in employment, unemployment and non-participation per capita between 1982 and 1998. As previously mentioned, employment performances of both countries diverge drastically during that period. The transatlantic employment gap increases by 10.12 pp between 1982 to 1998. The rising discrepancy in employment between the two countries is due both to rising employment opportunities in the U.S. and to deteriorating employment prospects in France. Indeed, aggregate employment per capita rises by 7.58 pp in the U.S. while it decreases by 2.53 pp in France.

The rising employment discrepancy is explained by an excess fall in routine employment in France. Routine employment stays stable (-0.09 pp) in the U.S. over the 1982 to 1998 period. On the contrary, it plummets by -7.21 pp in France because of a massive drop in routine employment prospects (-7.52 pp). Hence, despite starting with higher routine employment per capita, France reaches a much lower level than the U.S. in 1998.

The rising employment discrepancy is also due to a lack in abstract employment growth in France. It only increases by 2.56 pp. This is explained by a strong compositional shift (5.89 pp) reflecting the rise in skill supply dampened by declining employment propensities (-2.40 pp). Meanwhile, in the U.S., abstract employment rises by 6.63 pp. This surge is due to both compositional shifts (4.38 pp) as well as rising employment propensities (2.29 pp). Manual employment increases to similar extent in both countries and is entirely accounted for by improving employment prospects.

The decline in French employment translates into a rise in unemployment by 3.36 pp entirely accounted for by rising unemployment propensities. In addition, the propensity of individuals to remain out of the labor market completely increases significantly with a contribution of 3.92 pp. This trend is dampened by compositional shifts (-3.66 pp). On the contrary, the rise in U.S. employment is explained both by a vigorous decline in unemployment (-3.25 pp) and non-participation (-4.33 pp). Propensity components strongly contribute to both the decline in unemployment and non-participation while compositional shifts contribute mainly to decrease non-participation. In a nutshell, between 1982 and 1998, the polarization of occupational employment occurs primarily through plummeting employment prospects in France while it manifests through a surge in employment opportunities and compositional shifts in the U.S.

Transatlantic employment outcomes between 1998 and 2017

	Level		Difference			
	1998	2017	Propensity (C1)	Composition (C2)	Interaction (C3)	Total (C4)
France						
Employment	60.32	64.39	3.04	-0.81	1.83	4.07
Abstract	18.02	23.21	-0.64	5.66	0.17	5.19
Routine	32.30	29.63	-0.10	-4.45	1.88	-2.67
Manual	10.00	11.55	3.78	-2.01	-0.22	1.54
Unemployment	7.99	6.85	-0.35	-0.71	-0.08	-1.14
Non-Participation	31.69	28.76	-2.69	1.52	-1.76	-2.93
U.S.						
Employment	72.56	68.82	-4.58	0.08	0.77	-3.74
Abstract	24.51	27.34	-0.91	3.72	0.02	2.83
Routine	37.46	29.23	-6.54	-2.55	0.86	-8.23
Manual	10.59	12.25	2.86	-1.09	-0.11	1.67
Unemployment	3.48	3.19	-0.07	-0.28	0.06	-0.30
Non-Participation	23.96	27.99	4.66	0.20	-0.83	4.03

Table 1.5 – Employment changes between 1998 and 2017

Notes: levels are in percentage while differences are in percentage points. The sum of the propensity (C1), composition (C2) and interaction (C3) components amounts to the total change (C4).

Table 1.5 reports the decomposition of changes in employment, unemployment and non-participation per capita between 1998 and 2008. The employment performances of both countries converge during that period. The transatlantic employment gap declines by 7.80 pp between 1998 and 2017. The declining discrepancy in employment between the two countries is due both to rising employment opportunities in France and deteriorating employment prospects in the U.S. Indeed, aggregate employment per capita rises by 4.07 pp in France while it decreases by 3.74 pp in the U.S.

In contrast to the previous period, the declining employment discrepancy is explained by a fall in routine employment and a lack in abstract employment growth in the U.S. Routine employment drops by -8.23 pp reflecting both a decline in the likelihood to be employed in such occupations (-6.54 pp) and a compositional shift in the working age population (-2.55 pp) to a lesser extent. On the contrary, in France, routine employment declines only by -2.67 pp. It is almost entirely accounted for by a compositional shift in the working age population (-4.45 pp).

The declining employment discrepancy is also due to a lack in abstract employment growth in the U.S. It grows only by 2.83 pp in the U.S. against 5.19 pp in France. These surges in abstract employment are entirely due to compositional shifts in the working age population in both countries. Manual employment increases to a similar extent in both countries reflecting rising employment prospects.

The decline in U.S. employment entirely stems from a 4.03 pp rise in non-participation induced by increasing propensities of individuals to remain outside the labor market. On the contrary, unemployment per capita remains stable which points out that it is not a relevant indicator for U.S. employment performances during that period. The rise in French employment translates into both a decline in non-participation and in unemployment to a lesser extent by -2.93 pp and -1.14 pp, respectively. The decline in non-participation arises mostly from the propensity component while the decline in unemployment manifests through both propensity and composition components. To sum up, between 1998 and 2017, the polarization of occupational employment occurs through massive job losses in the U.S. while it manifests through a surge in employment opportunities in France.

1.5.2 Aggregate relevance of socio-demographic groups

Despite displaying different employment dynamics across periods, both countries experience abstract and manual employment gains and routine employment losses at some point in time. I assess the aggregate importance of socio-demographic groups in accounting for occupational employment dynamics.

Figure 1.5 depicts employment change decompositions for each socio-demographic group for the overall 1982 to 2017 period.[14] Abstract employment increases by 7.75 pp in France between 1982 and 2017. Prime-aged individuals with more than a high school degree account for most of this increase through their rising group size which reflects a rise in skill supply. They contribute for 8.60 pp. In the U.S., the overall rise in abstract employment is of 9.46 pp. Prime-aged individuals with more than a high school degree contribute for 6.87 pp. Nevertheless, prime-aged women with more than a high school degree contribute twice as much as prime-aged men with similar education levels. It is also noteworthy that senior individuals with more than a high school degree also contribute to the abstract employment rise in both countries but to a much lesser extent.

Routine employment falls dramatically in both country between 1982 and 2017. It decreases by -9.88 pp in France and by -8.32 pp in the U.S. Routine employment losses are mostly endured by low-skilled young and prime-aged individuals. For those groups, the fall in routine employment occurs both through deteriorating employment prospects and the drop in their group size. In France, those groups contribute for a -16.96 pp decline in routine employment. Roughly -9.67 pp arise from the declining propensity to work in such jobs and roughly -10.42 pp from the declining group size. Comovements in propensities and group sizes dampen the fall by approximately 3.12 pp. In the U.S., they contribute for -11.46 pp in the decline in routine employment from which -5.84 pp arise from the propensity component and -7.22 pp from the composition shifts. Comovements in propensities and group sizes dampen this fall by 1.60 pp. Such patterns reflect the consequences of task-biased technological change, globalization as well as the shift in the skill composition of the workforce. In both countries, prime-aged high-skilled individuals slightly dampen the fall in routine employment with a contribution of 5.36 pp and 2.21 pp in France and the U.S., respectively. This is in line with Beaudry, Green, and Sand (2016) who argue that there has been a reversal in the demand for skills

[14] Results for unemployment and non-participation are available in Figure A.1.

in the 2000s in the U.S. that pushes high-skilled workers down the occupational ladder towards jobs traditionally performed by lower-skilled workers.

Manual employment rises in both countries between 1982 and 2017. It increases by 3.66 pp in France and 2.71 pp in the U.S. The rise in manual employment is primarily accounted for by low-skilled prime-aged individuals in both countries with a contribution of 2.00 pp in France and 1.04 pp in the U.S. The rise in manual employment propensities is especially strong for women reflecting their rising labor market participation over the period. Prime-aged high-skilled workers also contribute to the increase in manual employment but to a much lesser extent in France (0.88 pp) compared to the U.S (1.60 pp). This contribution of prime-aged high-skilled individuals highlights their occupational downgrading.

Thus, prime-aged individuals are at the core of the polarization of occupational employment over the last four decades. However, low-skilled workers suffer severe employment losses and only benefit from limited employment gains. Thus, labor market policies should focus on promoting low-skilled employment by expanding labor demand as France did since the mid 1990s with its labor cost reduction policies targeted on low-paid workers. However, the sustainability of the employment gains arising from those policies remains partly threatened by further technological and trade developments. In that respect, the development of training programs might facilitate the transition of low-skilled workers towards occupations that offer more stable employment prospects. Furthermore, policies should increase incentives for low-skilled young and senior workers to participate in the labor market as they account for most of the transatlantic employment deficit.

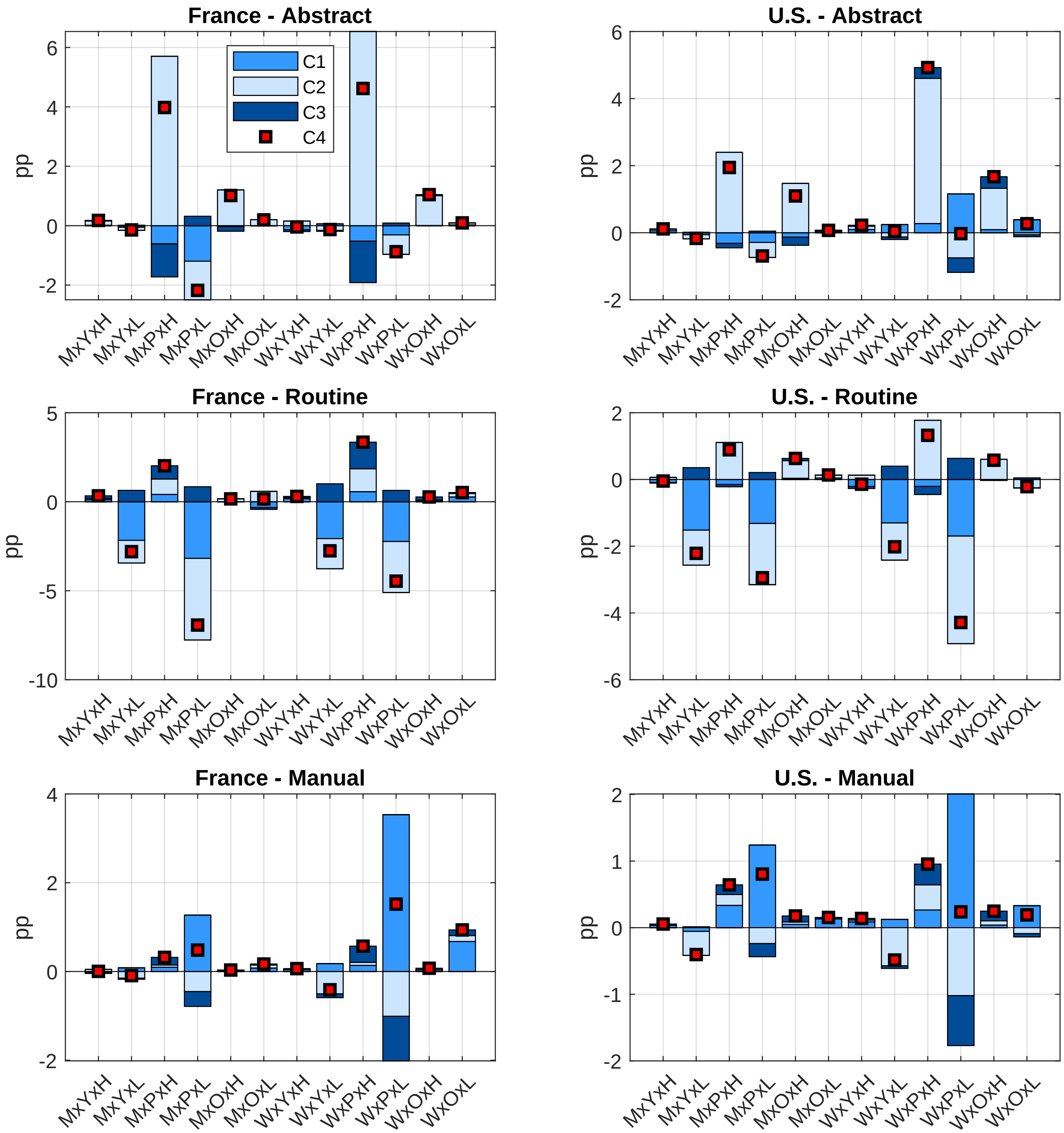

Figure 1.5 – Employment changes by socio-demographic groups between 1982 and 2017

Notes: men (M), women (W), 15-24 year-olds (Y), 25-54 year-olds (P), 55-64 year-olds (O), with at most a high school degree (L), with more than a high school degree (H). C1, C2 and C3 are defined respectively as the propensity, composition, interaction components with C4 capturing the total change, i.e. $C4 = C1 + C2 + C3$. Values are in percentage points (pp).

1.6 Labor market transitions

Until now, this chapter focused on labor market dynamics from a stock perspective. Nonetheless, they are the aftermath of individual transitions across labor market states. In this section, I identify the most important transitions for the employment dynamics between 1982 and 2017.

1.6.1 Average transition rates

Table 1.6 displays the average transition rates for both countries over the 1982 to 2017 period. As Charlot, Fontaine, and Sopraseuth (2019) do, I first look at the average annual transition rates to grasp some preliminary understanding of cross-country differences in labor market transitions. Despite differences in the time period covered and data construction, results are qualitatively the same. Three main observations arise.

	France					U.S.				
T\T+1	A	R	M	U	N	A	R	M	U	N
A	93.04	1.73	0.18	1.84	3.21	77.65	13.47	2.96	1.74	4.18
R	1.37	89.93	0.59	3.54	4.57	9.88	76.05	3.80	3.72	6.55
M	0.65	2.41	87.10	4.01	5.82	7.31	13.14	65.08	3.59	10.89
U	6.32	20.17	8.49	45.27	19.75	8.63	29.45	11.15	24.26	26.51
N	1.86	3.70	1.86	5.62	86.97	3.24	8.69	5.15	4.74	78.17

Table 1.6 – Average annual transition rates over 1982 to 2017
Notes: values are in percentage. A, R, M, U and N refer to abstract, routine, manual employment, unemployment and non-participation, respectively. See section 1.2 for details on data construction.

First, the probability to remain in a given state is much greater in France than in the U.S. For example, the probability to remain in routine jobs between two years is of 89.93% in France against 76.05% in the U.S., while the probability to remain out of the labor market is of 86.97% and 78.17%, respectively. Hence, the French labor market appears more inert than the U.S. Second, there is a much higher probability to switch between occupational groups in the U.S. compared to France. For example, the probability of routine workers to switch occupations between two years is on average of 1.96% in France against 13.68% in the U.S. The greater U.S. occupational mobility occurs both upward and downward the occupational ladder. For instance, the probability for abstract workers to switch towards lower-paid occupational groups is of 16.43% in the U.S. against 1.91% in France while the probability for manual workers to switch towards higher-paid occupational groups is of 20.45%

in the U.S. against 3.06% in France. Third, transitions from employment towards non-employment seem to occur disproportionately through non-participation in the U.S compared to France. For instance, the probability for manual workers to exit the labor market, conditionally on becoming non-employed, is of 75.21% in the U.S. against 59.21% in France. The probability of routine workers to exit to labor market, conditionally on becoming non-employed, is of 63.79% in the U.S. against 56.35% in France. Hence, employment changes occur mainly through participation adjustments rather than unemployment changes in the U.S. with respect to France.

1.6.2 Job polarization and occupational mobility

I now investigate which transition rates are the most important in accounting for the evolution of occupational employment. In doing so, I identify whether the adjustment occurs through job mobility or non-employment. I proceed by conducting counterfactual experiments in the spirit of Cortes, Jaimovich, Nekarda, and Siu (2014). In that respect, I allow all transition rates to evolve except one that is held at its initial level. To make sure that transition rates from a given state sum to one, the difference between the observed and the counterfactual transition rates is reallocated to the probability of remaining in the initial state. I then impute counterfactual stocks by using the law of motion captured by equation (1.1) with the counterfactual transition matrix.

Figure 1.6 plots the difference between the observed and counterfactual stocks in percentage points between 1982 and 2017. For clarity, I only report the results for the top three most important transition probabilities accounting for the increase in abstract and manual employment and the decrease in routine employment.[15] In France, the rise in abstract employment is primarily due to a decline in outflows from abstract jobs. Abstract employment increases because less abstract workers switch to routine jobs or exit the labor market in France between 1982 and 2017. Indeed, abstract employment per capita would have been 3.41 pp lower than observed in 2017 if the abstract to routine transition rate would have remained at its initial level. Furthermore, the rise in abstract employment per capita would have been mitigated by 1.22 pp if the abstract to non-participation transition rate would have stayed constant. In the U.S., on the contrary, the rise in abstract employment is mainly accounted for by inflows. For instance, the increase in abstract employment is mitigated by 4.64 pp, 1.59 pp and 1.41 pp for constant inflows from routine jobs, non participation and manual

[15] Table A.4 summarizes the results for all the counterfactual experiments.

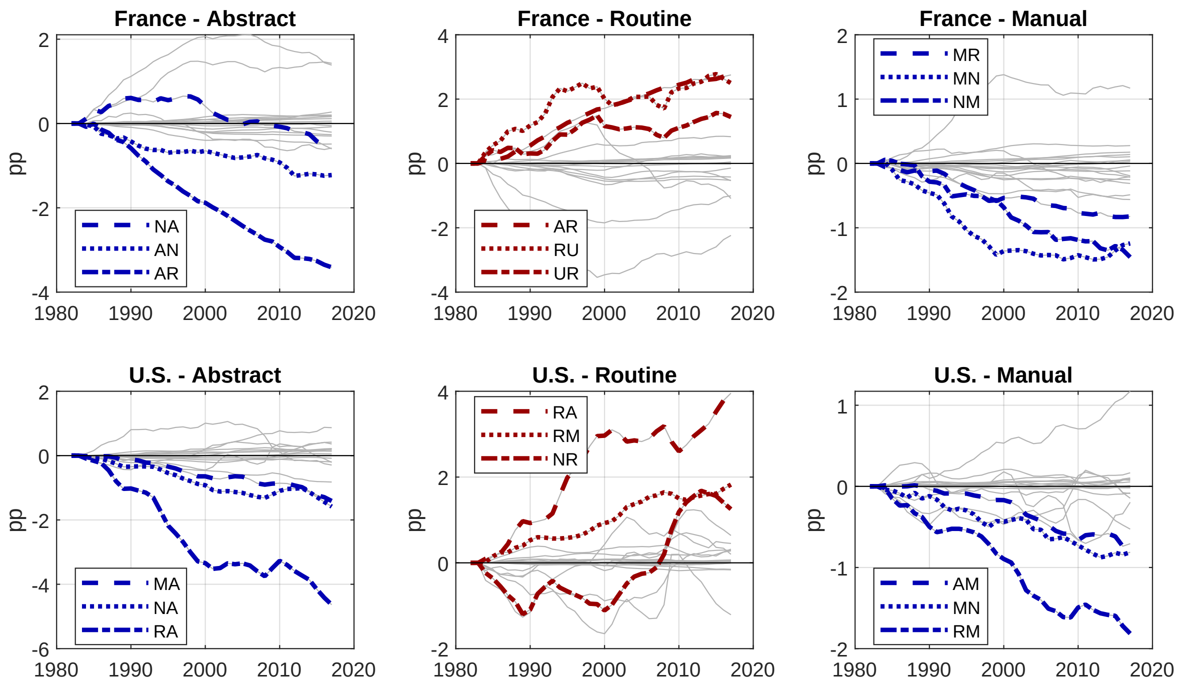

Figure 1.6 – Difference between observed and counterfactual stocks between 1982 and 2017
Notes: values are in percentage points. Legends display the top three most important transition rates accounting for the rise in abstract and manual employment as well as for the decline in routine employment.

jobs, respectively. This indicates the relevance of occupational mobility as well as participation adjustments in accounting for the rise in abstract employment in the U.S. between 1982 and 2017.

The disappearance in routine employment is primarily due to a decline in occupational mobility towards routine jobs as well as spells of unemployment in France. It results from lower abstract to routine transitions as well as increasing routine separations and decreasing routine finding rates. For instance, the decline in routine employment is mitigated by 2.75 pp for a constant abstract to routine inflow rate and by 2.50 pp and 1.44 pp for constant routine separation and finding rates, respectively. In the U.S., the decline in routine employment is mostly the result of a surge in job mobility and a fall in labor market entry. The fall in routine employment is mitigated by 3.96 pp and 1.82 pp for constant routine outflows towards abstract and manual jobs, respectively, while it is mitigated by 1.25 pp for constant routine inflows from non-participation.

In France, the surge in manual employment results from rising labor market participation and fewer labor market exits as well as from a decline in occupational mobility towards routine jobs. The rise in manual employment is mitigated by 1.46 pp and 1.24 pp for constant manual inflows and outflows with non-participation, respectively. A steady manual to routine transition rate mitigates the surge in manual employment by 0.82 pp. In the U.S., the rise in manual employment is primarily due to higher manual inflows from both routine and abstract jobs and to lower manual outflows towards non-participation. Indeed, the rise in manual employment is mitigated by 1.81 pp and 0.71 pp for constant manual inflow rates from routine and abstract jobs, respectively. A steady manual to non-participation transition rate mitigates the rise in manual employment by 0.81 pp.

Hence, workers adapt to labor market changes through rising occupational mobility and participation transitions in the U.S. while they react through less occupational mobility as well as unemployment and participation transitions in France. In that respect, labor market policies that promote occupational mobility could dampen aggregate employment losses by allowing displaced workers to transit towards in-demand occupations. Such policies include government- and employer-sponsored training programs. Those programs could potentially allow workers to switch occupations when their job prospects become too scarce. The aim is to facilitate exits from long unemployment spells, to avoid a decline in labor market participation with attractive employment opportunities, or to allow within firm occupational mobility when firms expect large organizational changes.

1.7 Conclusion

Over the past four decades, France has recorded a persistent employment deficit with respect to the U.S. that reached a peak in the late 1990s. Nevertheless, the pervasive effects of technological change and globalization have shaped the occupational employment structure of both countries. They both experienced job polarization. In light of this process, I revisit the long-run structural analysis initiated by Piketty (1998) by investigating the extent to which occupational and socio-demographic changes shape the transatlantic employment gap.

I find that the transatlantic employment gap reflects a deficit in French routine and manual employment overly represented by low-skilled young and senior workers who have higher non-participation and unemployment propensities. Nevertheless, the transatlantic employment gap changes significantly over time. It first widens through a surge in employment in the U.S. and a fall in employment in France between 1982 and 1998. On the contrary, it contracts through a surge in employment in

France and a decline in employment in the U.S. between 1998 and 2017. Low-skilled workers are at the core of this reallocation process as they account for most of the employment losses. Those changes occur through rising occupational mobility and participation transitions in the U.S. while they occur through less occupational mobility as well as both unemployment and participation transitions in France. Hence, the transatlantic employment gap does not only reflect a disfunctioning labor market but also the occupational reallocation of labor that affects the employment prospects and participation decisions of specific socio-demographic groups.

Those findings have several implications in terms of labor market policies and the role of the welfare state. Insuring workers against the income losses associated with the risk of unemployment might not be sufficient when the pace of technological change and globalization outpaces the ability of workers to adapt their skills. On the one hand, labor market policies should stimulate labor demand for low-skilled workers though their sustainability remains partly threatened by further technological and trade developments. On the other hand, they should also provide larger incentives to labor market participation for socio-demographic groups that face significant participation decisions and declining employment prospects. Finally, they should promote occupational mobility in order to dampen aggregate employment losses by allowing displaced workers to transit towards in-demand occupations.

Chapter 2

Job Polarization and Unskilled Employment Losses in France

2.1 Introduction

Over the past four decades, technological change has deeply shaped the occupational structure of developed economies, including France. Employment shares of both low- and high-paid jobs increased simultaneously, while the share of middle-paid jobs decreased. The automation of routine jobs shrank the middle class. Autor, Levy, and Murnane (2003), Goos, Manning, and Salomons (2009) and Oesch (2013) first describe this change in the occupational structure in the United States and in Europe as job polarization. Autor and Dorn (2013) further argue that technological change shifted employment opportunities of low-skilled workers towards manual service jobs which are not substitutable with new technologies. Those jobs are not subject to automation because they require social interaction skills and manual dexterity that new technologies do not yet possess. Thus, low-skilled workers experienced a decline in employment opportunities in routine jobs, compensated by a surge in manual service jobs. At first sight, those findings suggest that technological change appears to only restructure rather than shrink unskilled employment prospects.

Despite experiencing a similar reallocation process, European countries underwent different employment outcomes especially with respect to the U.S. They usually exhibit lower employment levels. For instance, Prescott (2004) argues that European countries feature lower levels of labor supply with respect to the United-States. He highlights that most of the differences in labor supply are accounted for by high labor tax rates in European countries. Those tax rates deter labor supply by reducing the value of work. Rogerson (2008) deepens the analysis initiated by Prescott (2004) by focusing on the sectoral reallocation of labor induced by technological change. In spite of the productivity catch-up with the U.S., European countries did not reallocate labor across sectors to the same extent leading to lower labor market performances. He claims that the sectoral reallocation of labor has been obstructed by high tax rates in Europe. Those high tax rates have created an incentive to perform many economic activities in the non-market sector rather than in the market service sector. Nonetheless, little is known on how job polarization relates to changes in employment outcomes. Even less is known on the repercussion of economic policies on employment outcomes resulting from this reallocation process.

This chapter revisits how taxation policies interact with technological change and assess the extent to which they shape unskilled employment outcomes in France between 1982 and 2008.[1] It deepens our understanding of the effects of technological change and labor taxation policies on employment outcomes by considering the task-biased nature of technological change and the distributive aspect of labor taxation policies. The French case is especially relevant. France experienced both job polarization prompted by technological change and significant changes in unskilled employment outcomes. A striking feature of the French labor market is that the surge in manual jobs was not sufficient to counterbalance the fall in routine jobs reflecting deteriorating unskilled employment prospects. Nevertheless, this process was not smooth over time and coincided with important changes in labor taxation policies. Specifically, unskilled employment declined over the 1982-1994 period while it stabilized over the 1994-2008 period. In the meantime, France imposed high and increasing labor tax rates in the first subperiod while it conducted distributional labor taxation policies in the second subperiod. The joint occurrence of those events makes of France a suitable candidate to study the intertwined effects of economic policies and technological change.

In order to grasp how unskilled employment outcomes are molded by technological change and labor taxation policies, this chapter relies on a parsimonious general equilibrium model with endogenous occupational choice built on Rogerson (2008), Acemoglu and Autor (2011), and Autor and Dorn (2013). The model is calibrated to account for the overall decline in unskilled employment in France

[1] The time-span studied starts in 1982 because data at the occupational level are not available in the French Labor Force Survey (FLFS) prior to this date. It ends in 2008 in order to avoid the influence of the great recession which goes beyond the frame of this study.

between 1982 and 2008. Then, I produce a counterfactual analysis to determine how labor taxation policies affect employment outcomes as technological change occurs. I also use the model to measure the extent to which technological change and taxation policies account for unskilled employment dynamics. In order to do so, I examine the contribution of technological and labor taxation trends to the decline in unskilled employment in France between 1982 and 2008.

Three main results arise from this approach. First, technological change induced unskilled employment losses in France between 1982 and 2008. Second, unskilled employment losses prompted by technological change were more important with higher and increasing average labor tax rates which explains why unskilled employment losses mostly concentrated from 1982 to the mid 1990s. Third, the implementation of payroll tax reduction policies targeted on low-paid workers has mitigated the declining trend in unskilled employment since the mid 1990s. Those taxation policies are especially effective as technological change occurs.

This approach sheds a new light on the effects of technological change and taxation policies on employment outcomes by considering jointly three key features: the polarizing structure of occupational employment induced by the task-biased nature of technological change, the distributional aspect of labor taxation policies and the substitutability of manual services with non-market services. Those features jointly interact with each other. Technological change reallocates unskilled workers from routine jobs that are highly substitutable by capital towards manual jobs which produce market services themselves substitutable by non-market services ultimately deteriorating unskilled employment outcomes. In the midst of this reallocation process, taxation policies affect unskilled employment outcomes both through the substitutability of market and non-market services as well as the occupational choice of unskilled workers. On the one hand, the level of labor taxation affects unskilled employment outcomes by distorting the incentive to produce manual services markedly or non-markedly. Hence, labor taxation interacts with technological change by changing the relative value of unskilled employment with respect to non-employment. As technological change occurs, this channel becomes more prominent since more unskilled workers are faced with choosing between market and non-market work rendering them more prone to deteriorating employment prospects. On the other hand, distributional taxation policies distort the occupational choice of unskilled workers. They alter the occupational structure which makes unskilled workers more or less confronted to choose between market and non-market work depending on the policy at stake. Technological change modulates the efficiency of those policies in terms of employment outcomes.

The main contribution of this chapter is to link changes in the employment structure initially described by Autor and Dorn (2013) with changes in the unskilled employment level in France by addressing the issue of the interaction between labor taxation policies and technological change. It stresses the importance of considering the reallocation process of labor induced by biased technological change when designing labor taxation policies. The distributional aspect of labor taxation policies is especially relevant since manual service jobs are located at the bottom of the occupational wage distribution. Unskilled workers in such jobs are usually subject to lower tax rates compared to higher-paid workers employed in routine and abstract jobs. Oesch (2009) also looks at how some institutions and economic policies affect unskilled employment outcomes in European and Anglo-Saxon countries between 1991-2006. He finds that unskilled job prospects are enhanced by active labor market policies and monetary policies that fully exploit economies' growth potential. Though, he ignores technological change and labor taxation policies. Oesch (2013) sheds light on the determinants that shaped the occupational structure in Britain, Denmark, Germany, Spain and Switzerland between 1990 and 2008. He focuses on five underlying driving forces namely technology, globalization, education, migration, and institutions. He also provides a deeper comparison between the UK and Germany since they both conducted important changes in their wage-setting institutions but in opposite directions. The author recommends that governments take action at both ends of the occupational distribution to gain from those occupational shifts. Governments should invest into tertiary education to provide firms with highly educated workers enabling them to exploit technological improvements. He also advocates investments in vocational training and the establishment of a minimum wage to drive firms to invest in workers' productivity. Albertini, Hairault, Langot, and Sopraseuth (2016) also study the effects of technological change and labor market policies on employment but emphasize the role played by the minimum wage in France. The following approach focuses on the interaction between technological change and labor taxation through non-market work.

A secondary contribution is to further the analysis initiated by Prescott (2004) and Rogerson (2008) in at least three ways. First, this chapter studies the occupational reallocation of labor induced by biased technological change rather than the sectoral reallocation of labor known as structural change. Indeed, Prescott (2004) finds that differences in labor tax rates account for cross-country differences in aggregate hours worked while Rogerson (2008) further notices that those high tax rates prevented a proper development of the service sector in Europe. In the specific case of France, Piketty (1998) and Cahuc and Debonneuil (2004) identify the underdeveloped sectors. They claim that if France had the same employment rate in the sales and hospitality industry as the United States, there should be an additional 2.8 million employed workers in 1996 and 3.4 million in 2001. This last figure almost represents the number of unemployed workers in France in 2015. While the effects of structural change on employment outcomes have been extensively treated, little is known yet on how task-biased technological change affects them. In this chapter, we provide insights on that matter. Second, the present study focuses on unskilled employment rather than sectoral employment which is at the core of the deterioration of employment outcomes and the design of labor market policies in France. Despite the fact that technological change affects all types of jobs, it noticeably deteriorates unskilled employment outcomes. Looking only at the sectoral level hides which groups of individuals are most affected. Thus, it limits our understanding of the effects of taxation policies on the reallocation of labor induced by technological change. Third, this paper stresses the importance of the distributional aspect of taxation policies. Since job polarization reallocates middle-paid jobs towards low-paid jobs, distributional labor taxation policies surely interact in a specific way with this reallocation process by affecting the occupational choice of workers. Hence, studies using aggregate tax rates are missing an important part of the story for France.

The remainder of this chapter is organized as followed. Section 2.2 documents the reader with stylized facts on unskilled employment, occupational employment and wage dynamics, and labor taxation policies in France. In section 2.3, I present a parsimonious general equilibrium model with endogenous occupational choice built on Rogerson (2008), Acemoglu and Autor (2011), and Autor and Dorn (2013). In section 2.4, I calibrate the model. In section 2.5, I use the model to conduct a counterfactual analysis in order to determine how labor taxation policies interact with technological change. I also assess to which extent technological change and labor taxation account for unskilled employment outcomes in France between 1982 and 2008. Section 2.6 concludes.

2.2 Stylized facts

This section presents three key observations obtained from the French Labor Force Survey (FLFS). First, France experienced job polarization between 1982 and 2008. Second, the unskilled employment rate declined significantly from 1982 to the mid 1990s while it has stabilized since then concomitantly to the implementation of labor taxation policies. Third, this decline is entirely due to a fall in unskilled routine employment. The expansion of unskilled manual jobs was not sufficient to absorb the unskilled routine employment losses. Appendix B.2 describes the data and its cleansing.

2.2.1 The deterioration of unskilled employment outcomes

The French labor market is characterized by low and deteriorating unskilled employment performances. This feature is at the core of labor market policy design in France. Nevertheless, the deterioration of unskilled employment outcomes is not linear over time.

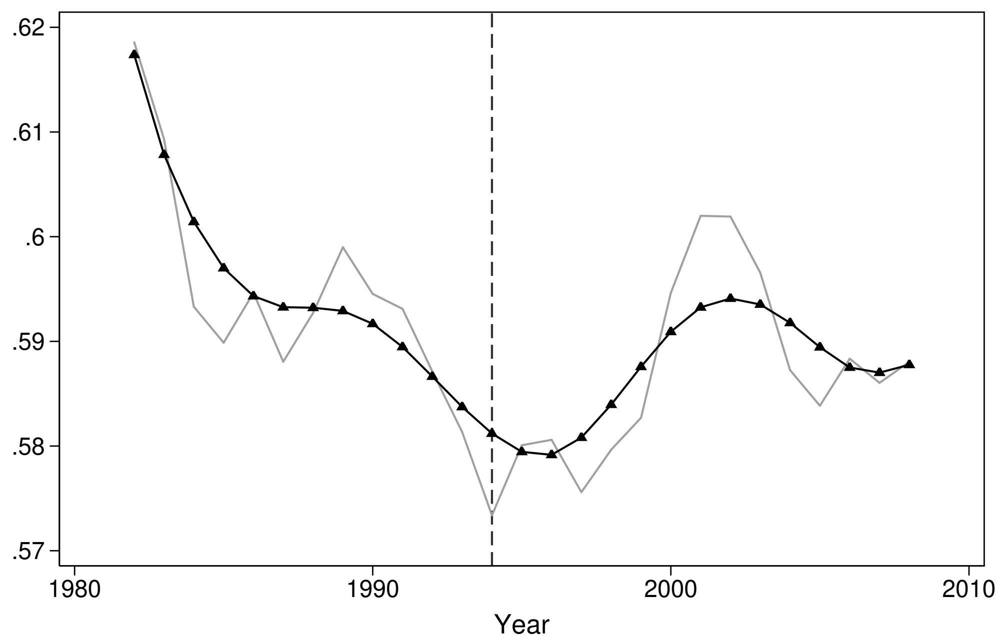

Figure 2.1 – Unskilled employment rate over 1982-2008
Notes: Data are constructed as described in appendix B.2. Sample includes 15-64 year old individuals during the sample year. Unskilled individuals are defined as individuals who have at most a high-school degree (Bac). The pattern is corrected for 1990, 2003 breaks (grey) and then smoothed (black) using a locally linear model with a .5 bandwidth.

Figure 2.1 displays the unskilled employment rate. It is defined as the ratio of employees with at most a high-school degree over the working age population with at most a high-school degree, while the skilled employment rate is defined as the ratio of employees with more than a high-school degree over the working age population with more than a high-school degree

$$e_t^s = \frac{E_t^s}{P_t^s} \tag{2.1}$$

where $s \in \{SK, UN\}$ and SK, UN refer to skilled and unskilled demographic groups, respectively. From 1982 to 2008, the unskilled employment rate declined by 2.96 percentage points (pp) even though it experienced a rise from the mid 1990s to the early 2000s. Indeed, the unskilled employment rate fell by slightly less than 3.62 pp from 61.74% to 58.12% between 1982 and 1994 while it rose by 0.66 pp from 58.12% to 58.78% between 1994 and 2008. Despite the persistent rise in women's participation to the labor market, the rise in unskilled employment does not seem to be a persistent trend. The unskilled employment rate displays a downward trend over the entire period. France has suffered significant unskilled employment losses from 1982 to 1994 while this trend has been mitigated since then.

2.2.2 Job polarization

Simultaneously to the deterioration of unskilled employment outcomes, the occupational employment structure polarized in France between 1982 and 2008.

A polarizing employment structure

Figure 2.2 displays changes in employment shares across the occupational mean net wage distribution. Like the United-States, France has been experiencing job polarization. Employment shares increase simultaneously at the bottom and the top of the occupational wage distribution while they decrease at the middle of the wage distribution between 1982 and 2008. Those changes reflect significant changes in the occupation employment structure. For example, the first percentile of employees working in the lowest paid occupations in 1982 has seen its employment share increase by a smoothed .32 pp. This rise represents a 32% increase. As in the United-States, top expanding jobs regroup a large variety of occupations (Tables B.1 and B.2). There are high-paid abstract occupations such as engineers and research managers in computer sciences, teachers certified in secondary education

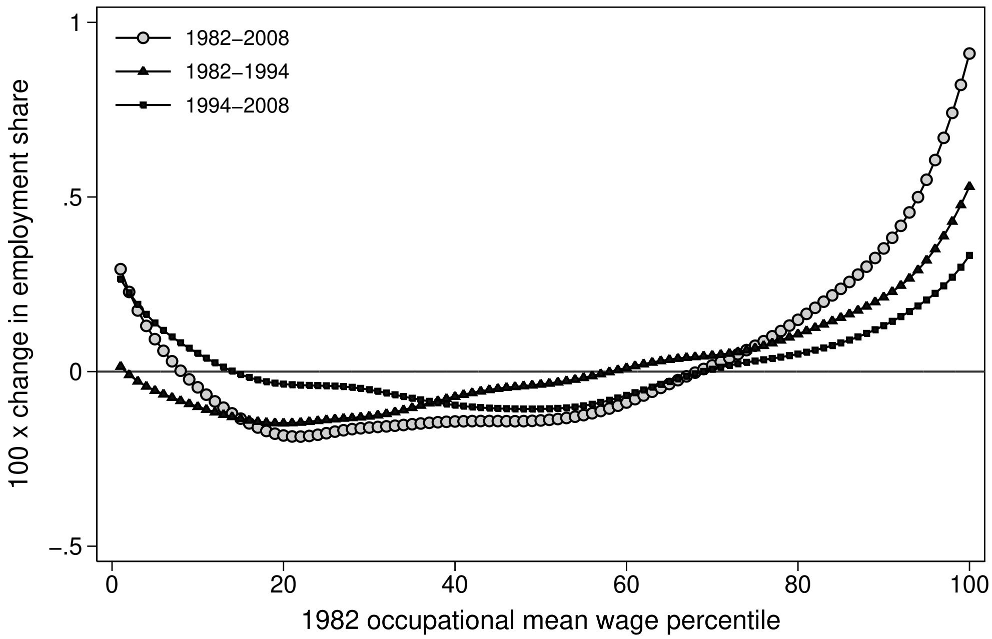

Figure 2.2 – Job polarization over 1982-2008

Notes: Data are constructed as described in appendix B.2. Sample includes salary workers who are 15-64 year old during the sample year. Changes are smoothed by using a locally linear model with a .5 bandwidth.

but also low-paid manual services such as childcare assistants, housekeepers, caregivers, cooks and kitchen assistants, and so forth. In most declining jobs, one can find many middle-paid routine jobs which are mostly low-skilled manufacturing and clerical jobs such as unskilled production workers in textile, secretaries, typists and stenographers, and various unskilled industrial workers. The decline in shares of middle-paid occupations and the rise in shares of high-paid occupations occur over the entire time period considered. On the contrary, the growth in low-paid occupational shares lacks between 1982 and 1994 when unskilled employment outcomes significantly deteriorate. Most of the rise in low-paid occupations occurs between 1994 and 2008 concomitantly to the stabilization of unskilled employment.

The contribution of manual service occupations

As highlighted by Acemoglu and Autor (2011), the growth in employment shares for high-paid occupations is consistent with the canonical model of skill-biased technical change. However, the growth at the bottom of the wage distribution is at odds with the standard theory of skill-biased technical change. Autor and Dorn (2013) find that it is due to the reallocation of labor from routine occupations which are substitute to ICT capital to low-skilled manual service jobs which are not substitute to ICT capital. Routine manufacturing jobs and clerical jobs are replaced by low-skilled manual service jobs such as child care, nursing, cooking and hospitality jobs.

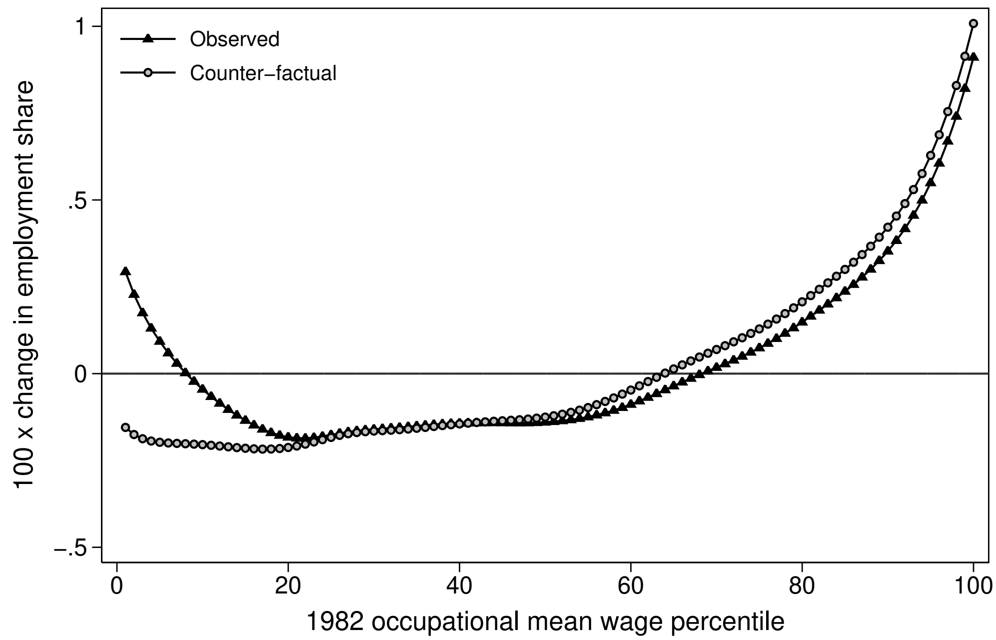

Figure 2.3 – Counterfactual change in the occupational structure over 1982-2008
Notes: Data are constructed as described in appendix B.2. The methodology used to produce the counterfactual curve is detailed in appendix B.3.1. The counterfactual curve captures changes in the occupational structure that would prevail if the share of manual occupations would remain at its initial level. Changes are smoothed by using a locally linear model with a .5 bandwidth.

In order to identify which jobs are expanding at the bottom of the occupational wage distribution, I build a counterfactual occupational employment structure. It aims at capturing the contribution of manual service jobs to the rise of low-paid occupation employment shares.[2] In this counterfactual experiment, I assume that the employment shares in manual occupations remain at their initial level. The retrieved weights are then reallocated uniformly across the other occupations such that the sum of occupational employment shares is equal to one.[3] Counter-factual changes in employment shares between 1982 and 2008 are displayed in Figure 2.3. The spike at the bottom of the wage distribution completely disappears once I assume that manual occupational employment shares remain at their

[2]Table B.3 displays the allocation of job codes across task groups.
[3]Appendix B.3.1 describes precisely the counterfactual re-weighting method. This method redistributes weights uniformly across the distribution. This explains why employment shares slightly increase for higher percentiles whereas the smoothing hides the rise for the middling percentiles. These increases are solely of technical nature and do not have any economic meaning.

initial level. The curve becomes strictly increasing as suggested by the standard theory of skill-biased technical change. For example, the first percentile of least-paid occupations should have experienced a smoothed 12% decline in its employment share instead of a smoothed 32% increase between 1982 and 2008. Therefore, low-skilled manual service jobs contributed for all of the rise in employment shares located at the bottom of the occupational wage distribution.

2.2.3 Occupational wage dynamics

According to Autor and Dorn (2013), job polarization captures the rise in manual and abstract labor demand and the decline in routine labor demand. Such reallocation process led to a polarization of workers compensation in the U.S. Those data are not available for France since only net wages are observable in the FLFS. They do not polarize and even reveal a decline in occupational net wage inequalities. I argue that this is not due to socio-demographic compositional shifts but rather to changing occupational net wage schedules.

The decline in occupational net wage inequalities

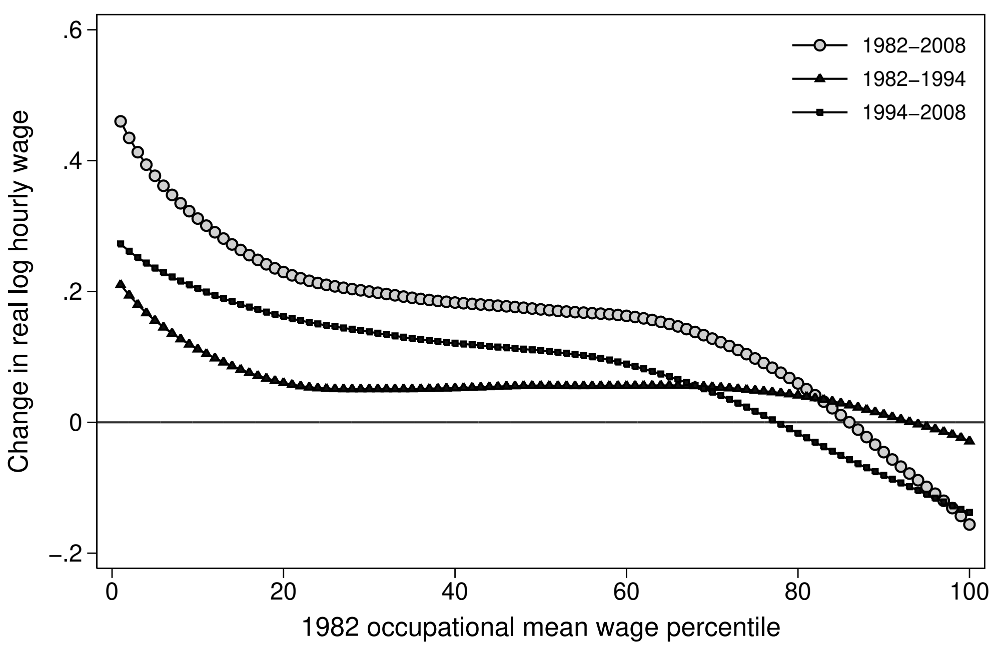

Figure 2.4 – Occupational net wage changes over 1982-2008

Notes: Data are constructed as described in appendix B.2. Sample includes salary workers who are 15-64 year old during the sample year. Changes are smoothed by using a locally linear model with a .5 bandwidth.

Figures 2.4 displays changes in real log hourly net wage at the occupational level over the entire time period studied. Wages are net of employer and employee social security contributions but not of the income tax. There are two striking facts. First, there is a strong decline in occupational net wage inequalities in France between 1982 and 2008. Real hourly net wages grow more rapidly for low-paid jobs than for middle-class jobs and high-paid jobs. This pattern is consistent both over the whole period and across sub-periods suggesting that it is an ongoing process. This reflects the rise in labor demand for manual jobs as in the U.S. However, it also reflects other factors such as significant changes in wage-setting institutions. For example, the minimum wage persistently increases between 1982 and 2008 in France. Despite the rise of low-paid occupations' net wages, the labor cost of those jobs has been contained by the implementation of labor cost policies focused on low-paid workers.

Second, the real hourly net wage declines for high-paid jobs. In France, high-paid workers have seen their real hourly net wages decline both in absolute terms and with respect to low and middling-paid occupations. This pattern is present over the entire time period but is exacerbated from 1994 to 2008 which might be the result of labor taxation policies. Since wages are reported net of employee and employer social security contributions, changes in labor tax scheme across the wage distribution could induce a decline in real net wages. Such changes in the labor tax scheme have occurred in France since the mid 1990s through the implementation of labor cost reduction policies focused on low-paid jobs financed by a rise in taxation on high-paid jobs as observed by Bozio, Breda, and Guillot (2016) and Catherine, Landier, and Thesmar (2015). Based on those wage data, one might think that France did not experienced the same reallocation process as in the U.S. Despite the unavailability of labor cost data, Bozio, Breda, and Guillot (2016) impute total workers' compensation costs using fiscal data and a microsimulation model. They find that the dynamics of workers' total compensation across the wage distribution is consistent with the theory of skill-biased technological change. This suggests that labor taxation policies had a significant impact on wages across the distribution. I argue that one might expect they also have a significant impact on employment outcomes.

The role of socio-demographic compositional shifts

The drastic decline in net wage inequalities across occupations between 1982 and 2008 motivates a decomposition analysis in order to shed light on its determinants. The first step is to investigate whether those changes are accounted for by shifts in the socio-demographic composition of workers within occupations or if they are due to shifts in occupational net wage schedules such as changes in labor taxation. I rely on DiNardo, Fortin, and Lemieux (1996) and Fortin, Lemieux, and Firpo (2011) to provide such aggregate decomposition of occupational net wage changes. Appendix B.3.2 provides details on the methodology.

Observed changes in the occupational wage distribution ΔW_O^p are decomposed into a composition effect ΔW_X^p and a wage structure effect ΔW_S^p such that

$$\Delta W_O^p = \Delta W_X^p + \Delta W_S^p \tag{2.2}$$

for percentiles $p = 1, ..., 100$. The wage structure effect captures occupational net wage changes that would have prevailed if workers' socio-demographic characteristics in 2008 would have remained the same as in 1982. The composition effect is then computed as the difference between observed changes and the wage structure effect. Thus, it captures changes induced by shifts in workers' socio-demographic characteristics between 1982 and 2008. I rely on twenty socio-demographic groups to control for the influence of these compositional shifts depending on:

- Gender: men and women;
- Age as a proxy for work experience: 15-24, 25-34, 35-44, 45-54 and 55-64 year olds;
- Education: with at most a high school degree and with more than a high school diploma.

Figure 2.5 depicts the aggregate wage decomposition. Changes in occupational net wages are mostly captured by the wage structure effect. It entirely captures the decline in occupational net wage inequalities as well as the fall in net wages for high-paid occupations. To determine whether the wage structure effect pattern is widespread among socio-demographic groups, I depict counterfactual changes in occupational net wages in Figure B.1. I compute changes in occupational net wage subsequently for gender, age and educational subgroups. Furthermore, I re-weight each observation such that their other characteristics are the same as for the entire workforce in 1982. In that way, I control both for compositional shifts but also for differences in characteristics of the considered group from those of the aggregate workforce. The declining pattern is shared by most socio-demographic groups. This suggests that the determinant of this pattern is not group specific. Nevertheless, two points are worth mentioning. From a gender perspective, the rise in net wages for low-paid

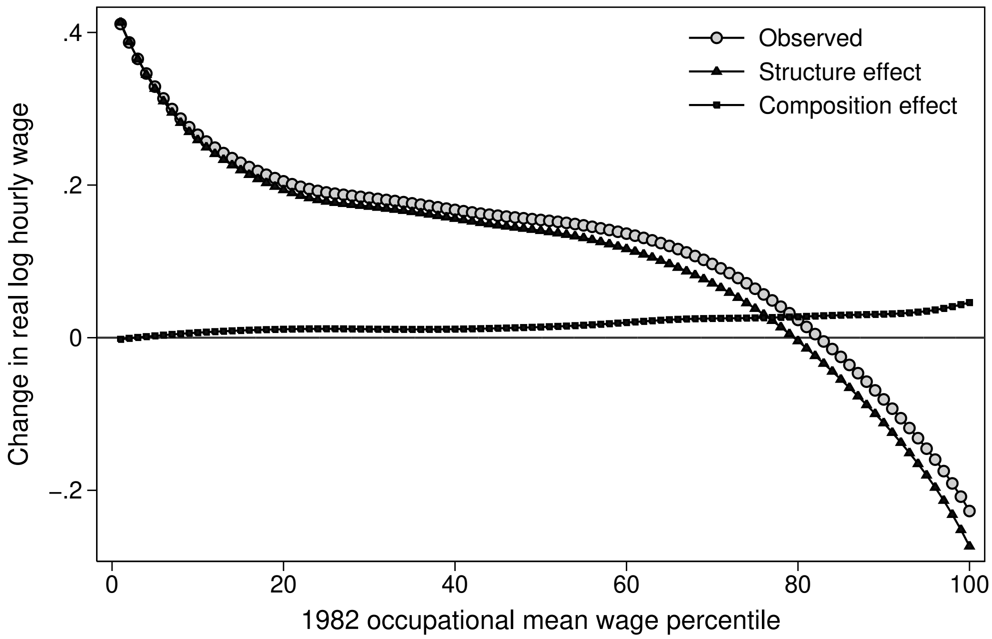

Figure 2.5 – Aggregate decomposition of occupational net wage changes over 1982-2008
Notes: Data are constructed as described in appendix B.2. The methodology used to produce the aggregate decomposition of occupational net wage changes is explained in appendix B.3.2. Changes are smoothed by using a locally linear model with a .5 bandwidth.

occupations is mainly accounted for by women. From an age perspective, occupational net wages polarize only for 15-24 year olds. This pattern has a negligible effect on aggregate wage changes since high-paid jobs are mainly held by workers above 24 years of age as shown in Figure B.2.

On the contrary, compositional shifts have a negligible effect on the overall wage distribution. It is noteworthy that it contributes to increase occupational net wage inequalities. Occupational net wage growth is slightly higher for high-paid occupations compared to low- and middle-paid occupations. Contrarily to the wage structure effect, it is possible to compute explicitly the contribution of each characteristic to the composition effect. To grasp the role played by each characteristic, Figures B.3 and B.4 depict the detailed decomposition of the aggregate composition effect and changes in socio-demographic characteristics across the occupational net wage distribution, respectively. Changes in educational and age composition contributed to increase net wage inequalities through the rise in educational attainment and aging especially in high-paid jobs. On the contrary, the rise in women's labor market participation pushed down occupational net wages uniformly across the distribution.

Those findings suggest that the observed decline in occupational net wage inequalities as well as the fall in net wages for high-paid jobs are not the result of socio-demographic compositional shifts but rather of changes of net wage schedules. This is in line with Bozio, Breda, and Guillot (2016) and Catherine, Landier, and Thesmar (2015) who claim that labor taxation policies shaped the net wage distribution in France hiding the increase in wage inequalities stemming from technological change.

2.2.4 Labor taxation policies

The decline in unskilled employment outcomes occurred concomitantly with significant changes in labor taxation policies. In this paper, I claim that they altered the effects of technological change on unskilled employment in France. Labor taxation is acknowledged for being particularly high in France as observed by Prescott (2004) and Rogerson (2008). Furthermore, the literature suggests that low-skilled employment is much more sensitive to its labor costs compared to skilled employment.[4] Therefore, labor taxation might impact strongly unskilled employment and the reallocation of labor induced by technological change.

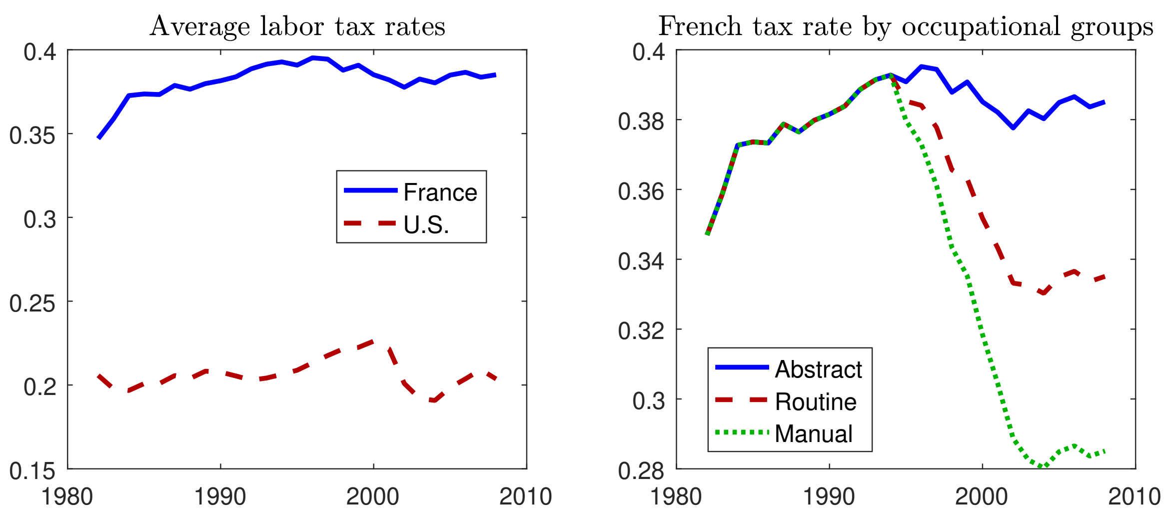

Figure 2.6 – Labor tax rates

Notes: The left panel displays the average labor tax rates for France and the U.S. The average tax rate on labor income is computed by dividing labor income tax revenues which include the household income tax and social security taxes by the economy-wide labor income. Those time series are built by McDaniel (2007). The right panel depicts the French labor tax rate by occupational groups. Those labor tax rates are imputed as described in appendix B.4.

[4] On the one hand, Kramarz and Philippon (2001) and Gianella (1999) find that the elasticity of employment to the labor cost of low wage workers is close to one. On the other hand, Hamermesh (1993) and Cahuc and Carcillo (2012) claim that the elasticity of employment to the labor cost is decreasing with the wage. The higher the wages, the less employment is sensitive to its cost. One plausible explanation is that capital labor substitution might not be the same across the wage distribution.

In the left panel of Figure 2.6, I display the French and U.S. average labor tax rates computed by McDaniel (2007). From 1982 to 2008, the French average labor tax rate increased by 3.82 pp from 34.69% to 38.51%. From 1982 to 1994, it increased by 4.39 pp from 34.69% to 39.08%. From 1994 to 2008, the average labor tax rate stayed relatively stable and even declined slightly to reach 38.51%. Furthermore, the French average labor tax rate is particularly high with respect to many other developed countries. For example, the French average labor tax rate was almost twice as high as its U.S. counterpart in 1994.

There is a drawback from only referring to the average labor tax rate. It hides the implementation of labor cost reduction policies targeting low-paid workers. In the right panel of Figure 2.6, I display the average French labor tax rates by occupational groups that include those policies.[5] The decomposition of the average labor tax rate by occupational group is justified by the fact that manual workers are on average located below routine workers who are themselves below abstract workers in the occupational wage distribution. From 1994 to 2008, France massively relied on payroll tax reduction policies focused on low-paid workers to increase employment and counter the rise in labor cost induced by other economic policies such as the increase in the minimum wage and the 35-hour workweek. Those policies costed more than 20 billion euros in 2008 which represents more than one percent of French gross domestic product at the time while they used to cost only 3.1 billion euros in 1995. According to Ourliac and Nouveau (2012), the main policy evaluations report that those payroll tax subsidies saved between 400,000 and 1,100,000 jobs depending on the time span, the reforms studied and the methodology used.

To sum up, France has been subject to job polarization from 1982 to 2008. There has been a reallocation of workers from middle-paid jobs towards low-paid and high-paid jobs. However, high-paid workers in France have seen their real net wage grow less rapidly and even decline due to the implementation of labor taxation policies which aimed at increasing unskilled employment since 1994.

[5] Appendix B.4 describes the computation of labor tax rates by occupational group. It also provides a brief history of differentiated payroll tax reduction policies introduced since 1994.

2.2.5 An incomplete reallocation of unskilled labor

The contribution of unskilled employment

I now turn to the aggregate employment rate skill decomposition in order to understand how the dynamics of the unskilled employment rate contributed to the dynamics of the aggregate employment rate between 1982 and 2008. Its contribution depends on the evolution of the skill composition of the working age population.

Therefore, I decompose the aggregate employment rate e_t into a skilled and an unskilled component, which can themselves be broken down across tasks

$$e_t = \theta_t^{SK} \sum_{k \in \{m,r,a\}} e_t^{SK,k} + \theta_t^{UN} \sum_{k \in \{m,r,a\}} e_t^{UN,k} \tag{2.3}$$

with $e_t^{s,k} = E_t^{s,k}/P_t^s$ the ratio of employed workers of skill level $s \in \{SK, UN\}$ in occupational group $k \in \{m, r, a\}$ over the working age population with skill level s and m, r, a referring respectively to manual, routine and abstract occupational groups and $\theta_t^s = P_t^s/P_t$ the ratio of skill s working age population over the entire working age population. Then, changes in the aggregate employment rate are exactly decomposed into an employment effect and into a skill composition effect

$$\begin{aligned}\Delta e_{t-x,t} = & \underbrace{\sum_{k \in \{m,r,a\}} \left(\theta_{t-x}^{SK} \Delta e_{t-x,t}^{SK,k} + \theta_{t-x}^{UN} \Delta e_{t-x,t}^{UN,k}\right)}_{\text{Employment effect}} \\ & + \underbrace{\sum_{k \in \{m,r,a\}} \left(e_t^{SK,k} \Delta\theta_{t-x,t}^{SK} + e_t^{UN,k} \Delta\theta_{t-x,t}^{UN}\right)}_{\text{Skill composition effect}}\end{aligned} \tag{2.4}$$

with $\Delta y_{t-x,t}$ the percentage point change of variable y between year t and year $t-x$. On the one hand, the employment effect reflects changes in employment rates by skill level for a given initial skill structure of the working age population. It gives the contribution of changes in employment opportunities by skill level and task to the dynamics of the aggregate employment rate for a given skill structure. A negative employment effect between date t and date $t-x$ means that a given individual has less chance of being employed at date t with respect to date $t-x$ for a given initial skill structure. On the other hand, the skill composition effect reflects changes in the skill composition of the working age population for given final employment rates by skill level. It gives the contribution of changes in the skill composition of the working age population to the dynamics of the aggregate employment rate for given employment opportunities.

	Employment effect			Skill composition effect			Total
	Skilled	Unskilled	Total	Skilled	Unskilled	Total	
1982 – 1994	-0.31	-3.32	-3.63	1.30	-0.99	0.31	-3.32
1994 – 2008	0.41	0.59	1.00	11.67	-8.50	3.17	4.17
1982 – 2008	0.03	-2.72	-2.69	13.05	-9.50	3.55	0.86

Table 2.1 – Decomposition of aggregate employment changes

Notes: Values are in percentage points. The sum of skilled and unskilled components for a given effect gives the total contribution of that effect to the change in the aggregate employment rate for a given period.

Table 2.1 reports the results of the change in aggregate employment rate decomposition by skill. From 1982 to 2008, the aggregate employment rate increased by .86 pp. However, this increase is mostly due to a change in the skill composition of the working age population. If the skilled and unskilled employment rates were fixed at their final level, the aggregate employment rate would have risen by 3.55 pp. This rise is explained by an increase in the relative supply of skilled individuals who are characterized by a higher employment rate with respect to unskilled individuals. On the contrary, if the skill composition of the working age population had remained constant, the aggregate employment rate would have fallen by 2.69 pp. This entire decline would have stemmed from a fall in the unskilled employment rate (-2.72 pp) between 1982 and 2008. Unskilled employment opportunities have shrunk over the last three decades.

By decomposing the overall period in two sub-periods, the story slightly changes. From 1982 to 1994, the employment effect had a negative impact on the aggregate employment rate. For a constant skill composition of the working age population, the aggregate employment rate should have fallen by 3.63 pp. The unskilled employment rate would have contributed for 91% of this decline. From 1994 to 2008, the employment effect had a small positive effect on the aggregate employment rate. For a constant skill composition of the working age population, the employment rate should have increased by 1.00 pp. The unskilled employment rate would have contributed for 59% of this increase. This suggests that the differentiated payroll tax subsidies implemented since the mid 1990s had potentially a positive impact on aggregate employment. However, the employment effect was not sufficient to counterbalance its initial negative impact on the aggregate employment rate. For any of the periods studied, the skill composition effect had a positive effect on the aggregate employment rate. Between 1982 and 1994, this effect was not sufficient to counterbalance the negative employment effect. Between 1994 and 2008, the skill composition effect deepened the positive impact of the employment effect. Indeed, it contributed for 66% of the rise in the aggregate employment rate in the latter period.

To summarize, the aggregate employment rate experienced a slight rise between 1982 and 2008 that was induced by an increase in relative skill supply. Without this change in relative skill supply, the aggregate employment rate would have fallen by 2.69 pp because of the declining unskilled employment rate. Unskilled workers have seen their employment opportunities decline significantly especially from 1982 to the mid 1990s.

Job polarization in France: an incomplete labor reallocation process

Studies on job polarization such as Autor and Dorn (2013) and Albertini, Hairault, Langot, and Sopraseuth (2016) assume that skilled workers fill in abstract jobs while unskilled workers perform in routine or manual jobs. This would imply that the fall in unskilled employment reflects an incomplete reallocation of labor from routine jobs towards manual jobs. Many unskilled workers would lose their jobs during the polarization process. It is then essential to check if the negative unskilled employment effect mostly comes from routine employment.

	Employment effect								
	Skilled				Unskilled				Total
	M	R	A	Total	M	R	A	Total	
1982 – 1994	0.02	0.12	-0.44	-0.31	2.21	-6.35	0.81	-3.32	-3.63
1994 – 2008	0.13	0.51	-0.23	0.41	2.65	-2.42	0.36	0.59	1.00
1982 – 2008	0.12	0.54	-0.63	0.03	4.92	-8.82	1.18	-2.72	-2.69

Table 2.2 – Employment effect decomposition by task

Notes: Values are in percentage points. The sum of abstract (A), routine (R) and manual (M) components for a given skill group gives the total contribution of that group to the employment effect for a given period.

Table 2.2 reports the employment effect decomposed by task. As expected, the negative impact of the employment effect on the aggregate employment rate comes from the unskilled employment effect and especially from routine employment. The unskilled routine employment effect represents a fall of 8.82 pp between 1982 and 2008. The unskilled manual employment effect tends to absorb part of the fall in unskilled routine employment. It contributes for an 4.92 pp increase. However, the unskilled manual employment effect is insufficient to counterbalance the unskilled routine employment effect. The unskilled abstract employment effect also tends to go against the routine employment effect with an increase of 1.18 pp but it is even lower than the unskilled manual employment effect. It is noteworthy that the skilled employment effect was almost insignificant (0.03 pp) between 1982 and 2008. The skilled abstract component was negative (-0.63 pp) while the manual and routine components were positive by respectively 0.12 pp and 0.54 pp. Abstract employment did not rise sufficiently to absorb the rise in skill supply in contrast to manual and routine employment.

Those facts seem consistent with our intuition that France has suffered significant unskilled employment losses through the polarization of its occupational structure between 1982 and 2008. Unskilled routine employment opportunities have shrunk while unskilled manual employment opportunities increased but not sufficiently to counterbalance unskilled routine employment losses. I suggest that labor taxation policies might impact the outcomes arising from technological change because the incentive to work in manual jobs -which are located at the bottom of the wage distribution- or to remain in non-employment is deeply influenced by labor taxation policies.

2.3 A general equilibrium model

In this section, I rely on a parsimonious general equilibrium model with occupational choice that aims at understanding the unskilled employment losses suffered by France in a context of technological change and labor taxation policy changes from 1982 to 2008. In order to do so, the model is built on Rogerson (2008), Acemoglu and Autor (2011), and Autor and Dorn (2013). Three exogenous trends drive the model's dynamics. There are technology trends embodied by changes in the capital price and in relative non-market productivity as well as labor taxation policies trends.

2.3.1 The environment

There are three main sectors which are perfectly competitive: a goods sector, a service sector and a non-market sector. They use three inputs which are unskilled labor, skilled labor and capital. Those inputs are used to accomplish manual, routine and abstract tasks. Therefore, each worker is characterized by a set of skills $\{a, r, m\}$ with a, r and m referring to abstract, routine and manual tasks, respectively. There is a unit mass of skilled labor which is only used to perform abstract tasks and thus characterized by the set of skill levels $\{1, 0, 0\}$.[6] There is a unit mass of unskilled labor that can accomplish two types of tasks, i.e. routine and manual tasks. Unskilled workers have the same ability to accomplish manual tasks. However, they are heterogeneous with respect to their ability to perform routine tasks, which is captured by the efficiency parameter $\eta \in [0; +\infty[$ with density function $f(\eta) = e^{-\eta}$ as in Autor and Dorn (2013). Consequently, each unskilled worker is characterized by a skill set $\{0, \eta, 1\}$. Capital can also perform routine tasks.

2.3.2 Production

Goods

Firms in the goods sector maximize their profit Π_g subject to their production technology. Their technology is characterized by the fact that they use abstract l_a and routine l_r labor as well as capital K as inputs. Thus, the representative firm program in the goods sector is

$$\begin{aligned} \Pi_g &= max\ Y_g - p_k K - w_r l_r - w_a l_a \\ s.t. &\quad Y_g \leq l_a^{1-\beta} \left[((1-\alpha_k) l_r)^\mu + (\alpha_k K)^\mu\right]^{\frac{\beta}{\mu}} \end{aligned} \tag{2.5}$$

with w_r, w_a routine and abstract wages, p_k the rental rate of capital, α_k the capital input share, and $\mu, \beta \in [0; 1]$. The price of the good is normalized to one. In order to produce goods, firms rely on abstract labor as well as routine tasks performed by a combination of routine labor and capital. The aggregate routine input $X = [((1-\alpha_k) l_r)^\mu + (\alpha_k K)^\mu]^{\frac{1}{\mu}}$ is represented by a Constant Elasticity of Substitution (CES) function in order to capture the substitutability between routine labor and capital. The elasticity of substitution between routine tasks accomplished by unskilled workers and those produced by capital is $\sigma_r = \frac{1}{1-\mu}$. Capital is a substitute for routine labor which means that $\sigma_r > 1$ or equivalently $\mu > 0$. The first order conditions for routine and abstract tasks are respectively

$$w_a = (1-\beta)\, l_a^{-\beta} \left[((1-\alpha_k) l_r)^\mu + (\alpha_k K)^\mu\right]^{\frac{\beta}{\mu}} \tag{2.6}$$

$$w_r = \beta (1-\alpha_k)^\mu l_r^{\mu-1} l_a^{1-\beta} \left[((1-\alpha_k) l_r)^\mu + (\alpha_k K)^\mu\right]^{\frac{\beta}{\mu}-1}. \tag{2.7}$$

[6] One could have assumed instead that skilled workers have a set of skills $\{1, 1, 1\}$ with $w_a > w_r, w_m$. Thus, skilled workers would always choose to produce abstract tasks.

Those equations describe the wage rates for workers who accomplish respectively abstract tasks and routine tasks. The first order condition for capital is

$$p_k = \beta\alpha_k^{\mu}K^{\mu-1}l_a^{1-\beta}\left[((1-\alpha_k)l_r)^{\mu}+(\alpha_k K)^{\mu}\right]^{\frac{\beta}{\mu}-1}. \tag{2.8}$$

Capital in efficiency terms is produced and supplied in a competitive framework. The production technology of capital is described by

$$K = Y_k\frac{e^{\delta_k t}}{\theta} \tag{2.9}$$

with Y_k the amount of final goods used to produce capital, δ_k the growth rate of capital productivity and $\theta = e^{\delta_k}$ an efficiency term. Capital fully depreciates at each period. The price of capital is equal to its marginal cost

$$\begin{aligned} p_k &= \frac{Y_k}{K} \\ &= \theta e^{-\delta_k t}. \end{aligned} \tag{2.10}$$

In contrast to Rogerson (2008), technological change in the goods sector is captured by a fall in the price of capital stemming from the growth of capital productivity $\delta_k > 0$. At the beginning of time $t = 0$, the price of capital is equal to one. As time passes, the price of capital decreases until it converges to zero. As the price of capital falls, firms in the goods sector substitute capital for unskilled workers in order to perform routine tasks.

Market services

The representative firm in the market service sector maximizes its profit subject to its production function. It only uses unskilled labor in order to accomplish manual tasks

$$\begin{aligned} \Pi_{ms} &= max\ pY_{ms} - w_{ms}l_{ms} \\ s.t. \quad & Y_{ms} \leq A_{ms}l_{ms} \end{aligned} \tag{2.11}$$

with p the relative price of services $\frac{p_s}{p_g}$ since the price of goods is normalized to one. I normalize the market service marginal productivity of labor to unity ($A_{ms} = 1$) as in Autor and Dorn (2013). The first order condition for manual labor in market services is

$$w_{ms} = A_{ms} p. \tag{2.12}$$

This equation describes the wage provided for manual tasks in the market service sector.

Non-market services

Households can also produce manual services in non-employment. This activity provides no wage but is not taxed. This feature is captured by non-market work. The non-market production technology only uses manual tasks. This assumption is realistic since this sector produces substitutes for low-skilled manual services such as cooking, childcare work, gardening and so forth. The non-market service technology is

$$Y_n = A_n l_n \tag{2.13}$$

$$A_n = e^{(t-1)\delta_n} \tag{2.14}$$

with l_n the labor allocated to the execution of manual tasks in non-market services and A_n the relative non-market labor productivity. Non-market labor productivity is assumed to change over time. A_n is initially normalized to unity and changes at a δ_n annual rate. Rogerson (2008) suggests that non-market productivity has declined with respect to market service productivity in Europe. One should expect a negative growth rate during the calibration exercise.[7] Time allocated in the non-market production sector can thus change. On the one hand, when non-market labor productivity declines, producing unskilled manual services in the non-market sector becomes less rewarding. Therefore, less labor will be allocated to the non-market sector because the opportunity cost of not working in the market service sector will rise. On the other hand, while the wage obtained by working in the market service sector is subject to taxation, the non-market sector provides no wage but is entirely protected from taxation. Consequently, when the labor tax rate on market service

[7] This is only due to the modeling of technological change in the non-market sector. One could obtain a positive growth rate by assuming labor saving technological change of the form $Y_n = A_n + l_n$.

labor increases, more unskilled workers are allocated to the non-market sector. This mechanism illustrates how labor taxation can induce unskilled employment losses.

2.3.3 Occupational choice

Unskilled workers choose to work either in the goods or the service sector and thus accomplish either routine or manual tasks. An unskilled worker with an ability level in routine tasks of η decides to accomplish routine tasks and thus work in the goods sector if the net wage for routine tasks is higher than the net wage for market service work

$$\eta\,(1-\tau_r)\,w_r \quad \geq \quad (1-\tau_{ms})\,w_{ms} \tag{2.15}$$

with τ_{ms}, τ_r and τ_a the average labor tax rates respectively on manual market service, routine and abstract wages. There is a threshold level $\overline{\eta}$ such that when an unskilled worker has a skill level $\eta > \overline{\eta}$, he chooses to accomplish routine tasks. When an unskilled worker is characterized by $\eta < \overline{\eta}$, he accomplishes manual tasks. The threshold level is such that

$$\overline{\eta} \quad = \quad \frac{(1-\tau_{ms})\,w_{ms}}{(1-\tau_r)\,w_r}. \tag{2.16}$$

Unskilled labor allocated to the goods sector is a function of the threshold $\overline{\eta}$

$$\begin{aligned} l_r &= \int_{\overline{\eta}}^{+\infty} \eta e^{-\eta} d\eta \\ &= (1+\overline{\eta})\,e^{-\overline{\eta}}. \end{aligned} \tag{2.17}$$

The threshold level $\overline{\eta}$ is determined within the general equilibrium framework and is consequently endogenous.

Unskilled labor allocated to manual tasks is defined by two conditions. Firstly, manual tasks are executed by workers characterized by a skill level $\eta < \overline{\eta}$ such that

$$\begin{aligned} l_s &= \int_0^{\overline{\eta}} e^{-\eta} d\eta \\ &= 1 - e^{-\overline{\eta}}. \end{aligned} \tag{2.18}$$

Secondly, unskilled workers can choose to allocate their labor either to the market service sector or to the non-market service sector

$$l_s = l_{ms} + l_n \tag{2.19}$$

which states that total labor allocated to manual tasks is equal to the sum of labor allocated in the market and the non-market service sector. The allocation of labor between the market service and the non-market sectors depends on consumer preferences. The intuition is that the allocation of unskilled labor is sequential. First, unskilled workers determine whether to work in the goods or the service sectors (market service or non-market), and thus whether they accomplish routine or manual tasks. Then, they choose to work either in the market service sector or in the non-market sector.

Skilled workers work in the goods sector and accomplish abstract tasks. For simplicity and as in Autor and Dorn (2013), I assume that skilled labor supply is inelastic such that

$$l_a = 1 \tag{2.20}$$

In other words, skilled workers allocate their entire time endowment to execute abstract tasks. Therefore, it is assumed that there is no non-employment for skilled labor.

2.3.4 The representative consumer

The representative consumer chooses consumption levels for goods, market services and non-market services given prices and wages. By choosing the amount of market and non-market services to consume, the representative consumer chooses the amount of labor unskilled workers dedicate to market work and to non-market work. This choice is central in this model due to the presence of taxation. Unskilled workers either work in the market sector and then receive a net wage, or they work to non-market production and receive no wage but the output coming from the non-market sector is not taxed. Therefore, I assume that the utility function is a CES function composed of goods and a composite service good

$$C = \left[a_g C_g^{\varepsilon} + (1-a_g) F(C_{ms}, C_n)^{\varepsilon}\right]^{\frac{1}{\varepsilon}} \tag{2.21}$$

where $\varepsilon < 1$, C_g, C_{ms} and C_n are respectively consumption of goods, market services and non-market produced goods. The composite service good is also a CES function composed of market services and non-market services

$$F(C_{ms}, C_n) = \left[a_s C_{ms}^{\nu} + (1-a_s) C_n^{\nu}\right]^{\frac{1}{\nu}} \tag{2.22}$$

where $\nu < 1$. The elasticity of substitution between goods and services both in the market and the non-market sectors is $\sigma_g = \frac{1}{1-\varepsilon}$ while the elasticity of substitution between market services and non-market production goods is $\sigma_s = \frac{1}{1-\nu}$. I assume that $\sigma_g > 1$ and $\sigma_s < 1$ or equivalently that $\varepsilon < 0$ and $\nu > 0$. Those assumptions mean that goods and the composite service good are complementary, while market services and non-market services are substitutes. The program of the representative consumer is

$$\begin{aligned}
\underset{\{C_g, C_{ms}, C_n, l_n\}}{max} \quad & \left[a_g C_g^{\varepsilon} + (1-a_g) F(C_{ms}, C_n)^{\varepsilon}\right]^{\frac{1}{\varepsilon}} \\
s.t. \quad & C_g + pC_{ms} = \sum_{i \in \{a,r,ms\}} (1-\tau_i) w_i l_i + T \\
& 1 - e^{-\overline{\eta}} = l_{ms} + l_n \\
& C_n = A_n l_n
\end{aligned} \tag{2.23}$$

with T capturing lump-sum transfers. Given prices, wages and lump sum transfers from the government, the representative agent chooses the path of the following variables $\{C_g, C_{ms}, C_n, l_n\}_t$. I search for an interior solution. First order conditions for respectively C_g, C_{ms} and the combined conditions for C_n and l_n give

$$a_g C^{1-\varepsilon} C_g^{\varepsilon-1} = \lambda \tag{2.24}$$

$$a_s(1-a_g) C^{1-\varepsilon} F(C_{ms}, C_n)^{\varepsilon-\nu} C_{ms}^{\nu-1} = \lambda p \tag{2.25}$$

$$(1-a_g)(1-a_s) C^{1-\varepsilon} F(C_{ms}, C_n)^{\varepsilon-\nu} C_n^{\nu-1} A_n = \lambda (1-\tau_{ms}) w_{ms} \tag{2.26}$$

with λ the Lagrangian multiplier associated to the household budget constraint. By combining the first order condition for C_g and C_{ms}, I get

$$p = \frac{a_s(1-a_g)}{a_g}\frac{F(C_{ms},C_n)^{\varepsilon-\nu}C_{ms}^{\nu-1}}{C_g^{\varepsilon-1}}. \tag{2.27}$$

This equation states that the marginal rate of substitution between goods and market services is equal to the marginal rate of transformation between goods and market services. By using the first order condition for C_{ms} and the combined conditions for C_n and l_n, I obtain the following equation

$$\frac{(1-\tau_{ms})\,w_{ms}}{p} = \frac{(1-a_s)}{a_s}\left(\frac{C_n}{C_{ms}}\right)^{\nu-1} A_n. \tag{2.28}$$

This equation states that the marginal rate of substitution between market and non-market services is equal to the *distorted* marginal rate of transformation between market services and non-market services. By using the previous equation and the manual wage rate equation, manual labor in market services is expressed as a linear function of non-market work

$$l_{ms} = \left(\frac{A_{ms}}{A_n}\right)^{\frac{v}{1-v}}\left(\frac{(1-\tau_{ms})\,a_s}{(1-a_s)}\right)^{\frac{1}{1-v}} l_n. \tag{2.29}$$

2.3.5 Market clearing conditions

In order to close the model, it needs to be consistent with market clearing conditions

$$Y_g = C_g + p_k K \tag{2.30}$$

$$Y_{ms} = C_{ms} \tag{2.31}$$

$$Y_n = C_n. \tag{2.32}$$

Since capital is generated from a fraction of output, the market clearing condition of the goods sector states that the output from the goods sector is divided between consumption for final goods and capital formation. Furthermore, the government constraint holds such that there is no deficit

$$T = \sum_{i\in\{a,r,ms\}} \tau_i w_i l_i. \tag{2.33}$$

2.3.6 Equilibrium

The general equilibrium is defined as a set of 20 sequences $\{Y_g, Y_{ms}, Y_n, C_g, C_{ms}, C_n, l_r, l_s, l_{ms}, l_n, l_a, p, w_r, w_{ms}, w_a, \overline{\eta}, K, p_k, T, A_n\}_t$ that solves equations (2.6), (2.7), (2.8), (2.16), (2.17), (2.20), (2.10), (2.11), (2.12), (2.18), (2.19), (2.13), (2.14), (2.23), (2.27), (2.29), (2.30), (2.31), (2.32) and (2.33) for $t = 27$ periods going from 1982 to 2008. The solution describes the path of variables across time. In order to obtain qualitative and quantitative results, the model is solved numerically because this system is non-linear. Since the model can be seen as a sequence of static programs, standard solvers for non-linear system of equations can be used. In this case, the initial guess needs to be updated at each step because the model displays non-stationary behaviors induced by the exogenous trends.

2.4 Calibration

The model is calibrated to match unskilled employment rates by task in 1982 and 2008. It accounts for the unskilled employment losses suffered by France between 1982 and 2008. The employment rate data used are the times series computed in subsection 2.2.5.

The data reveal that the unskilled employment rate has declined between 1982 and 2008. The unskilled manual employment rate has increased while the unskilled routine employment rate has significantly declined.[8] France occupational structure has polarized all over the last three decades. Furthermore, manual wages have increased more rapidly than for middle-paid and high-paid jobs mostly intensive in respectively routine and abstract tasks. The model is able to capture such predictions under two specific conditions obtained by computing its asymptotic equilibrium (appendix B.5). First, the consumption elasticity of substitution between goods and the composite service good is lower than the scaled production elasticity of substitution $\varepsilon < \mu/\beta$. Second, goods and the composite service good are complements $\varepsilon < 0$. Furthermore, the literature has found that routine labor is substitutable with capital which translates theoretically into an elasticity of substitution

[8] In order to build a parsimonious model of labor allocation, I keep two simplifying assumptions made in the standard model of Autor and Dorn (2013): skilled agents can only accomplish abstract tasks while unskilled agents can only accomplish routine or manual tasks. The fact that this paper focuses on the decline of unskilled employment and that the skilled employment effect reported in Table 2.1 is not significant justifies the former assumption. The fact that the share of unskilled individuals working in abstract jobs is stable between 1982 and 2008 and that most of the unskilled employment effect is coming from manual and routine jobs justifies the latter assumption. Therefore, I include unskilled abstract employment within unskilled routine employment.

Empirical targets

Year	e^{UN}	$e^{UN,r}$	$e^{UN,m}$	$1-e^{UN}$	Labor share
1982	.6174	.5498	.0676	.3826	.7684
2008	.5878	.4671	.1207	.4122	.6539

External parameters

β	A_{ms}	ν	τ_{1982}	$\tau_{a,2008}$	$\tau_{r,2008}$	$\tau_{ms,2008}$
.67	1	.45	.35	.39	.34	.29

Calibrated parameters

δ_k	α_k	δ_n	a_s	a_g	ε	μ
.031	.40	-.016	.37	.96	-.84	.42

Table 2.3 – Calibration and empirical targets

between capital and routine labor larger than unity ($\mu > 0$). One should expect to obtain parameter values that fulfill those conditions once imputed.

Practically, the calibration strategy consists in calibrating seven constant parameters (δ_k, α_k, δ_n, a_s, a_g, ε, μ) in order to match seven moments that include unskilled employment rates by task in 1982 and 2008 (e_t^{UN}, $e_t^{UN,k}$ for $t = 1982, 2008$ and $k \in \{m, r\}$) and the decline in total labor income share given seven external parameters (β, A_{ms}, ν, τ_{1982}, $\tau_{a,2008}$, $\tau_{r,2008}$, $\tau_{ms,2008}$). Concerning external parameters, I rely whenever it is possible on the literature or empirical evidence. In order to parametrize the routine input share parameter in the goods sector β, I rely on the EU KLEMS (O'Mahony and Timmer, 2009) sector level data since output data at the occupational or task level are not available.[9] I set the goods sector routine input share β to its 1982 value of .67. I also use the EU KLEMS data to compute the initial level and the change in total labor income share between 1982 and 2008 in order to calibrate respectively α_k the capital weight parameter and δ_k the growth rate of capital productivity. I find that the total labor share represented 76.8% of total income in 1982 and declined by 11.45pp between 1982 and 2008. For the tax rates data by task, I use the data displayed in the right panel of Figure 2.6. I set the elasticity of substitution between market services and non-market services to 1.82 ($\nu = .45$) like Rogerson (2008), who relies on empirical estimates in

[9] I assume that the agriculture, forestry, fishing, mining, quarrying, manufacturing, electricity, gas and water supply, construction, wholesale and retail trade, repair, transportation and storage sectors are routine intensive sectors while the information, communication, financial, insurance, real estate, professional scientific, technical, administrative and support service sectors are abstract intensive sectors. Those two groups of sectors constitute a proxy for the model's goods sector. I use the accommodation, food service, community, social and personal service sectors as a proxy for the market service sector.

the literature. Market service marginal productivity A_{ms} is normalized to one.

By solving the model for 1982 and 2008, and using previously discussed external parameter values, observed employment rate data, and the decline in labor income share, the seven parameters δ_k, α_k, δ_n, a_s, a_g, ε, μ can be imputed. Table 2.3 reports the results of the calibration. As expected, non-market labor productivity declines, goods and the composite good are complements, and routine labor and capital are substitutes. The utility weight of goods a_g is particularly high. This comes from the fact that the model's goods sector includes much more than the manufacturing industry. It includes also many jobs in high-skilled services industries while the model's market service sector represents only manual unskilled services. The market service weight in the composite service good a_s is comparable to Rogerson (2008)'s calibrated value.

2.5 Results

In this section, I use the calibrated model to grasp the decline of unskilled employment in France in a context of technological change and labor taxation policy change. To do so, I first display the model's intuitions and assess its fit to observed patterns of unskilled employment rates. Second, I investigate the intertwined effects of labor taxation and technological change. Third, I assess to which extent technological change and labor taxation policies are accountable for the decline in unskilled employment.

2.5.1 The obstructed reallocation of unskilled labor

In this subsection I display the intuitions and the fit of the model to the data. Intuitions are derived from the deterministic simulation of the model depicted in Figure B.5 and analytically grounded on the asymptotic equilibrium displayed in appendix B.5.

The model replicates the observed changes in occupational employment and net wage structures in France between 1982 and 2008. As in Autor and Dorn (2013), the allocation of unskilled labor between manual and routine tasks depends upon the relative magnitudes of the consumption and production elasticities which shape the occupational employment structure. As time passes, the price of capital falls. Capital becomes less and less expensive. Since capital and routine labor are substitutes, i.e. $\mu \in [0; 1]$, it thus becomes cheaper to produce the aggregate routine input X

with capital rather than with routine labor. Relative demand for routine labor falls which induces a decline in routine employment. On the demand side, households become richer as the price of capital falls. Since goods and services are complementary, i.e. $\varepsilon < 0$, the demand for services increases with the demand for goods. This explains the rising share of manual employment and the declining share of routine employment (Figure B.6). France experiences job polarization. In order to produce more market services, producers have to increase wages paid for manual labor relatively to routine labor so that they can absorb unskilled labor from the goods sector into the market service sector. All wages rise. Even though the relative demand for routine labor decreases, the routine wage has to rise in order to keep some workers in the goods sector. Capital and routine labor are imperfect substitutes. However, net wage rates do not grow at the same pace. The manual to routine net wage ratio tends to grow while the abstract to manual net wage ratio decreases reflecting the complementarity of goods and manual services and the substitutability between capital and routine labor (Figure B.7). This is in line with the observed changes in occupational net wages. The increasing relative price of services is due to the substitution of capital for routine labor which then induces an increase in the demand for manual services.

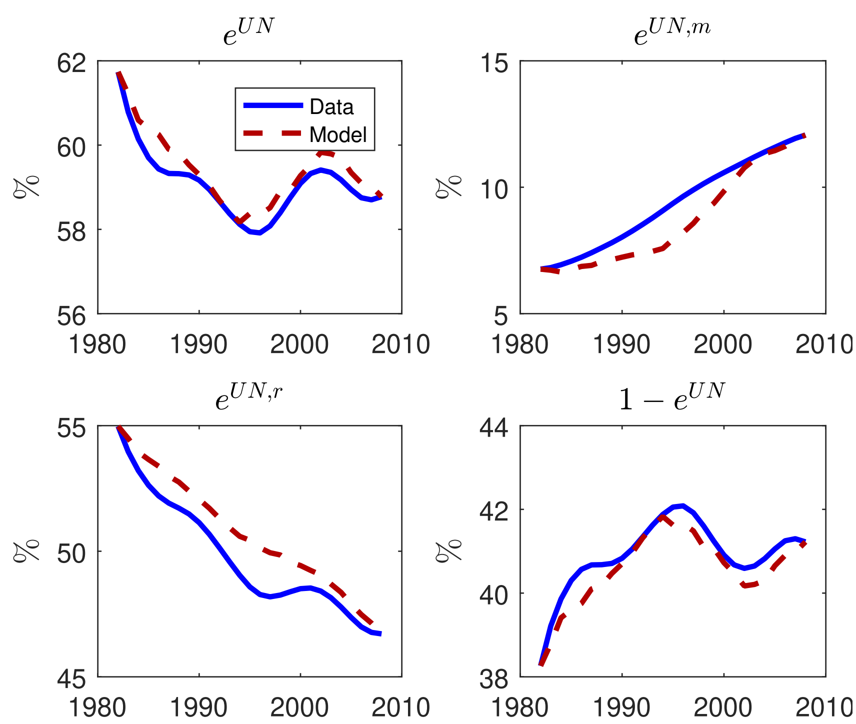

Figure 2.7 – Unskilled employment rate by occupational group

Notes: Values are in percentage. e^{UN}, $e^{UN,m}$, $e^{UN,r}$ refer to aggregate, manual and routine unskilled employment rates, respectively while $1 - e^{UN}$ refers to unskilled non-employment. Solid blue lines display observed time series while red dashed lines display simulated time series from the calibrated model.

In contrast to Autor and Dorn (2013), the model also captures a decline in unskilled employment. Figure 2.7 displays the unskilled employment rates by task for the model and for the data. The model fits approximately the dynamics of unskilled employment rate patterns despite the fact that only initial and final observations are matched in the calibration. The decline in unskilled employment is explained by a sharp decline in routine employment. The rise of manual employment is not sufficient to counterbalance the decline in routine employment. The reallocation of unskilled labor from routine jobs towards market services is partially obstructed due to the existence of the non-market sector since market services are substitutable with non-market services. The extent of the reallocation of unskilled labor is determined notably by labor taxation which increased from 1982 to 1994. Therefore, part of unskilled labor is not reallocated to the market service sector but to the non-market sector. This is established analytically by computing the asymptotic equilibrium of the model (Appendix B.5). However, the decline in unskilled employment has been mitigated since 1994 concomitantly to the implementation of distributional labor taxation policies.

To summarize, under empirically relevant parametric assumptions, the diffusion of ICT capital led to job polarization in France between 1982 and 2008. In contrast to Autor and Dorn (2013), the rise of unskilled manual employment does not fully counterbalance the decline in unskilled routine employment inducing significant unskilled employment losses from 1982 to the mid 1990s. Then, unskilled employment stabilizes simultaneously with the implementation of payroll tax reduction policies on low-paid workers.

2.5.2 Labor taxation and technological change

In this subsection, I study how labor taxation policies affect the employment outcomes arising from technological change. I show mainly that higher and non-redistributive labor taxation policies amplify unskilled employment losses induced by technological change. In order to do so, I build three counterfactual experiments. I consider three economies with different labor taxation policies. The first economy is the observed case with the French taxation levels and payroll tax subsidies targeted on low-paid workers. The second economy has French taxation levels but no payroll tax subsidies. The third economy has U.S. taxation levels without payroll tax subsidies. For each of those economies, I compare the evolution of the unskilled employment rate with and without technological change (δ_k and δ_n) between 1982 and 2008, which gives the unskilled employment losses induced by job polarization. Table 2.4 displays the results of the counterfactual analysis.

Case	Description	$\Delta e^{UN}_{1982-2008}$	ΔC_{ij}
$C1$	French taxation with subsidies with technological change	-2.96	-4.12
$C2$	French taxation with subsidies without technological change	1.16	
$C3$	French taxation without subsidies with technological change	-6.13	-4.88
$C4$	French taxation without subsidies without technological change	-1.26	
$C5$	U.S. taxation without subsidies with technological change	-3.50	-3.55
$C6$	U.S. taxation without subsidies without technological change	0.06	

Table 2.4 – Counter-factual analysis - Technological change and labor taxation
Notes: Values are in percentage points.

Higher labor tax rates enhance unskilled employment losses due to technological change:

$$\Delta C_{34} < \Delta C_{12} < \Delta C_{56}.$$

With French labor tax rate levels and no payroll tax subsidies ($C3$ and $C4$), unskilled employment losses induced by technological change are sharper. The unskilled employment rate declines by 6.13 pp with technological change ($C3$) while it falls only by 1.26 pp without technological change ($C4$). Thus, the unskilled employment rate decline induced by technological change amounts to 4.88 pp. Unskilled employment losses are more severe in this case because labor taxation interacts with technological change. As job polarization occurs because of technological change, routine jobs disappear. Unskilled routine workers are substituted by capital and are progressively reallocated either in manual jobs or in non-employment. Since labor tax rates are high for all workers including manual workers, a larger share of unskilled routine workers is reallocated towards non-employment because of the low value of manual jobs relative to non-employment. Unskilled employment becomes more sensitive to taxation as job polarization occurs because non-market services are substitutes for market services.

With U.S. taxation levels and no payroll tax subsidies ($C5$ and $C6$), the unskilled employment rate declines by 3.50 pp with technological change ($C5$) while it increases by 0.06 pp without technological change ($C6$). Thus, the unskilled employment losses induced by technological change with U.S. taxation levels are substantially reduced. They amount to a 3.55 pp decline in the unskilled employment rate which is lower than any of the three cases studied. U.S. tax rate levels are almost two times lower than French tax rate levels at any given point in time. Therefore, the relative value of manual jobs with respect to non-employment is larger than in the previous case. As job polarization occurs because of technological change, routine jobs still disappear and unskilled routine workers are still progressively reallocated either in manual jobs or in non-employment. However, the share of unskilled routine workers reallocated towards manual jobs is larger than in the previous case because of the higher relative value of manual jobs with respect to non-employment.

In the French economy with payroll tax subsidies ($C1$ and $C2$), unskilled employment losses induced by job polarization are inbetween the two previous cases. The unskilled employment rate declines by 2.96 pp with technological change ($C1$) while without technological change ($C2$) the unskilled employment rate rises by 1.16 pp between 1982 and 2008. Thus, the unskilled employment losses induced by technological change in the French economy with payroll tax subsidies targeted on low-paid workers amount to a 4.12 pp decline. In this case, both manual and routine labor tax rates decline significantly which increases the value of both types of jobs with respect to non-employment dampening employment losses in those jobs. Furthermore, workers are taxed differently depending on the task they perform because manual jobs are mostly located in the first percentiles of the occupational wage distribution while routine jobs are located in the middle and abstract jobs at the top of the occupational wage distribution. The decline in labor tax rate levels induced by the implementation of payroll tax subsidies targeted on low-paid workers is higher for manual workers than for routine workers. Those differentiated labor tax rates across types of workers change the relative value of manual jobs to routine jobs. The opportunity cost of working in routine jobs rather than manual jobs increases which incites some unskilled workers to switch from routine to manual jobs. This mechanism deepens the reallocation of labor induced by technological change from routine jobs to manual jobs.

Those counterfactual experiments suggest that the unskilled employment losses induced by technological change are enhanced by high and non-redistributive taxation policies.

2.5.3 Accounting for the decline in unskilled employment

In this subsection, I assess to which extent technological change and changes in labor taxation policies are accountable for the evolution of the unskilled employment rate between 1982 and 2008. In order

	Δe^{UN}	$\Delta e^{UN,r}$	$\Delta e^{UN,m}$	$\Delta(1-e^{UN})$
Overall Period 1982-2008				
Data	-2.96	-8.27	5.31	2.96
Model ($\delta_k \times \delta_n \times$Taxation Policy)	-2.96	-8.27	5.31	2.96
Technological Change ($\delta_k \times \delta_n$)	-4.57	-8.45	3.88	4.57
δ_k	-4.70	-5.53	0.83	4.70
δ_n	-0.02	-2.76	2.74	0.02
Interaction	0.14	-0.16	0.30	-0.14
Taxation Policy	1.16	0.19	0.97	-1.16
Interaction	0.45	-0.01	0.46	-0.45
From 1982 to 1994				
Data	-3.62	-5.93	2.31	3.62
Model ($\delta_k \times \delta_n \times$Taxation Policy)	-3.57	-4.38	0.82	3.57
Technological Change ($\delta_k \times \delta_n$)	-1.90	-3.44	1.54	1.90
δ_k	-1.78	-2.10	0.31	1.78
δ_n	-0.13	-1.31	1.18	0.13
Interaction	0.02	-0.03	0.05	-0.02
Taxation Policy	-1.52	-0.91	-0.60	1.52
Interaction	-0.15	-0.03	-0.12	0.15
From 1994 to 2008				
Data	0.66	-2.34	2.99	-0.66
Model ($\delta_k \times \delta_n \times$Taxation Policy)	0.61	-3.88	4.49	-0.61
Technological Change ($\delta_k \times \delta_n$)	-2.68	-5.01	2.33	2.68
δ_k	-2.92	-3.43	0.52	2.92
δ_n	0.12	-1.45	1.57	-0.12
Interaction	0.12	-0.13	0.25	-0.12
Taxation Policy	2.68	1.11	1.57	-2.68
Interaction	0.61	0.02	0.59	-0.61

Table 2.5 – Accounting for the decline in unskilled employment

Notes: Values are in percentage points. Data and model lines display the observed and the simulated changes in unskilled employment rates for the corresponding period. The contribution of technological and labor taxation trends is obtained by shutting down all but the considered trend.

to compute the contribution of each type of trends to the dynamics of the unskilled employment rate, I subsequently shut down technology and taxation policy trends. Results are reported in Table 2.5.

The contribution of technological change

In order to account for the role played by technological change, I shut down taxation policy trends. I also provide the separate contribution of each technology trend, i.e. capital diffusion δ_k and change in relative non-market productivity δ_n.

Technological change ($\delta_k \times \delta_n$) has a negative impact on the dynamics of the unskilled employment rate. Between 1982 and 2008, it contributes for a 4.57 pp decline in the unskilled employment rate. The unskilled employment losses induced by technological change are substantial both from 1982 to 1994 with a contribution of -1.90 pp and from 1994 to 2008 with a contribution of -2.68 pp. This is because technological change increases the relative value of manual jobs and non-employment with respect to routine jobs. Therefore, part of the losses in routine jobs induced by capital substitution are reallocated in manual jobs and part are reallocated in non-employment.

I now analyze the two technology trends separately. The negative contribution of technological change is mostly due to the fall in capital price (δ_k) which displaces unskilled workers mostly from routine jobs toward non-employment by reducing the relative value of routine jobs to non-employment and manual jobs all over the period studied. Only a small portion of unskilled routine workers are displaced into manual jobs. The decline in relative non-market productivity (δ_n) explains most of the reallocation from routine jobs towards manual jobs. It has an ambiguous effect on unskilled employment. On the one hand, it increases the relative value of manual jobs with respect to routine jobs. Thus, some routine workers are reallocated towards manual jobs but a fraction of them will also be reallocated towards non-employment. On the other hand, it also increases the relative value of manual jobs with respect to non-employment which reallocates non-employed workers towards manual jobs. This trend has almost no effect (-0.02 pp) on unskilled employment between 1982 and 2008 which suggests that the two effects almost compensate each other over the entire period. Moreover, the capital efficiency and non-market productivity trends produce an interaction effect that contributes for a 0.14 pp increase in the unskilled employment rate between 1982 and 2008. The interaction effect comes from the non-linearities of the model. The interaction of capital diffusion and the decline in non-market productivity enhances the manual employment gains. Both technology trends are needed to replicate simultaneously the polarization of the employment structure and the rise in unskilled manual services observed in the data.

Those results indicate that technological change played a crucial role in the decline in unskilled employment and the reallocation of routine labor towards manual jobs during the last three decades in France. Technological change incompletely reallocated unskilled workers from routine towards manual jobs.

The contribution of labor taxation policies

I now turn to the contribution of changes in labor taxation policies to the unskilled employment rate dynamics. To do so, I turn off the technology trends.

Despite the initial unskilled employment losses induced by the rise in labor tax rates in France, the unskilled employment gains generated by payroll tax subsidies focused on low-paid workers are larger. Taxation policies contributed for a 1.16 pp increase in the unskilled employment rate between 1982 and 2008.

From 1982 to 1994, labor tax rates were high and increased. They contributed for a 1.52 pp decline in the unskilled employment rate. This type of fiscal policy reduces unskilled employment through routine and manual jobs which accounts for a 0.91 pp and 0.60 pp decline in the unskilled employment rate, respectively. High and increasing labor tax rates decrease the relative value of both routine and manual jobs with respect to non-employment. The negative impact of high and increasing labor tax rates on labor supply is well known in the literature and has been identified by Prescott (2004) as a important factor to explain differences in labor supply across countries such as France and the U.S.

From 1994 to 2008, payroll tax subsidies focused on low-paid workers were implemented with the explicit aim of increasing employment. Those taxation policies contributed positively to the unskilled employment rate dynamics with a 2.68 pp increase.[10] It increased unskilled employment through both routine (1.11 pp) and manual (1.57 pp) employment by increasing the relative value of routine and manual jobs. Nevertheless, the rise in manual employment is slightly higher than the rise in routine employment. This is because payroll tax subsidies are decreasing with the wage. Therefore, manual jobs which are located at the very bottom of the wage distribution benefited of higher payroll tax subsidies which increased the relative value of manual jobs with respect to routine jobs and non-employment. By comparing counterfactual changes in the unskilled employment rate $C1$ and $C3$ in Table 2.4, one can have an idea of the additional unskilled employment losses that would have occurred had labor cost reduction policies targeted on low-paid workers not been implemented. The

[10]There are 30,682,930 unskilled individuals aged between 15 and 64 year old in 1994. Therefore, payroll tax reduction policies targeted on low-paid workers *per se* generated $30,682,930 \times 2.68\% = 822,303$ unskilled jobs between 1994 and 2008. According to Ourliac and Nouveau (2012), studies on the subject claim that payroll tax reduction policies targeted on low-paid workers saved at least 400,000 jobs in a worst case scenario and 1,100,000 jobs in the best case in France between 1993 and 2009.

unskilled employment rate would have decreased by 6.13 pp instead of 2.96 pp between 1982 and 2008. In other words, unskilled employment losses would have more than doubled.

This accounting exercise shows that high and increasing labor tax rates contributed to the decline in unskilled employment between 1982 and 1994 while this trend has been mitigated by the implementation of labor cost reduction policies focused on low-paid workers, i.e. payroll tax subsidies targeted on low-paid workers.

The interaction effect

The sum of the contribution of technological change and taxation policies does not add up to the total change in the unskilled employment rate (-2.96 $\neq$ -3.41). The residual is explained by the interaction of job polarization and labor taxation policies. As mentioned in section 2.5.2, the interaction effect is due to the fact that job polarization is changing the allocation of labor across market activities and the effect of taxes is different across tasks because of the substitutability of non-market services for market services.

This effect contributes for an 0.45 pp increase in the unskilled employment rate. When computing the contribution of technological change, all labor tax rates are constant. They are set to the initial tax rate value in 1982. When studying labor taxation policies, technology trends are turned off and labor tax rates change. Therefore, the separate contributions of technological change and labor taxation policies do not include the residual effect that arises from the interaction of job polarization with labor taxation policies.

On the one hand, the interaction effect contributed for a 0.15 pp decline in the unskilled employment rate between 1982 and 1994. Indeed, as job polarization occurred because of technological change, part of unskilled workers were reallocated towards manual jobs but also to non-employment. Since labor tax rates were high and increasing, the relative value of manual and routine jobs with respect to non-employment declined which increased the share of unskilled workers reallocated to non-employment. On the other hand, the interaction effect contributed for a 0.61 pp increase in the unskilled employment rate between 1994 and 2008 which compensated the initial negative interaction effect. Job polarization still occurred. However, the relative value of manual and routine jobs with respect to non-employment increased because of the implementation of labor cost reduction policies focused on low-paid workers which increased the share of unskilled workers reallocated to manual jobs instead of non-employment. This suggests that payroll tax subsidies targeted on low-paid workers are especially effective at increasing unskilled employment during job polarization.

To sum up, job polarization induced significant unskilled employment losses in France between 1982 and 2008. High and increasing labor tax rates enhanced the unskilled employment losses induced by job polarization between 1982 and 1994 while this trend has been mitigated by the implementation of labor cost reduction policies targeted on low-paid workers which are especially effective when job polarization occurs.

2.5.4 Discussion

This framework proposes an explanation for the deterioration of unskilled employment outcomes in France where technological and labor tax changes are pivotal. Within that framework, those trends are able to capture most unskilled employment dynamics between 1982 and 2008 which are at the core of France's deteriorating employment outcomes. This is achieved despite the frugality of the model analyzed and the fact that it is calibrated to match only the overall decline in unskilled employment rates and labor income share. The quantitative analysis must be viewed as a step toward deepening the analysis initiated by Prescott (2004) and Rogerson (2008) in assessing the determinants of the deterioration of European employment outcomes. Nonetheless, this approach underlines the importance of taking into account the task biased nature of technological change when designing labor taxation policies.

Several important aspects are omitted in this analysis that undoubtedly affect employment and occupational dynamics. Amongst them two are particularly worth mentioning in regard to the provided analysis: the minimum wage and globalization. The minimum wage increased significantly in France all over the period studied. Albertini, Hairault, Langot, and Sopraseuth (2016) highlight that it deepened unskilled employment losses arising from routine-biased technological change in France. The rising minimum wage obstructed the reallocation of workers from routine towards manual jobs. Oesch (2013) also highlights the role of wage regulations in Germany and the UK between 1990 and 2008. Both countries conducted important changes in their wage-setting institutions though in opposite directions. The UK introduced an increasing minimum wage while Germany underwent deregulation with the Hartz reforms. Surprisingly, employment rose for jobs located at the bottom of the wage distribution in the UK while it deteriorated in Germany. The author recommends the establishment of a minimum wage combined with investments in vocational training in order to encourage firms to invest in their workers' productivity rather than rely on a stagnant low-wage sector. In that respect, wage regulations have ambiguous effects on the reallocation of workers across occupations. It can reduce low-paid occupational employment if the minimum wage is high and binding or accelerate the reallocation of workers towards low-paid service jobs. In that regard, the employment losses attributed to technological change in this analysis are overestimated. Part of them might emanate from the minimum wage. Furthermore, the minimum wage probably affects the occupational choice of unskilled workers. It incites workers to choose manual service jobs where the minimum wage is frequently binding with respect to other occupations. This would accelerate the decline in routine employment but also potentially incite some workers to get out of non-employment by increasing the relative value of manual service jobs.

Globalization also affects employment outcomes in France. Harrigan, Reshef, and Toubal (2018) argues that offshoring reduced employment growth in France between 1994 and 2007 especially in manufacturing. Their results point to a substitution effect of foreign for domestic low-skilled labor. Malgouyres (2016) argues that the increase in import competition from China in France has a strong negative effect both on local employment and total labor income especially in manufacturing. Those employment losses have spillover effects beyond manufacturing. He estimates that for each local manufacturing job destroyed due to import competition, there is a loss of 1.5 jobs outside manufacturing. Those results suggest that globalization has large adverse effects on employment. Nonetheless, both papers rely on data posterior to 1994 and the rise in Chinese import competition started in 2001 with its entry in the World Trade Organization. As shown previously, this period is characterized by the stabilization of unskilled employment outcomes in France. Thus, those findings do not undermine the explanation provided in this paper for the deterioration of unskilled employment prior to 1994. They also imply that estimates probably undervalue the amount of unskilled jobs preserved by the distributional labor taxation policies implemented since 1994.

2.6 Conclusion

This chapter studies the evolution of unskilled employment in a context of job polarization and changes in labor taxation policies in France between 1982 and 2008. I rely on *five* main observations. France experienced a decline in unskilled employment *(i)* and a polarization of its occupational employment structure *(ii)* between 1982 and 2008. The rise in manual employment was not sufficient to counterbalance the decline in routine employment *(iii)*. Occupational net wage inequalities declined sharply *(iv)* partly because of labor taxation policies. France had a high and increasing average labor tax rate until 1994, and has implemented massive payroll tax reduction policies on low-paid workers since then *(v)*. In order to jointly grasp those facts, I rely on a parsimonious general equilibrium model with occupational choice. In this model, labor taxation interacts with technological change because as technological change occurs, unskilled workers are reallocated from middle-paid routine jobs toward low-paid manual jobs that produce services easily substitutable with non-market services. This makes the incentive to work in manual jobs especially sensitive to labor taxation policies. Therefore, unskilled employment becomes more responsive to labor taxation as labor reallocates. Second, I calibrate the model to account for the overall decline in unskilled employment. I allow for technological and labor taxation trends. I compute the extent to which each trend accounts for the overall decline in unskilled employment. Three key results arise from this approach. First, technological change induced significant unskilled employment losses in France between 1982 and 2008. It displaced unskilled workers from routine jobs toward manual jobs and non-market work leading to job polarization. The rise in unskilled manual employment was not sufficient to counterbalance the decline in unskilled routine employment. Second, unskilled employment losses induced by technological change were enhanced by the high and increasing labor tax rates between 1982 and the mid-1990s. Third, since the mid-1990s, the declining trend in unskilled employment has been mitigated by the implementation of payroll tax reduction policies targeted on low-paid workers. These policies have been especially effective in a context of job polarization because of the interaction effect; without them, unskilled employment losses would have more than doubled.

Chapter 3

Routine-Biased Technological Change and Hours Worked over the Business Cycle

Co-authored with Idriss Fontaine

3.1 Introduction

A core purpose of macroeconomics is to grasp an understanding of the business cycle. In that respect, modern macroeconomics provides two dominant theories of the business cycle: the Real Business Cycle (RBC) and the New-Keynesian (NK) theories. To discriminate between the two theories, a long-standing but widely open literature uses VAR techniques to measure the effects of technology shocks on labor input. Galí (1999) provided what is considered to be compelling evidence that technology shocks have recessionary effects on hours worked endorsing the NK over the RBC framework. In this paper, we revisit the technology-hours debate by reassessing the provided evidence in light of Routine-Biased Technological Change (RBTC), i.e. a specific type of technological development.

Technological change has dramatically shaped the labor market of developed economies in the last four decades. Strong evidence notably recollected by Autor and Dorn (2013) and Goos, Manning, and Salomons (2014) depicts a polarization of the labor market in most advanced economies. Middle-paid jobs are robustly disappearing while high-paid and low-paid jobs are expanding generating a surge in wage inequalities especially in the U.S. The main hypothesis offered to explain job polarization is the routine-biased technological change hypothesis. It conveys the idea that technological change, manifested through the diffusion of new information, communication and robotic technologies, is biased towards *replacing* labor in routine tasks. In this context, technological change significantly shifts the composition of labor demand away from middle-paid jobs because they mainly require routine tasks that are easily automated by new technologies. On the contrary, high-paid jobs involve cognitive abilities and low-paid jobs require manual dexterity and face-to-face interactions that are less inclined to automation. While RBTC has been extensively thought as a long-run gradual process, recent research argues that those shifts in the composition of labor demand occur mainly during economic downturns (Jaimovich and Siu, 2018). In that respect, RBTC and thus the heterogeneity of labor input might be key to untangle the debated effect of technology shocks on hours worked over the business cycle.

In contrast, benchmark RBC and NK theories treat labor as an homogeneous factor. In that case, RBC model predicts that a positive technology shock induces an expansionary effect on hours worked.[1] The labor market is pivotal. Technology shocks shift labor demand which increases the wage, and produce a substitution effect that incites households to increase hours worked. On the contrary, the NK theory predicts that a positive technology shock has a recessionary effect on hours worked.[2] Nominal rigidities are crucial since they constrain firms to the demand. Therefore, a positive technology shock increases the performance of inputs. However, firms adjust hours worked downward because of the sluggish demand. Less inputs are required to reach the same amount of output.

The evidence provided in Galí (1999) in favor of the NK theory relies on a Structural Vector Autoregressive model (SVAR). This approach allows him to interpret the observed negative correlation between hours worked and labor productivity. He breaks down structural shocks into technological and non-technological components. The identification of the technology shock hinges on long-run exclusion restrictions as pioneered by Blanchard and Quah (1989). The author argues that the aggregate technology shock is the only disturbance that has a permanent effect on labor productivity. He finds that the response of hours worked conditional on a technology shock is negative and that technological shocks are not able to generate recognizable business cycles. At first sight, these results seem difficult to reconcile with the RBC theory and are interpreted as evidence in favor of the NK

[1] Among others, examples include Kydland and Prescott (1982), King, Plosser, and Rebelo (1988), Plosser (1989) and King and Rebelo (1999).

[2] Examples include Smets and Wouters (2007), Galí (2008), Walsh (2005), Trigari (2009) and Galí (2010).

theory.

In this paper, we reassess Galí (1999)'s findings by investigating whether shifts in the composition of labor demand induced by RBTC can account for the recessionary effect of technology shocks. In light of this process, we then reevaluate the importance of technological shocks in driving aggregate fluctuations. Considering RBTC and thus labor as an heterogeneous factor might weaken Galí (1999)'s conclusion by casting doubts on his identification strategy. The acknowledgment of RBTC implies that the technology shock he identified entangles distinct disturbances that impact labor productivity permanently. These disturbances have presumably very different implications for our understanding of the effect of technology shocks on hours worked over the business cycle. For instance, RBTC might generate a sharp reallocation process stemming from significant shifts in the task composition of labor demand. This phenomenon could induce a decline in hours worked. This fall would not only be due to nominal rigidities - as supported by the NK theory - but also to the real effect of a vigorous reallocation process induced by technological change.

We basically deal with this identification issue by decomposing Gali's technology shock into two main components. The first component affects labor demand uniformly in the long run regardless of the task performed. We define it as a neutral technology shock. The second component affects the task content of hours worked in the long run. It includes two elements that shift the task composition of labor demand and supply. We defined them correspondingly as RBTC and a task-supply shock. We proceed first of all by building quarterly time series of hours worked and task premiums by using the Outgoing Rotation Groups from the Current Population Survey between 1989 and 2017. We define abstract, routine and manual occupational groups as in Cortes, Jaimovich, Nekarda, and Siu (2014). Task premiums are controlled for composition bias, and relative hours worked are computed in efficiency units to account for demographic and skill heterogeneity as suggested by Autor, Katz, and Kearney (2008). Then, we estimate a SVAR model to disentangle the effects of neutral technology shocks from those of task-related shocks. We identify those disturbances by deriving long-run exclusion and sign restrictions from a general equilibrium model built upon a wide strand of literature on skill- and task-biased technological change. Estimating a SVAR subject to combined long-run exclusion and sign restrictions is a challenging assignment that we undertake by using an approach recently developed by Arias, Ramirez, and Waggoner (2014).

Our main results suggest that the aggregate technology shock identified as in Galí (1999) captures strong shifts in the task composition of labor demand as well as a decrease in hours worked. This observation validates our insight that RBTC matters and justifies our decomposition of technology shocks into neutral and task-related components. In doing so, we find that hours worked and especially routine hours drop after RBTC. Neutral and task-supply shocks have no conclusive effects or at least of smaller magnitude on hours worked. Thus, we argue that most of the fall in hours worked is due to a shift in the task composition of labor demand due to RBTC. Furthermore, disentangling technological shocks is key when assessing the drivers of aggregate fluctuations. Technological shocks are not able to generate recognizable business cycles when we rely on Galí (1999)'s identification restrictions while they generate the bulk of aggregate fluctuations through RBTC when we disentangle them.

A meaningful implication of our results is that task heterogeneity matters for the study of business cycles. In that sense, our main contribution is to the business cycle literature. By investigating the effect of RBTC on hours worked, we reassess Galí (1999)'s evidence on the effect of technology shocks on hours worked in the light of the heterogeneity of labor. In that way, we closely relate to Balleer and van Rens (2013). The authors analyze the effects of skill-biased and investment-biased technological change on hours worked over the business cycle. We distinguish ourselves from them in at least two ways. First, we study task-biased rather than skill-biased technological change. We argue that abstract, routine and manual occupational groups react differently to technological change both in the long run and over the business cycle. Thus, it is worth investigating labor heterogeneity from a task perspective. Second, we differentiate ourselves with respect to our identification scheme. Using the empirical strategy of Arias, Ramirez, and Waggoner (2014), we are able to disentangle neutral from task-biased structural technology shocks. In their complete specification with long-run sign restrictions, Balleer and van Rens (2013) do not identify jointly skill-biased and neutral technology shocks. As a result, our empirical strategy allows us to break down technology shocks into shocks affecting labor uniformly and differently across tasks.

We also contribute to the polarization literature in at least two ways. Firstly, seminal papers such as Autor, Levy, and Murnane (2003), Autor and Dorn (2013) and Goos, Manning, and Salomons (2014) claim that job polarization is primarily generated by routine-biased technological change in the long run. Barany and Siegel (2018) further study the drivers of employment reallocation across sectors and occupations within a general equilibrium model. They find that the occupational bias of technology is by far the most important driver of productivity and employment reallocation trends. However, nothing guarantees that such shocks drive business cycle fluctuations in occupational hours worked. By decomposing productivity disturbances into a neutral and a task-biased component, we are able to tell whether technological change affects labor uniformly or differently across task groups over the business cycle. One limitation of our approach is that we do not provide a more exhaustive decomposition of disturbances. This issue lies outside the range of our paper.

Secondly, we believe to be the first attempting to identify RBTC over the business cycle within a SVAR framework. Some studies focus mainly on recessionary events rather than on the overall economic cycle. For example, Cortes, Jaimovich, Nekarda, and Siu (2014) claim that displacement of routine workers mostly occur during recessionary events. The collapse of routine per capita employment is accounted mainly by inflows and outflows between routine employment and non-employment that have little to do with demographic trends. Jaimovich and Siu (2018) further relate recent jobless recoveries to job polarization. Other studies look at the business cycles properties of occupational employment but do not explicitly look at RBTC. For instance, Foote and Ryan (2015) claim that middle-skill occupations are more cyclical than other occupations partly because they are found in more volatile industries. They also claim that middle-skill job matches are the most quickly dissolved when a recession occurs because of weak long-run prospects. Charlot, Fontaine, and Sopraseuth (2019) argue that half of unemployment variations comes from the ins and outs of routine employment. Such patterns suggest that the disappearance of routine jobs has a non-negligible influence in shaping unemployment fluctuations. To our knowledge, Shim and Yang (2016) is the only paper to study occupational employment fluctuations by using a SVAR.[3] The authors attempt to study the effect of an aggregate technology shock on hours worked identified as in Galí (1999). The core of our study argues that this identification strategy entangles shocks that have different implications on hours worked over the business cycle.

The chapter is organized as followed. In section 3.2, we develop a general equilibrium model with RBTC. We derive theoretical long-run restrictions in order to identify the corresponding shocks. In

[3]Strickly speaking, Breidemeier, Juessen, and Winkler (Forthcoming) also study the dynamics of occupational employment but in the context of fiscal policy shocks.

section 3.3, we describe the data, and display some stylized facts. In section 3.4, we present the VAR model and the identification strategy. In section 3.5, we present the outcomes of the VAR analysis. Section 3.6 concludes.

3.2 A general equilibrium model

In this section, we develop a general equilibrium model to study the effects of technology shocks over the business cycle.[4] This approach has two purposes: deriving long-run restrictions to identify structural shocks in the data and showing that routine automation generates a persistent decline in hours worked even in the absence of nominal rigidities. We display the model and present the main implications of the results.

3.2.1 The model

Firms

Consider an economy in which firms produce output Y_t by combining different tasks in the form of abstract $H_{a,t}$, routine $H_{r,t}$, manual $H_{m,t}$ labors, and automation capital K_t. They maximize their profits:

$$\Pi_t \quad = \quad Y_t - W_{a,t}H_{a,t} - W_{r,t}H_{r,t} - W_{m,t}H_{m,t} - R_tK_t.$$

where $W_{i,t}$ and R_t refer to the wage of workers performing task i for $i \in [a, r, m]$ and the rental rate of capital, respectively. The production function is increasing and concave in all its arguments, and exhibits constant return to scale. A Constant Elasticity of Substitution production function satisfies those properties. The production technology is described by the following function

$$Y_t \quad = \quad \left[\alpha_a H_{a,t}^{\frac{\varepsilon-1}{\varepsilon}} + \alpha_r \left[\eta H_{r,t}^{\frac{\mu-1}{\mu}} + (1-\eta)\, K_t^{\frac{\mu-1}{\mu}}\right]^{\frac{\mu}{\mu-1}\frac{\varepsilon-1}{\varepsilon}} + \alpha_m H_{m,t}^{\frac{\varepsilon-1}{\varepsilon}}\right]^{\frac{\varepsilon}{\varepsilon-1}} \tag{3.1}$$

where $\eta \in [0, 1]$ and α_j are distribution parameters with $\alpha_a + \alpha_r + \alpha_m = 1$. The elasticity of substitution between tasks is $\varepsilon > 0$ while the elasticity of substitution between capital and routine labor

[4]The model is built upon a wide strand of literature on skill- and task-biased technological change. We rely notably on Krusell, Ohanian, RÌos-Rull, and Violante (2000), Lindquist (2004), Cantore, Ferroni, and León-Ledesma (2017), Greenwood, Hercowitz, and Krusell (1997) and Barany and Siegel (2018).

is $\mu > 0$. In line with Autor and Dorn (2013), we assume that automation technologies and routine labor are substitutes $\mu > 1$. We also assume that automation devices are more substitutable with routine labor than with other tasks and that tasks are complements $\varepsilon < 1$. First-order conditions associated to abstract, manual, routine labors and automation capital are respectively

$$W_{a,t} = X_{1,t}^{\frac{1}{\varepsilon-1}} \alpha_a H_{a,t}^{\frac{-1}{\varepsilon}} \tag{3.2}$$

$$W_{m,t} = X_{1,t}^{\frac{1}{\varepsilon-1}} \alpha_m H_{m,t}^{\frac{-1}{\varepsilon}} \tag{3.3}$$

$$W_{r,t} = X_{1,t}^{\frac{1}{\varepsilon-1}} \alpha_r X_{2,t}^{\frac{\varepsilon-\mu}{\varepsilon(\mu-1)}} \eta H_{r,t}^{\frac{-1}{\mu}} \tag{3.4}$$

$$R_t = X_{1,t}^{\frac{1}{\varepsilon-1}} \alpha_r X_{2,t}^{\frac{\varepsilon-\mu}{\varepsilon(\mu-1)}} (1-\eta) K_t^{\frac{-1}{\mu}} \tag{3.5}$$

where $X_{1,t} = \alpha_a H_{a,t}^{\frac{\varepsilon-1}{\varepsilon}} + \alpha_r X_{2,t}^{\frac{\mu}{\mu-1}\frac{\varepsilon-1}{\varepsilon}} + \alpha_m H_{m,t}^{\frac{\varepsilon-1}{\varepsilon}}$ and $X_{2,t} = \eta H_{r,t}^{\frac{\mu-1}{\mu}} + (1-\eta) K_t^{\frac{\mu-1}{\mu}}$.

Under the assumption of perfect competition, we obtain the following task premiums by combining equations (3.2) to (3.4)

$$\begin{aligned}
\log\left(\frac{W_{a,t}}{W_{r,t}}\right) &= \log\left(\frac{\alpha_a}{\alpha_r \eta}\right) - \frac{1}{\varepsilon}\log\left(\frac{H_{a,t}}{H_{r,t}}\right) \\
&\quad + \frac{\mu-\varepsilon}{\varepsilon(\mu-1)} \log\left(\eta + (1-\eta)\left(\frac{K_t}{H_{r,t}}\right)^{\frac{\mu-1}{\mu}}\right) \\
\log\left(\frac{W_{r,t}}{W_{m,t}}\right) &= \log\left(\frac{\alpha_r \eta}{\alpha_m}\right) - \frac{1}{\varepsilon}\log\left(\frac{H_{r,t}}{H_{m,t}}\right) \\
&\quad + \frac{\varepsilon-\mu}{\varepsilon(\mu-1)} \log\left(\eta + (1-\eta)\left(\frac{K_t}{H_{r,t}}\right)^{\frac{\mu-1}{\mu}}\right).
\end{aligned}$$

By analogy to Krusell, Ohanian, RÌos-Rull, and Violante (2000), we have capital-routine task substitutability if abstract and manual labors are less substitutable by automation capital than routine labor ($\mu > \varepsilon$). In that case, a rise in the automation capital stock will *ceteris paribus* increase (resp. decrease) the abstract (resp. routine) premium. This is the *capital-routine substitutability effect*. Furthermore, a rise in relative abstract to routine hours and routine to manual hours will ceteris paribus decrease respectively the abstract and routine premiums for any values of ε and μ. Those capture *relative supply effects*.

Households

The economy is inhabited by three types of infinitely lived agents grouped into abstract, routine and manual households. There is a measure θ_j of each type of agent $j = a, r, m$. The population is normalized to one such that $\theta_a + \theta_r + \theta_m = 1$. Agents are born at time zero. They are assigned to a particular task at birth and are endowed with a unit of time. Individuals supply their unit of time if employed and none if unemployed. In a given household, individuals are perfectly insured against unemployment such that they consume the same amount of goods $c_{j,t}$ whether they are employed or not. Representative household preferences of each type are captured by utility functions of the form

$$u_{j,t}\left(c_{j,t}, n_{j,t}\right) \quad = \quad \frac{c_{j,t}^{1-\sigma}}{1-\sigma} - \zeta_{j,t}\frac{n_{j,t}^{1+\psi}}{1+\psi} \tag{3.6}$$

where $n_{j,t}$ is the fraction of household j members employed. By doing so, we assume that fluctuations in labor inputs are arising from the extensive rather than the intensive margin. Parameters $\sigma > 0$ and $\psi > 0$ are respectively the coefficient of relative risk aversion and the inverse Frisch elasticity of labor supply. We introduce intratemporal preference shocks $\zeta_{j,t}$ in order to capture potential shifts in task supplies.

The law of motion of automation capital is

$$K_{t+1} \quad = \quad (1-\delta)K_t + Z_t I_t. \tag{3.7}$$

where δ is the depreciation rate of automation capital, I_t captures investment and Z_t embodies RBTC. The real price of investment goods is $1/Z_t$ since it captures the number of consumption units that must be exchanged to acquire an efficiency unit of the investment good. Hence, a positive shock in Z_t reduces the cost of investing in automation devices thus accelerating their diffusion across the economy.

A benevolent social planner governs the economy and maximizes the following welfare function by choosing sequences of individual consumption $c_{j,t}$, fraction of individuals employed within a household $n_{j,t}$ and automation capital K_{t+1}

$$\mathbb{W}_t = \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left[\Omega_a \theta_a U_{a,t}\left(c_{a,t}, n_{a,t}\right) + \Omega_r \theta_r U_{r,t}\left(c_{r,t}, n_{r,t}\right) + \Omega_m \theta_m U_{m,t}\left(c_{m,t}, n_{m,t}\right)\right] \tag{3.8}$$

subject to the aggregate resource constraint

$$Y_t = C_{a,t} + C_{r,t} + C_{m,t} + I_t \tag{3.9}$$

and equations (3.1), (3.6) and (3.7). Ω_j are the social planner's preference weights such that $\Omega_a + \Omega_r + \Omega_m = 1$. Aggregate consumption and hours worked are linked to their individual counterparts as $C_{j,t} = \theta_j c_{j,t}$ and $H_{j,t} = \theta_j n_{j,t}$. First-order conditions arising from the benevolent social planner's program are

$$\frac{\Lambda_t}{Z_t} = \beta \mathbb{E}_t \left[\Lambda_{t+1}\left(R_{t+1} + \frac{(1-\delta)}{Z_{t+1}}\right)\right] \tag{3.10}$$
$$\Lambda_t = C_{a,t}^{-\sigma} \theta_a^{\sigma} \Omega_a \tag{3.11}$$
$$\Lambda_t = C_{r,t}^{-\sigma} \theta_r^{\sigma} \Omega_r \tag{3.12}$$
$$\Lambda_t = C_{m,t}^{-\sigma} \theta_m^{\sigma} \Omega_m \tag{3.13}$$
$$W_{a,t} = \zeta_{a,t} H_{a,t}^{\psi} C_{a,t}^{\sigma} \theta_a^{-\psi-\sigma} \Omega_a \tag{3.14}$$
$$W_{r,t} = \zeta_{r,t} H_{r,t}^{\psi} C_{r,t}^{\sigma} \theta_r^{-\psi-\sigma} \Omega_r \tag{3.15}$$
$$W_{m,t} = \zeta_{m,t} H_{m,t}^{\psi} C_{m,t}^{\sigma} \theta_m^{-\psi-\sigma} \Omega_m \tag{3.16}$$

where Λ_t is the Lagrangian multiplier associated to the resource constraint. They display respectively the Euler equation, marginal utilities of consumption and labor supply conditions for each type of agent.

Finally, we close the model by assuming that shocks follow random walk processes

$$\log\left(Z_t\right) = \log\left(Z_{t-1}\right) + \nu_{z,t} \tag{3.17}$$
$$\log\left(\zeta_{a,t}\right) = \log\left(\zeta_{a,t-1}\right) + \nu_{a,t} \tag{3.18}$$
$$\log\left(\zeta_{r,t}\right) = \log\left(\zeta_{r,t-1}\right) + \nu_{r,t} \tag{3.19}$$
$$\log\left(\zeta_{m,t}\right) = \log\left(\zeta_{m,t-1}\right) + \nu_{m,t} \tag{3.20}$$

where $\nu_{j,t}$ are white noises for $j = z, a, r, m$.

Equilibrium

An equilibrium consists of a set of decision rules $H_j(S)$ and $C_j(S)$ for $j = a, r, m$ depending on the state variables $S = [K, Z, \zeta_a, \zeta_r, \zeta_m]$ that solve (i) the social planner's welfare maximization problem and (ii) the firms' first-order conditions. We have a system of eighteen equations (3.1) to (3.5), (3.7) and (3.9) to (3.20) describing the equilibrium processes of eighteen variables $(Y, I, C_a, C_r, C_m, \Lambda_t, K, R, H_a, H_r, H_m, W_a, W_r, W_m, Z, \zeta_a, \zeta_r, \zeta_m)_t$.

From there, our aim is twofold. First, we derive long-run restrictions that will be subsequently used to identify structural shocks in the data. Second, we show that RBTC can generate a fall in hours worked through routine labor when we have capital-routine substitutability even in the absence of nominal rigidities. We proceed by providing a comparative statics analysis displayed in Appendix C.1. We solve the initial steady state in which we normalize structural shocks to one. We conduct a comparative statics analysis by looking at the change of steady state after a permanent change in each shock (Table C.1). This gives us the long-run effect of permanent shocks.

3.2.2 Calibration

We now parametrize the model. We set the discount factor β to .99 and the depreciation rate δ to .025. We proxy the proportion of each type of agent θ_j by the average share of hours worked in each type of task corrected for composition biases over the 1989Q1 to 2016Q4 period which gives us $\theta_a = 43.98\%$, $\theta_r = 47.94\%$ and $\theta_m = 8.08\%$. The inverse Frisch elasticity of labor supply ψ is equal to 2. We assume log utility in consumption by setting the coefficient of relative risk aversion σ to 1. According to our assumptions and in line with the polarization literature, we assume that automation capital and routine labor are substitutes while tasks are complements by setting ε and μ equal to .5 and 1.5, respectively. The CES distribution parameter α_a is arbitrarily set to 1/3 while $\alpha_r = 0.6619$, $\eta = 0.7726$, and the social planner's preference weights $\Omega_a = 0.4633$ and $\Omega_r = 0.3114$ are calibrated simultaneously. They are calibrated such that the initial steady state wage premiums ($W_a/W_r = 1.5413$, $W_r/W_m = 1.4364$) and relative hours ($H_a/H_r = 0.9338$, $H_r/H_m = 6.0471$) are equal to their respective sample average.

3.2.3 Comparative statics

We now present the main results from the comparative statics analysis from which we derive identifying restrictions on the long-run effect of structural shocks. We also show that total hours worked decline through routine labor after RBTC when we have capital-routine substitutability and task complementarity. We summarize the theoretically-grounded restrictions in Table 3.1 and display the entire comparative statics analysis in Table C.1.

Shocks/Variables		$\frac{Y}{H}$	$\frac{W_a}{W_r}$	$\frac{H_a}{H_r}$
RBTC	(Z_t)	>0	>0	>0
Task supply	$(\zeta_{a,t},\zeta_{r,t})$	$*$	<0	>0

Table 3.1 – Comparative statics

Notes: We display signs of long-run responses to a positive one percent permanent change in corresponding shocks. We denote by * the ambiguous variation in the variable of interest.

We are able to disentangle task-supply shocks from RBTC in the data with sign restrictions on labor productivity, abstract premium and relative abstract to routine hours. RBTC is captured by a positive shock on Z_t. This shock increases labor productivity by reducing the cost of investing in automation capital accelerating its diffusion across the economy. Since automation capital and routine labor are substitutes, RBTC generates a compositional shift in labor demand away from routine labor. Thus, the abstract premium increases as well as abstract to routine hours. On the contrary, the routine premium decreases as well as routine to manual hours. Therefore, premiums and corresponding relative hours worked evolve in the same direction.

RBTC is not the only shock affecting the composition of labor in the long run. Task-supply shocks also affect premiums and relative hours in the long run. A positive abstract to routine relative supply shock occurs either through a decline in $\zeta_{a,t}$ or an increase in $\zeta_{r,t}$. A negative shock in $\zeta_{a,t}$ reduces the dis-utility of working of abstract workers. The abstract premium decreases while abstract to routine hours increase reflecting the rise in the supply of abstract labor. Labor productivity falls due to decreasing returns in abstract labor. The responses of the routine premium and routine to manual hours are close to zero. A positive shock in $\zeta_{r,t}$ shifts preferences of routine workers towards leisure. The abstract premium decreases while abstract to routine hours increase. The routine premium increases while routine to manual hours decrease. Routine labor supply decreases. Since routine labor becomes more costly, firms substitute capital for routine labor. In that case, labor productivity increases reflecting the higher productivity of abstract and manual workers. Hence, task premiums and corresponding relative hours evolve in opposite directions whether task-supply shocks arise from $\zeta_{a,t}$ or $\zeta_{r,t}$. However, the change in labor productivity is ambiguous.

It is also noteworthy that technological shocks are able to generate a persistent fall in total hours worked even in the absence of nominal rigidities. RBTC decreases total hours worked in the long run through a strong fall in routine labor. The intuition is as follows. RBTC stimulates the diffusion of automation capital by increasing the efficiency at which investment is transformed into automation devices. Firms substitute automation capital for routine labor as it becomes available leading to a persistent decline in routine hours. RBTC also reallocates labor towards abstract and manual jobs because of their complementarity with capital. However, the slight rise in abstract and manual hours does not counterbalance the decline in routine hours leading to a permanent fall in total hours. Thus, a RBC model is able to generate a persistent fall in total hours worked after a technological shock even without nominal rigidities. In this case, capital-routine substitutability is key.

3.3 Data

In this section, we first describe the data used to estimate the effects of technology shocks. Second, we display descriptive statistics to discuss salient facts about technological change and the polarization of the U.S. labor market both over the long run and the business cycle.

3.3.1 Data construction

We start by presenting the data and construction of time series used both in the descriptive and the VAR analysis. We seasonally adjust the resulting time series using the X-13 algorithm developed by the US Census Bureau.

Sample. We build quarterly series of task premiums, relative employment, relative supply, hours, real wages and population from the IPUMS CPS micro data from 1989Q1 to 2018Q1.[5] We cannot use IPUMS CPS before 1989Q1 because they do not provide information on wages. The Census Bureau reports that the CPS includes errors for these series prior to 1989. We use the Outgoing

[5] Flood, King, Rodgers, Ruggles, and Warren (2018): `https://cps.ipums.org/cps/`.

Rotation Group which provides information on wage and salary for individuals interviewed in their 4th and 8th waves. We restrict our attention to civilian non-military 16-64 year-old individuals with 0 to 39 years of potential experience.[6] We study wages and hours worked restricting further our sample by including only those employed in non-farm occupations with positive real hourly wages. We focus on private non-farm employment to stay as close as possible to Balleer and van Rens (2013).

Weekly hours worked. Our main measure of hours of work is the usual weekly hours worked at the main job. When this information is not reported we replace it by a second measure of hours worked existing in the CPS, namely actual hours. However, the latter is available only since 1994. Observations with no values for both actual and usual hours are considered as missing. Zero hour observations are also considered as missing. Finally, we trim observations on hours that lie within the 0.5 and the 99.5 percentiles of observations.

Real hourly wage. The hourly wage is computed as the ratio of usual weekly earnings over usual weekly hours worked at the main job. Usual weekly earnings include overtime, tips and commission. For hourly workers, usual weekly earnings are the maximum between the reported usual weekly earnings and the imputed weekly earning (reported hourly wage times usual weekly hours worked at the main job). We correct top-coded wage observations with a fixed factor method as Acemoglu and Autor (2011) do. Top-coded weekly earnings are multiplied by 1.5 in order to get an approximate of the mean above threshold (top-coded value). Other imputation methods are available but they all aim at correcting top-coded observations by some factor. Weekly earnings observations with zero earnings are treated as missing. We clean computed hourly wages by trimming observations less than 0.3 and above 99.7 percentiles of observations. All variables are obtained by weighting observations with the earning study weights. Hourly wage is also weighted by usual weekly hours worked at the main job. We use the non-seasonally adjusted monthly consumer price Index research series using current methods (CPI-U-RS) on all items in order to deflate hourly wages.[7] For quarters where the CPI-U-RS is not available, we use the non-seasonally CPI-U which is close to the CPI-U-RS

[6] Restrictions on years of potential experience are typical in the literature studying inequality such as in Autor and Dorn (2013), Acemoglu and Autor (2011) and Balleer and van Rens (2013). Those restrictions are probably justified economically because of plausible selection bias.

[7] `https://www.bls.gov/cpi/research-series/home.htm`.

after 2001 according to the BLS.[8] We compute the quarterly average CPI. Quarterly real wages are expressed in 2015Q1 dollars.

Task premiums. We compute task premiums by calculating composition-adjusted log wage ratio of abstract to routine workers ($W_{a,t}/W_{r,t}$) as well as routine to manual workers ($W_{r,t}/W_{m,t}$). Following Cortes, Jaimovich, Nekarda, and Siu (2014)'s task classification, we map individual wage data in three occupational groups namely abstract, routine and manual, and control for change in gender, ethnicity, marital status, education and potential experience.[9] Due to the extent of heterogeneity and the size of the sample available, we use two gender (men and women), four potential experience (0-9, 10-19, 20-29 and 30-39 years) and four educational (less than high school, high-school degree, some college, college degree and more) categories. Following Autor, Katz, and Kearney (2008), Acemoglu and Autor (2011) and Balleer and van Rens (2013), we estimate standard Mincerian earnings functions where log wages are explained by a constant, the ethnicity, the marital status and a quartic function of years of potential experience for each task-gender-education-experience group. This specification allows potential experience, ethnicity and marital status to have different effects on log wages of each group. The composition-adjusted average log wage for each of the 96 task-gender-education-experience groups for a given quarter is the predicted log wage from those regressions for each respective group keeping constant other control variables. Average log wages by task in each quarter are obtained by a weighted average of relevant task-gender-education-experience composition-adjusted average log wages using fixed weights equal to the mean share of total hours worked by each group over 1989Q1 to 2018Q1. We then compute task premiums by taking the corresponding log wage differentials.

Relative hours worked. Relative hours worked are defined as the log ratio of abstract to routine and routine to manual total hours worked in efficiency units. We first compute total hours worked (by all employed workers in the restricted sample) for each of the 96 task-gender-education-experience groups. We then account for the heterogeneity of workers by expressing total hours worked in efficiency units. We normalize each task-gender-education-experience composition-adjusted wage

[8] `https://www.bls.gov/cpi/data.htm`.

[9] Cortes, Jaimovich, Nekarda, and Siu (2014) base their study on four task groups. In our case, we aggregate their classification to three task groups. Abstract workers include non-routine cognitive workers. Routine workers encompass routine cognitive and routine manual workers while manual workers only include non-routine manual workers.

by the composition-adjusted wage of high-school graduate routine male workers with 15 years of potential experience in the contemporaneous quarter. We then compute an efficiency unit measure for each cell as the arithmetic mean of the latter corresponding relative wage measure over 1989Q1 to 2018Q1. Finally, we aggregate hours worked to three task groups by averaging relevant hours worked using efficiency unit measures as weights. We obtain our relative hours worked variables by taking the log ratio of abstract to routine and of routine to manual total hours worked in efficiency units.

Total hours worked. Total hours worked in task i and in aggregate at a quarterly rate are computed as

$$TotalHours_{i,t} = \frac{52}{4} AvgHours_{i,t} e_{i,t} \tag{3.21}$$

where $AvgHours_{i,t}$ is the average weekly usual hours worked and $e_{i,t}$ is the fraction of employed workers in the working age population for the corresponding task or in aggregate.

Labor productivity. Labor productivity is taken from Ohanian and Raffo (2012). It is defined as the ratio between real output and total hours worked. The availability of this variable restricts our analysis to the 1989Q1-2016Q4 period.

3.3.2 Stylized facts

We now document several stylized facts. Time series are consistent with shifts in the composition of labor demand away from routine towards abstract and manual labor both over the long run and the business cycle. Those shifts appear tightly linked with the negative unconditional correlation between productivity and hours worked described by Galí (1999).

Figure 3.1 plots the abstract and routine wage premiums corrected for composition bias (W_a/W_r, W_r/W_m) as well as logs of relative hours worked in efficiency units (H_a/H_r, H_r/H_m). The abstract premium increases significantly contrarily to the routine premium which decreases between 1989Q1 and 2016Q4. Indeed, the abstract premium is approximately equal to 0.47 log points at the end of the sample period. This implies that the wage of the average abstract worker is 60% higher than the wage of the average routine worker. The wage differential between these two occupational groups is

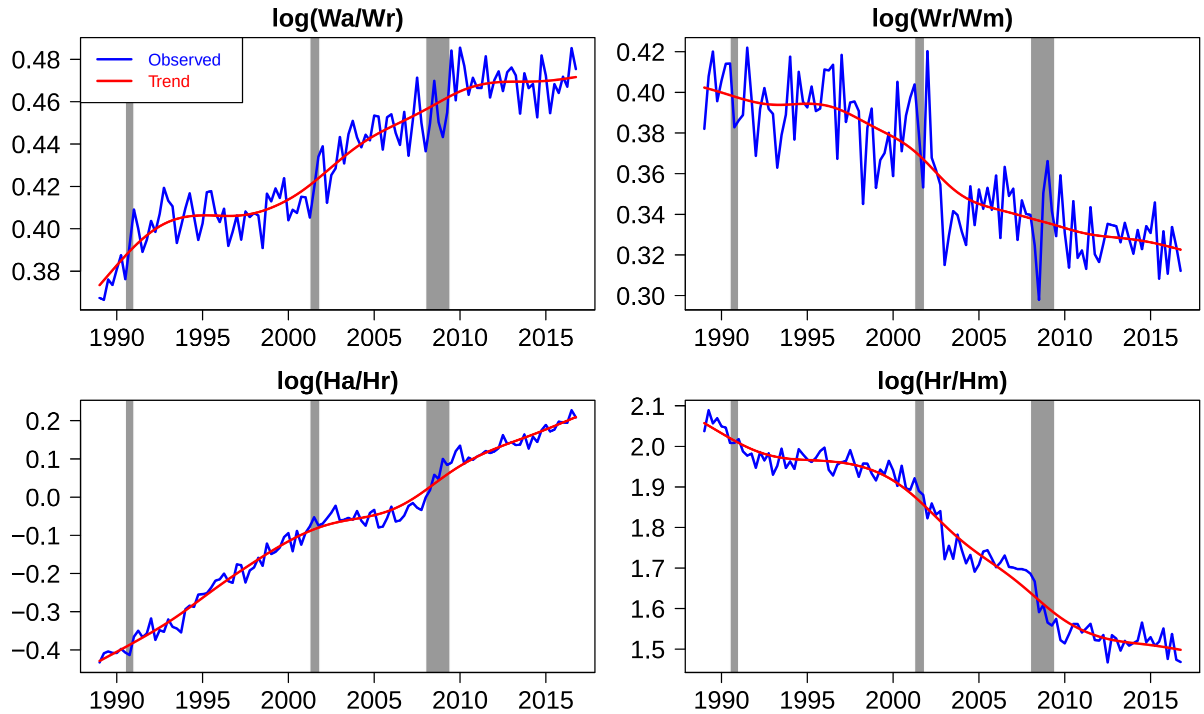

Figure 3.1 – Task premiums and relative hours over the 1989-2017 period

Notes: Data are constructed as described in subsection 3.3.1. All time series are seasonally adjusted using x13. Measures of task premiums are controlled for changes in experience, gender and educational attainment while relative hours are expressed in efficiency units. We capture trends by using the HP-filter ($\lambda = 1600$).

of 0.37 log points ($\approx 45\%$) at the beginning of our sample period. We observe the opposite qualitative pattern for the routine premium. In 1989Q1, the average routine worker earns a wage 49% higher than the average manual worker. In 2017Q4, the wage differential between routine and manual workers amounts to only 39%. Concomitantly, the amount of hours spent in abstract occupations relative to routine occupations increases sharply. The quantity of hours spent in routine occupations relatively to manual ones decreases significantly. Despite clear trends, these two measures of relative hours are not immune from cyclical fluctuations. During the Great Recession of 2008, abstract to routine hours substantially increase whereas routine to manual hours decrease. The mirroring dynamics of task premiums and relative hours worked reveals the long-run shifts in labor demand that lead to job polarization.

Figure 3.2 displays the evolution of total hours per capita at the aggregate level and by task. Job polarization manifests through a downward trend in the level of routine hours and upward trend in the levels of abstract and manual hours. In line with Jaimovich and Siu (2018), hours of work spent in routine jobs fall dramatically during busts. Such a finding suggests that job polarization

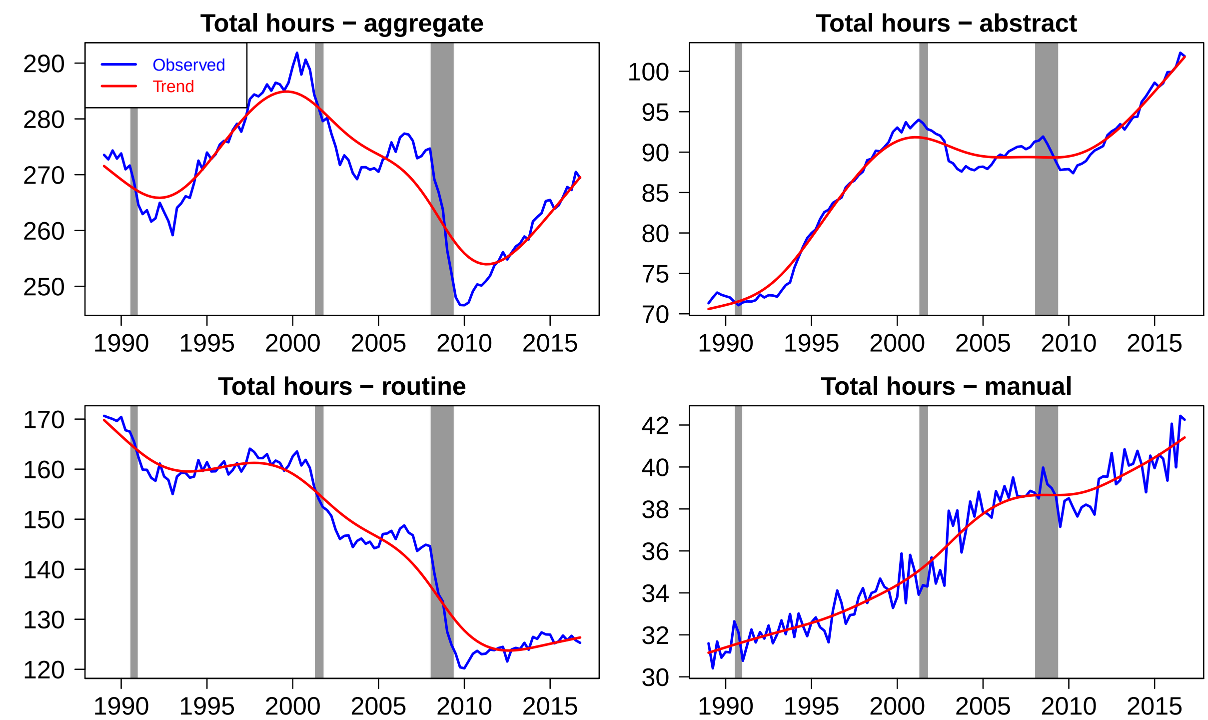

Figure 3.2 – Total usual hours per capita by task over the 1989-2017 period

Notes: Data are constructed as described in subsection 3.3.1. All time series are seasonally adjusted using x13. We capture trends by using the HP-filter ($\lambda = 1600$).

accelerates during recessions. However, a less documented finding is that the fall in hours worked also extends to abstract occupations. This is especially true for the last two recessions of our sample period. Furthermore, recovery is not perceptible for routine workers. This confirms that jobless recoveries are essentially accounted by the disappearance of routine jobs.

		Correlation				
	SD	W_r/W_m	H_a/H_r	H_r/H_m	Y/H	H
W_a/W_r	0.0090	-0.2126*	0.1767	-0.3005*	0.3942*	-0.3492*
W_r/W_m	0.0162	-	0.0648	0.2003*	-0.1010	0.1485
H_a/H_r	0.0204	-	-	-0.2934*	-0.0216	-0.4760*
H_r/H_m	0.0275	-	-	-	-0.3219*	0.5509*
Y/H	0.0075	-	-	-	-	-0.5250*
H	0.0147	-	-	-	-	-

Table 3.2 – Business cycle moments

Notes: SD stands for standard deviation. Data are constructed as described in subsection 3.3.1. Variables are in logs and HP-filtered with $\lambda = 1600$. Significance of at least five percent ($*$). Table C.3 displays the same business cycle moments for variables in first difference of their logarithm.

Table 3.2 reports business cycle moments for task premiums, relative hours as well as for labor productivity and total hours worked. Cyclical components are obtained with the HP-filter with a smoothing parameter λ of 1600. It appears that the long-run shifts in the composition of labor demand exhibited by time series seem to occur also over the business cycle. Indeed, the abstract and routine premiums are mildly negatively correlated: when the first one increases the second one tends to fall. Furthermore, the abstract premium (resp. routine) is negatively (resp. positively) correlated with routine to manual hours. However, we do not observe any significant correlation between the abstract premium and abstract to routine relative hours.

These compositional shifts in labor demand away from routine labor seem tightly linked to the negative correlation between productivity and hours worked documented by Galí (1999). The abstract premium is positively correlated with labor productivity but negatively correlated with total hours worked. The first correlation suggests a pro-cyclical pattern of the abstract premium. The second one could be seen as a first indication that positive changes in the abstract premium are associated with a fall in total hours. We find the opposite for the routine premium. Furthermore, abstract to routine hours are negatively correlated with total hours while routine to manual hours are positively correlated with them. Abstract to routine hours display no significant correlation with labor productivity whereas routine to manual hours are negatively correlated with the latter.

Those comments rely only on unconditional moments. In the following sections, we use a SVAR model to properly identify technology shocks and assess whether they account for a fall in hours worked through changes in the composition of labor demand.

3.4 A VAR model

In this section, we describe the VAR model, the estimation procedure and restrictions used to identify structural shocks discussed in this paper.

3.4.1 Bayesian estimation

The effects of structural shocks are estimated by modelling selected U.S. macroeconomic time series within a VAR framework. Our reduced-form VAR model can be written as follows:

$$Y_t = B_c + \sum_{k=1}^{p} B_k Y_{t-k} + \nu_t \tag{3.22}$$

with $B = [B_c, B_1, ..., B_k]$ the matrix of coefficients and ν_t the matrix of reduced-form residuals with covariance matrix $E(\nu_t \nu_t') = \Omega$. Our baseline set of endogenous variables Y_t includes growth rates of labor productivity, abstract premium, total hours worked, abstract to routine and routine to manual relative hours worked in the U.S. economy.[10] The ordering of variables into the vector Y_t is varying depending on the identified shocks. The sample spans the 1989Q1-2016Q4 period. This time length restriction follows the availability of the labor productivity variable.

Our reduced-form VAR is estimated within a Bayesian framework. We follow Balleer and van Rens (2013), Canova, Lopez-Salido, and Michelacci (2013) and Balleer (2012) by employing the Minnesota prior. Such a prior reflects the idea that the data generating process of the variables in level included in Y_t is a univariate unit root so that in first differences each of them is stationary. The prior incorporates a fixed residual variance determining the tightness on own lags, other lags as well as the decay of the lags. This reflects the belief that lower-order lag coefficients are more likely to matter. The Minnesota prior is flexible enough to allow the inclusion of a generous number of eight lags. It allows us to get rid of the inability of long restrictions to generate permanent effects of technology shocks.[11] Two additional points should be made about the use of the Minnesota prior in our context. First, it provides stable results in the presence of some "noisy" variations of the abstract premium due to some measurement errors. Second, it does not affect long-run restrictions. We check the robustness of our main results by considering alternative priors and specifications, and find that our key results do not depend on our initial choice.

[10] After testing for the presence of unit roots for each variable in level, all variables enter the VAR in first differences of their logarithm. Appendix C.2 provides the results of ADF and KPSS tests.

[11] Indeed, when Faust and Leeper (1997) show that long-run effects could not be precisely estimated in finite samples. Chari, Kehoe, and McGrattan (2008) demonstrate that researchers need extremely long time series to infer reliable long-run effects of technology shocks.

3.4.2 Identification

After the estimation of the reduced-form VAR model, the next step consists in identifying meaningful economic shocks. Concretely, we map reduced-form residuals ν_t to structural shocks ω_t which are serially and contemporaneously uncorrelated by imposing meaningful economic restrictions. The structural VAR model can be written as follows:

$$Y_t \quad = \quad A_0^{-1}A_c + \sum_{k=1}^{p} A_0^{-1}A_k Y_{t-k} + A_0^{-1}Q\omega_t \tag{3.23}$$

where ω_t is the matrix of structural shocks with covariance matrix $E\left(\omega_t\omega_t'\right) = I_N$ and $A_k = A_0 B_k$ the matrices of structural parameters with A_0^{-1} the structural impact matrix. The matrix Q is a rotation matrix that allows for sign restrictions with $QQ' = I_N$. We can link the covariance matrix of reduced-form residuals to some function of structural parameters by imposing restrictions since $E\left(\nu_t\nu_t'\right) = A_0^{-1}A_0^{-1\prime} = \Omega$. Specifically, we impose meaningful economic restrictions on the long-run structural impulse responses, which measures the long-run effects of structural shocks on variables:

$$LR \quad = \quad \left(I_N - \sum_{k=1}^{p} A_0^{-1}A_k\right)^{-1} A_0^{-1}Q. \tag{3.24}$$

This matrix can be directly mapped to reduced-form parameters with a sufficient number of restrictions since it is related to the long-run forecast error variance

$$LR'LR \quad = \quad \tilde{C}\Omega\tilde{C}' \tag{3.25}$$

with $\tilde{C} = \left(I_N - \sum_{k=1}^{p} B_k\right)^{-1}$ since $B_k = A_0^{-1}A_k$.

In this chapter, we employ two specifications summarized in Table 3.3. Specification I relies on a longstanding literature -initiated by Blanchard and Quah (1989) and Galí (1999)- employing long-run exclusion restrictions to identify technology shocks. In this case, the technology shock is the only shock that affects productivity permanently. We convert draws from the posterior distribution of reduced-form parameters to draws from the posterior distribution of structural parameters. Hence, we map reduced-form residuals to structural shocks uniquely for each Bayesian draw. This is done by ordering productivity first in the VAR and using a Cholesky decomposition of the long-run forecast

Specification I					
Order/Shock	Shock 1	Shock 2	Shock 3	Shock 4	Shock 5
	Technology		Other non-technology		
$\log(Y/H)$	$*$	0	0	0	0
$\log(H)$	$*$	$*$	0	0	0
$\log(W_{a,t}/W_{r,t})$	$*$	$*$	$*$	0	0
$\log(H_{a,t}/H_{r,t})$	$*$	$*$	$*$	$*$	0
$\log(H_{r,t}/H_{m,t})$	$*$	$*$	$*$	$*$	$*$
Specification II					
Order/Shock	Shock 1	Shock 2	Shock 3	Shock 4	Shock 5
	Supply	RBTC	Neutral	Other non-tech	
$\log(H_{a,t}/H_{r,t})$	> 0	> 0	0	0	0
$\log(W_{a,t}/W_{r,t})$	< 0	> 0	0	0	0
$\log(Y/H)$	$*$	> 0	> 0	0	0
$\log(H)$	$*$	$*$	$*$	$*$	$*$
$\log(H_{r,t}/H_{m,t})$	$*$	$*$	$*$	$*$	$*$

Table 3.3 – Specifications - Long-run exclusion and sign restrictions

Notes: The first column displays the variables used in the VAR as well as their ordering in ascending order. All variables are entered in first difference of their logarithm. > 0 indicates a positive long-run response of the variable to the shock identified in column, < 0 indicates a negative long-run response, 0 indicates a non-permanent response and $*$ indicates an unrestricted long-run response.

error variance: $chol(LR'LR)$.[12]

The second specification combines long-run sign and exclusion restrictions. The challenge is to convert draws from the posterior distribution of the reduced-form parameters with draws from the space of orthogonal matrices conditional on exclusion restrictions for Q to draws from the posterior distribution of candidate structural parameters. We retain from those candidate structural models only those for which the long-run impulse responses LR satisfy sign restrictions. We tackle this issue by using the algorithm developed by Arias, Ramirez, and Waggoner (2014). We provide details on the algorithm in Appendix C.3.

The algorithm employed in specification II has important economic implications. From our point of view, following this strategy is necessary for at least two reasons. First, using only zero long-run restrictions in a framework where the abstract premium is ordered first and labor productivity second is unsatisfactory. In that context, any positive long-run changes in the abstract premium could originate from an increase in W_a coupled with a rise in labor productivity (technological progress) or a fall in W_r coupled with a decline in labor productivity (technological regress). Second,

[12] The rotation matrix is implicitly equal to the identity matrix since we do not impose any sign restrictions.

the strategy proposed by Balleer and van Rens (2013) has its own drawbacks. They also combine zero and sign restrictions. In their context, the skill-biased technology shock implies variations in the same direction of the premium and labor productivity. Their skill-biased technology shock is identified, but the second shock is a mixture of neutral and unskilled-biased technology shocks. In Balleer and van Rens (2013)'s specification, the matrix of long-run effects is block recursive and the second shock is restricted to induce variations in the opposite direction than the one assumed for the skill-biased technology shock. The methodology developed by Arias, Ramirez, and Waggoner (2014) allows us to deal with the non block recursivity of our specifications. As a result, it enables us to disentangle task-biased from neutral technology shocks.

In specification II, we identify a neutral technology shock, a routine-biased technology shock and task-supply shocks. Routine-biased technology and task-supply shocks capture shifts in the task composition of labor demand. So we propose a new ordering of variables: the growth rates of first abstract to routine hours worked followed by the abstract premium, labor productivity and other variables. Both neutral technology and RBTC shocks affect labor productivity positively in the long run. We do not restrict the long-run response of labor productivity after a task-supply shock. Indeed, a positive abstract supply shock could decrease labor productivity because of diminishing returns in each input. In contrast, a negative routine supply shock could increase it due to the higher efficiency of abstract workers. RBTC affects relative hours and the task premium in the same direction while task-supply shocks affect those variables in opposite directions in the long run. Neutral shocks have no permanent effect on them. By definition, the relative amount of hours worked should not change because the demand for each type of task alters in the same direction and in equal proportion.

3.5 Results

In this section, we present results obtained from the structural VAR analysis. We display results from the two specifications in order to grasp the implication of each identification restriction. Thus, we first investigate the effect of technology shocks traditionally identified as in Galí (1999). Second, we disentangle the effects of RBTC, neutral and task-supply shocks as identified in specification II. Finally, we assess the importance of technological shocks for aggregate fluctuations under both specifications.

3.5.1 Specification I - Is Gali's technological shock neutral?

We present impulse response functions from a VAR with technology shocks identified as in Galí (1999). In that respect, there is a unique technology shock affecting labor productivity permanently. This identification strategy is consistent with a wide range of theoretical models such as standard RBC or demand-driven NK models. We proceed by ordering in the VAR growth rates of labor productivity followed by abstract premium, total hours worked and relative hours. In all Figures depicting impulse responses, we report the median and the Bayesian confidence interval of structural impulse responses. As diagnostic device, we also plot median target responses as defined by Fry and Pagan (2011).[13]

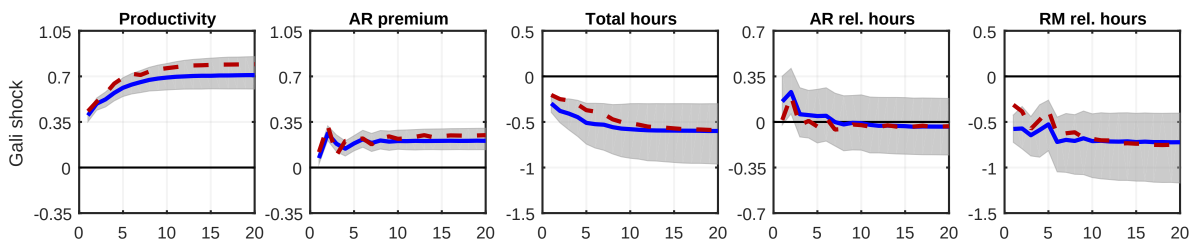

Figure 3.3 – Impulse response functions to Gali's technology shocks

Notes: Impulse responses to a one-standard deviation shock are reported. Solid lines represent the median of impulse responses. Grey areas correspond to the 68% of the posterior distribution. Dashed lines capture the median-target responses as defined by Fry and Pagan (2011).

Figure 3.3 plots the impulse responses of variables of interest to technology shocks. Positive technology shocks lead to an increase in labor productivity along with a fall in total hours worked. Both effects seem to be fully realized within 4-5 quarters. Our finding is clearly in line with Galí (1999). The drop in total hours is usually interpreted as evidence in favor of demand-driven NK models featuring price rigidities. The novelty of our approach relies on the inclusion in the structural VAR of variables capturing the shifts in task labor demand that led to job polarization, especially the abstract premium. Its response is significantly positive. Furthermore, routine to manual relative hours strongly decrease. Curiously, the response of abstract to routine hours is not significant probably

[13] According to Fry and Pagan (2011), median responses capture model uncertainty rather than sample uncertainty. They are not necessarily coming from the same structural model. The authors solve this issue by selecting the model for which impulse responses are the closest to pointwise posterior medians. Those selected impulse response functions are known as median targets. Nevertheless, this method does not necessarily provide a measure of the central tendency of structural models.

reflecting the influence of other shocks as shown subsequently. Those patterns suggest that technology shocks are biased towards replacing routine labor. They capture shifts in the task composition of labor demand away from routine workers.

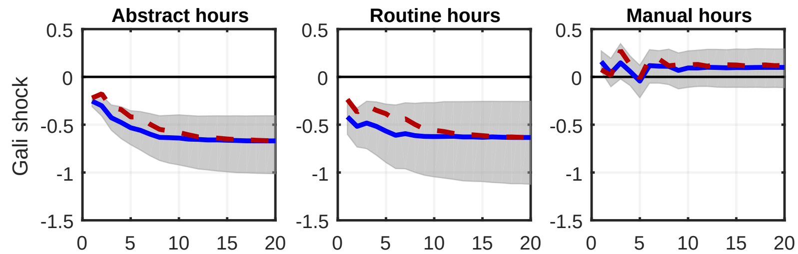

Figure 3.4 – Impulse response functions to Gali's technology shocks - Hours by task
Notes: Impulse responses to a one-standard deviation shock are reported. Solid lines represent the median of impulse responses. Grey areas correspond to the 68% of the posterior distribution. Dashed lines capture the median-target responses as defined by Fry and Pagan (2011).

Hence, we ask how those shifts in the task composition of labor demand manifest through changes in hours by task. To answer that question, we impute impulse responses of hours worked by task from relative hours and total hours measures included in the structural VAR. Figure 3.4 plots the corresponding impulse responses. Routine hours fall significantly after a technology shock while the response of manual hours remains insignificant throughout the adjustment path. This explains the negative response of routine to manual hours. Like routine hours, hours spent in abstract tasks decrease significantly explaining the non-significant response of abstract to routine hours. We show subsequently that this is partly due to the effects of shocks that are not yet identified but entangled with the currently identified shock. In a nutshell, the evidence indicates that Gali's technological shock appears biased towards replacing routine labor. This comforts the intuition that this shock actually entangles distinct structural disturbances that impact labor productivity permanently.

3.5.2 Specification II - RBTC, neutral and task-supply shocks

We now present results derived from the second specification for which the overall Gali's technological shock is disaggregated into neutral technology, RBTC and task-supply shocks. In doing so, we reorder endogenous variables of the VAR so that growth rates of abstract to routine hours, abstract premium and productivity enter first followed by our two measures of relative hours. Productivity is impacted positively by both neutral shocks and RBTC in the long run while we do not put any restriction for abstract supply shocks. Furthermore, RBTC affects the abstract premium and abstract to routine hours in the same direction while task-supply shocks affect those variables in opposite directions in the long run.

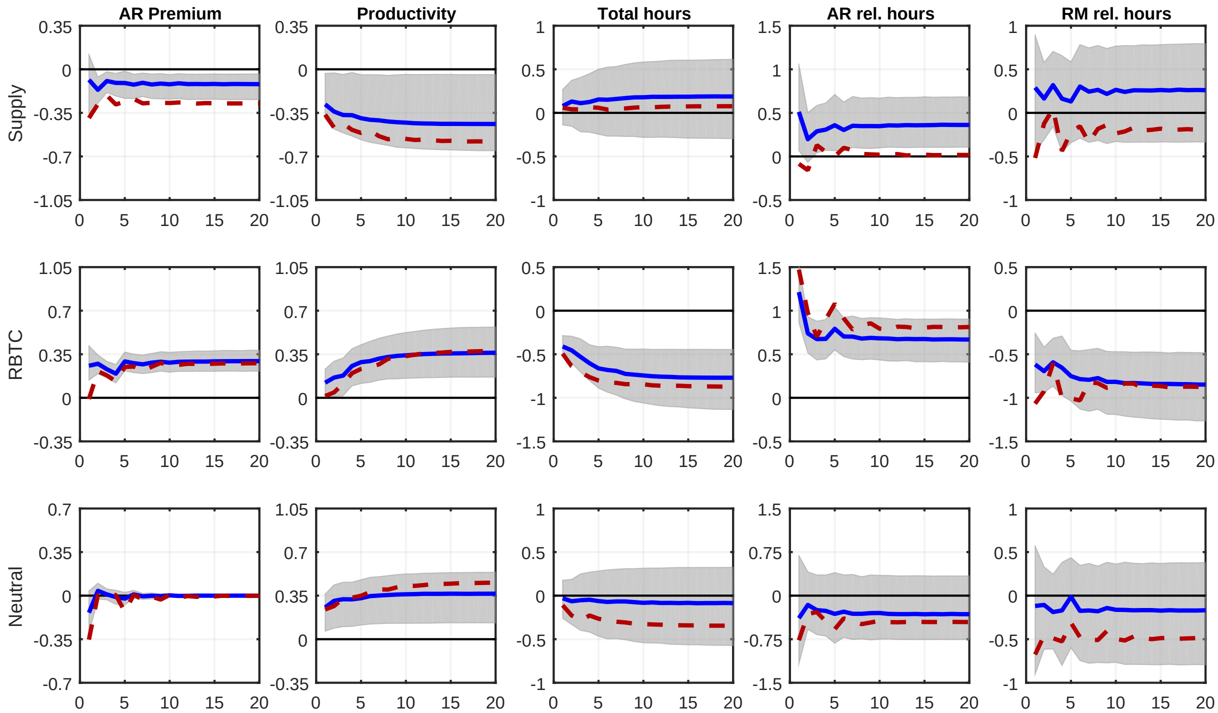

Figure 3.5 – Impulse response functions to task-supply, RBTC, and neutral technology shocks
Notes: Impulse responses to a one-standard deviation shock are reported. Solid lines represent the median of impulse responses. Grey areas correspond to the 68% of the posterior distribution. Dashed lines capture the median-target responses as defined by Fry and Pagan (2011).

Figure 3.5 displays the impulse responses of variables entered in the VAR. As expected, RBTC raises the abstract premium and abstract to routine hours significantly while it decreases routine to manual hours. This technology shock clearly captures shifts in the task composition of labor demand away from routine labor. Furthermore, it increases productivity and strongly decreases total hours worked. On the contrary, neutral shocks have a near zero effect on task-related variables reflecting the neutral aspect of those shocks. They only have a significant positive impact on productivity. Surprisingly, the median response of total hours worked is close to zero and responses are inconclusive about the sign. Abstract supply shocks slightly decrease the abstract premium and increase abstract to routine hours while decreasing productivity reflecting decreasing returns in abstract labor. Total hours' response is also close to zero and inconclusive about the sign. This indicates that the fall in hours worked is mostly due to shocks that are biased towards replacing routine labor. Those results nuance the NK argument that price rigidities explain the drop in hours worked after a positive technology shock. Our findings favor the idea that compositional shifts of labor demand away from routine labor are responsible for such a drop in hours worked.

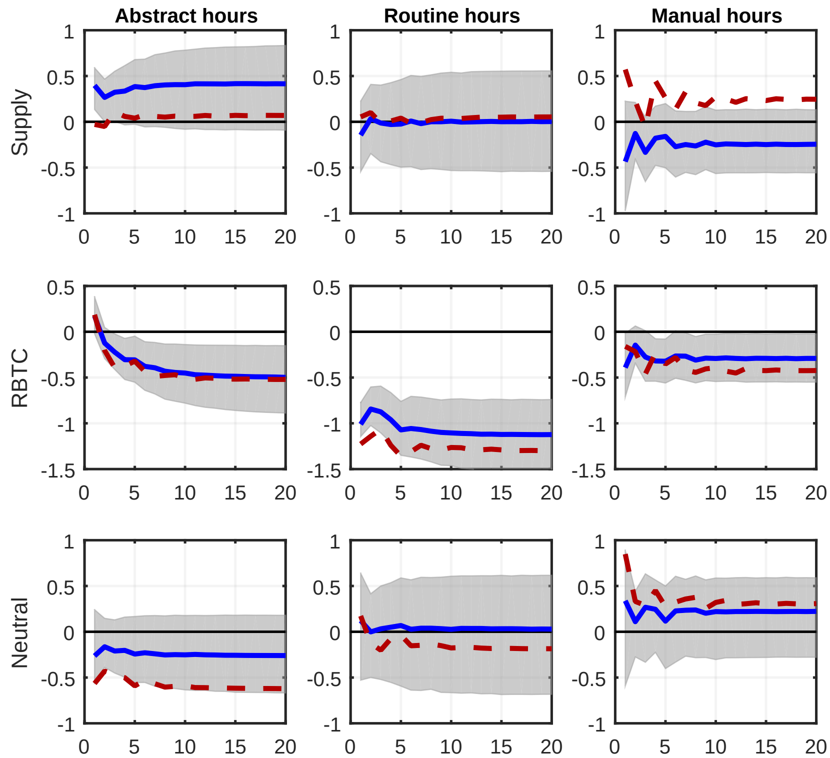

Figure 3.6 – Impulse response functions to RBTC shocks - Hours by task
Notes: Impulse responses to a one-standard deviation shock are reported. Solid lines represent the median of impulse responses. Grey areas correspond to the 68% of the posterior distribution. Dashed lines capture the median-target responses as defined by Fry and Pagan (2011).

We now scrutinize the dynamics of total hours by task displayed in Figure 3.6. Except for an increase in abstract hours after task-supply shocks, impulse responses of hours worked by task are insignificant and inconclusive after neutral and task-supply shocks. Such responses are consistent with the dynamics of abstract to routine hours and routine to manual hours observed previously. After RBTC, routine hours worked decrease sharply while the falls in abstract and manual hours are weaker but significant. Responses of hours worked reveal an important aspect of labor reallocation arising from RBTC. RBTC associates rising labor productivity and thus technological advancement with lower labor input. In addition, RBTC does not account for the observed upward trends in abstract and manual hours worked which are consequently the result of other economic forces.

As depicted in Figure 3.7, the task composition of hours worked shifts away from routine towards abstract and manual hours even though they all decline in level after RBTC. Therefore, RBTC generates job polarization over the business cycle along with a decline in hours worked. Moreover, the fall in hours worked arises mainly through routine hours due to the biased nature of RBTC.

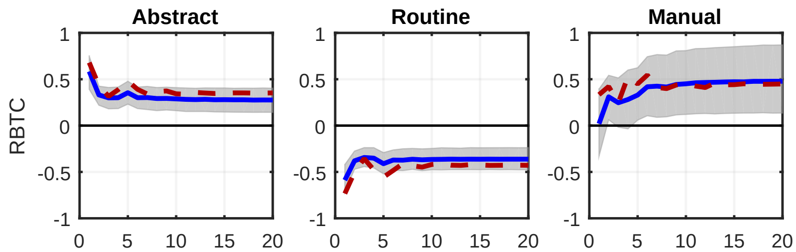

Figure 3.7 – Impulse response functions to RBTC shocks - Share of hours worked by task
Notes: Impulse responses to a one-standard deviation shock are reported. Solid lines represent the median of impulse responses. Grey areas correspond to the 68% of the posterior distribution. Dashed lines capture the median-target responses as defined by Fry and Pagan (2011).

Our explanation of the fall in hours worked after RBTC relies on the idea that technological shocks induce severe shifts in the composition of labor demand away from routine labor. Those significant shifts in labor demand reflect the substitution of capital for routine labor in order to perform routine tasks. In that respect, the process of labor reallocation induced by RBTC should occur primarily through the extensive margin namely employment per capita. By adding hours per worker by task in the VAR, we are able to decompose total hours worked impulse responses into intensive and extensive margin components. Figure C.1 displays the impulse responses for each of those components after a RBTC shock. It is clear that the response of hours worked to RBTC is mainly driven by the extensive margin namely employment especially for routine employment. Those findings corroborate the idea that the process of labor reallocation induced by RBTC is occurring especially through a drastic decline in routine employment per capita. In appendix C.5, we present a set of robustness checks that confirm those findings. Hence, most of the drop in hours worked arising from disturbances affecting labor productivity permanently stems from a shift in the task composition of labor demand due to RBTC.

3.5.3 Technological shocks and aggregate fluctuations

We now reassess the importance of technological shocks in explaining aggregate fluctuations in light of task-biased technological change. We show that disentangling technological shocks is crucial to determine the drivers of economic fluctuations. We proceed in two steps. First, we get a first insight into the relevance of technological shocks for aggregate fluctuations by looking at the Forecast Error Variance Decomposition (FEVD) under both specifications. Second, we look at historical decompositions of output and total hours worked to assess whether technological shocks generate recognizable business cycles.

How important are technology shocks for aggregate fluctuations?

Table C.4 displays a FEVD of the VAR based on the first specification at business cycle frequencies after one to 32 quarters. In that case, we only identify technological shocks defined as in Galí (1999). These shocks account for a significant share of the business cycle variance of labor productivity from 95% to 99% after respectively eight and 32 quarters. On the contrary, they explain a low share of the abstract premium volatility at first, that progressively increases with time from 20% to 26% after eight and 32 quarters. Furthermore, they explain almost none of the abstract to routine hours worked volatility with a share of around two percent at any horizon. They explain a larger share of fluctuations in routine to manual hours from 19% to 21% after eight and 32 quarters. Concerning total hours worked, they account for 23% of their volatility over all horizons. In Table C.5, we provide the FEVD for hours worked by task. We find that technology shocks explain from 29% to 32% of abstract hours fluctuations and approximately 16% for routine hours after eight and 32 quarters. On the contrary, manual hours fluctuations explained by technology shocks reach at most two percent after 32 quarters. It appears that fluctuations in aggregate labor productivity are well explained by technology shocks identified as in Galí (1999) contrarily to total hours and task-related variables. This is partly because the technology shock entangles a variety of neutral and task-biased disturbances that have different effects on those variables. This hides the contribution of each type of disturbances to the volatility of those variables.

Table C.6 displays a decomposition of the forecast error variance of the VAR based on specification II. Disentangling RBTC, neutral and task-supply shocks leads to a sizable increase in the share of the business cycle volatility explained by structural shocks of most variables compared to the first specification. For instance, structural shocks now explain 50% to 60% of the abstract premium volatility against 20% to 26% in specification I. This is also the case for total hours worked with a share of about 50% to 60% against approximately 24%. However, the contribution of each structural shock varies substantially across variables. RBTC accounts for 19% of the volatility of productivity after eight quarters against 29% for neutral shocks and 41% for task-supply shocks. Furthermore, RBTC captures most of the volatility of task-related variables. For example, it explains 37% of the volatility of the abstract premium against three percent for neutral shocks and ten percent for task-supply shocks. For total hours worked, RBTC captures around 40% of its volatility against six percent for neutral shocks and seven percent for task-supply shocks after eight quarters. As shown in Table C.7, this is primarily stemming from routine hours since RBTC accounts for 56% of their volatility after eight quarters while only for 12% and eight percent of the volatility of respectively abstract and manual hours. Those figures reflect the importance of RBTC in shaping total hours worked especially through routine hours over the business cycle these past four decades.

Do technological shocks generate recognizable business cycles?

We have shown that RBTC accounts for most of the fall in total hours impulse responses and that those shocks contribute substantially to total hours worked fluctuations. However, those results only describe the average movements in the data. We now follow Galí (1999) by asking whether those shocks generate recognizable business cycles. Thus, we decompose output, and total hours worked historical time series into technology and non-technology components and measure to which extent they account for observed fluctuations. Our focus is set on the median target model defined by Fry and Pagan (2011).

	Observed	Specification I		Specification II			
		Tech	Non-Tech	Supply	RBTC	Neutral	Other NT
corr(Y,H)	0.78*	-0.71*	0.99*	-0.75*	0.95*	-0.42*	0.98*
corr(H,Y/H)	-0.53*	-0.92*	0.29	-0.81*	-0.67*	-0.94*	0.73*
corr(Y,Y/H)	-0.01	0.93*	0.45*	1.00*	-0.41*	0.70*	0.85*

Table 3.4 – Unconditional and conditional correlations estimates

Notes: H, Y and Y/H refer to hours worked, output and labor productivity, respectively. We retrieve the cumulative contribution of each shock to (log) output, (log) hours worked and (log) productivity time series from estimated structural VAR models. We use the HP-filter ($\lambda = 1600$) on resulting time series to isolate business cycle fluctuations. Then, we compute correlations between H, Y and Y/H conditional on each structural shock. The corresponding components time series are depicted in Figures C.2 and C.3.

Table 3.4 displays unconditional and conditional correlation estimates between total hours worked, output and labor productivity from both specifications. We obtain results in line with Galí (1999) when we rely on his identification restrictions. Those results are interpreted as a failure of RBC theory to capture the essence of business cycle fluctuations for two reasons. First, technological shocks are not able to replicate the observed procyclicality of labor inputs (0.78). They generate negative comovements of hours worked and output (-0.71) while non-technological shocks generate positive comovements of those variables (0.99). This implies that the bulk of fluctuations are mainly driven by non-technological shocks while standard RBC theory claims that business cycles are driven by technological shocks. A look at the entire historical decomposition of output and hours worked (Figure C.4) confirms that non-technological shocks account for most of those variables' fluctuations under the first specification as observed by Galí (1999). Second, technology shocks should generate positive comovements of productivity and hours worked according to standard RBC theory which is not the case empirically (-0.92). It is usually interpreted as evidence supporting the new-Keynesian view of sticky prices.

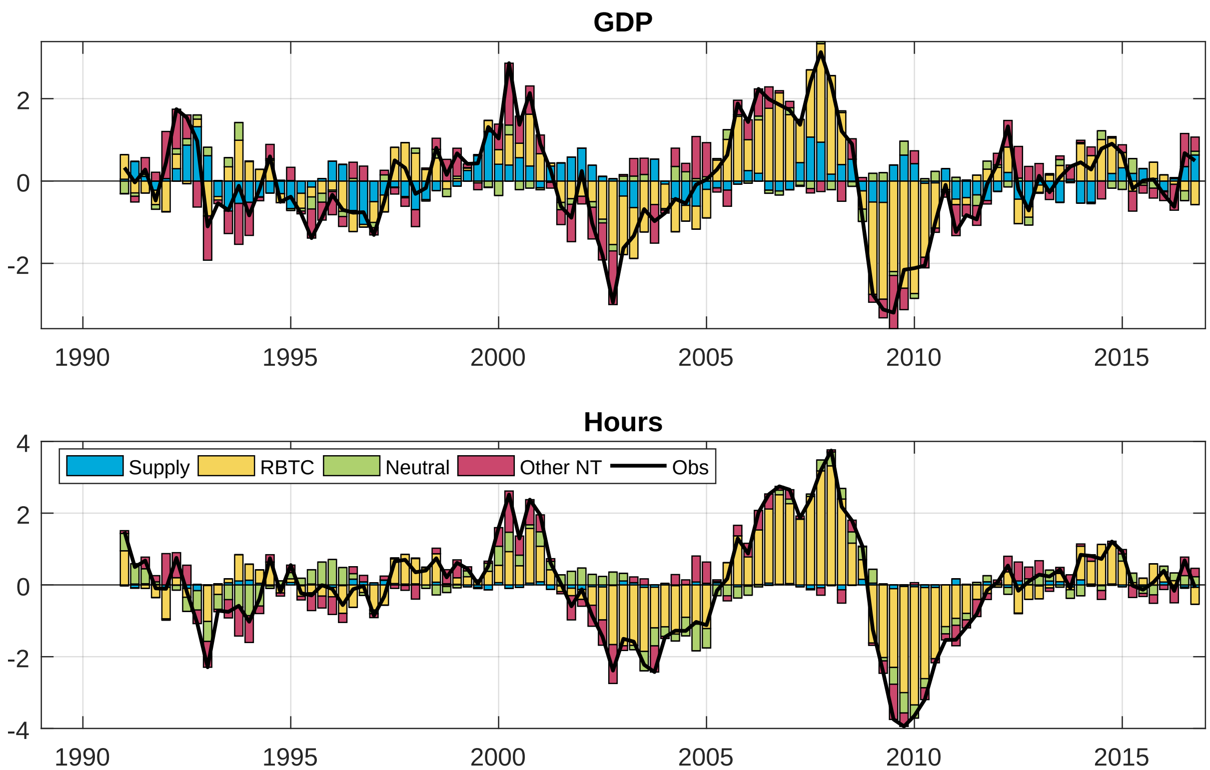

Figure 3.8 – Specification II - Historical decomposition of GDP and total hours.
Notes: We retrieve the cumulative contribution of each shock to (log) output and (log) hours worked time series from the estimated structural VAR identified using specification II restrictions. We use the HP-filter ($\lambda = 1600$) on the resulting time series to isolate business cycle fluctuations.

In contrast, we obtain a different picture when we disentangle technological shocks by relying on the second specification. RBTC generates positive comovements of output and hours worked (0.95) which is a central characteristic of business cycles while neutral technological (-0.42) and task-supply (-0.75) shocks capture negative comovements of those variables. Other non-technological shocks also generate positive comovements of output and hours worked (0.98). This suggests that both RBTC and other non-technological shocks are candidate drivers of aggregate fluctuations. In order to discriminate between the two types of shocks, we depict the entire historical decomposition of output and hours worked in Figure 3.8 to provide a wider picture of aggregate fluctuations. It is clear that RBTC is an important driver of business cycle fluctuations in hours worked and output under the second specification. Those shocks seem to drive the bulk of aggregate fluctuations especially since the early 2000s. Furthermore, RBTC generates negative comovements of hours worked and productivity (-0.67). While this seems to be at odds with standard RBC theory, this is coherent with the idea that technological change induces a decline in hours worked through capital labor substitutability. It is also noteworthy that neither technological nor non-technological shocks are able to capture the slight countercyclical productivity movements (-0.01) under the first specification. On the contrary, RBTC is the only type of disturbance that generates countercyclical productivity movements (-0.41) under our second specification. This finding is in line with Jaimovich and Siu (2012) who claim that the reallocation of labor away from routine jobs induced by technological change occurs especially during recessions. While a standard RBC model is not able to generate countercyclical productivity movements, a model of creative destruction can capture this feature. Outdated routine jobs, being easily substitutable by new technologies, are getting scrapped during recession because they become unprofitable leading to a rise in productivity.[14]

In a nutshell, those results suggest that business cycles seem driven by non-technology shocks when technological shocks are aggregated as in Galí (1999) while they are driven by task-biased technological shocks when relying on our second specification. Even though this analysis does not provide a thorough examination of the determinants of aggregate fluctuations, it stresses the importance of considering the nature of technological change.

[14]The reversal in the cyclicality of labor productivity is a recent feature that occurred in the mid 1980s. Caballero and Hammour (1994) claim that old firms, having an obsolete technology, can more easily become unprofitable and be scrapped in a recession than recent ones while Berger (2012) suggests that firms lay off unproductive workers during recessions. Both explanations imply countercyclical productivity movements. Among others, Barnichon (2010), Galí and van Rens (2014) and Garin, Pries, and Sims (2018) also document and propose alternative interpretations of the reversal in output and productivity comovements.

3.6 Conclusion

During the last four decades, the U.S. has experienced job polarization because technological change has been biased towards replacing routine labor. In light of such development, we reassess the evidence provided in Galí (1999) by asking if the observed shifts in the task composition of labor demand away from routine labor are accountable for the recessionary effect of technology shocks on hours worked. We then assess whether technological shocks are able to generate recognizable business cycles.

We build quarterly time series on hours worked, task premiums and relative hours from the IPUMS Current Population Survey to estimate the effect of structural shocks on the data. A preliminary look of the facts suggests that the composition of labor demand is shifting away from routine labor both over the long run and the business cycle. Furthermore, it appears that such phenomenon is tightly linked to the observed negative relationship between labor productivity and total hours worked first documented by Galí (1999).

We then estimate the effect of technological shocks by relying on a VAR model. We identify structural shocks by combining theoretically grounded long-run exclusion and sign restrictions. Those restrictions are derived from a Real Business Cycle model with capital-routine substitutability. This allows us to disentangle structural shocks from one another.

Our results show that technology shocks identified as in Galí (1999) are biased towards replacing routine labor. Then, we disentangle neutral shocks from routine-biased technological and task-supply shocks. We find that most of the decline in total hours worked is driven by routine-biased technology shocks through a strong fall in routine hours worked. We then provide a wider picture of business cycle fluctuations. We argue that business cycles seem driven by non-technology shocks when technological shocks are aggregated as in Galí (1999) while they are driven by task-biased technological shocks when they are disentangled.

Conclusion

In this concluding section, I first highlight the main results and their implications. Second, I discuss some limitations that should be addressed in future research. This thesis delves into the implications of technological change and labor taxation policies on transatlantic employment performances. It contributes to the field of labor economics and macroeconomics.

Chapter 1 examines U.S. and France employment performances between 1982 and 2017. It reassesses the long-run structural analysis initiated by Piketty (1998). It starts with an assessment of the French employment deficit over time. The low level of employment in France with respect to the U.S. is a persistent feature of the French labor market over the period considered. On the basis of a detailed decomposition of the transatlantic employment gap, I investigate the extent to which cross-country discrepancies in the socio-demographic composition and occupational prospects account for the transatlantic employment gap. I find that the French employment deficit reflects first and foremost a deficit in routine employment which is jeopardized by technological progress and manual employment. This lack in employment is predominantly captured by low-skilled young and senior workers who have higher non-participation and unemployment propensities. Nevertheless, the transatlantic employment gap changes significantly over time reflecting employment gains and losses in both countries. Low-skilled workers are at the core of this reallocation process as they account for most of the employment losses in both countries. Those shifts occur through rising occupational mobility and non-employment transitions in the U.S. while they occur through less occupational mobility as well as non-employment transitions in France. Hence, the transatlantic employment gap does not only reflect a disfunctioning labor market but also the occupational reallocation of labor that affects the employment prospects and participation decisions of specific socio-demographic groups. Those findings have several implications in terms of economic policies. French labor market policies should jointly support the labor demand and the labor market participation of low-skilled workers as well as occupational mobility in order to dampen the transatlantic employment gap.

Chapter 2 explores how technological change and labor taxation policies jointly affect unskilled employment outcomes in France between 1982 and 2008. In order to do so, I rely on a parsimonious general equilibrium model with occupational choice that jointly grasp the observed deterioration of unskilled employment and the polarization of occupational employment. I argue that the reallocation of unskilled labor from routine jobs towards manual jobs induced by technological change is partly obstructed by the presence of a non-market sector leading to both job polarization and unskilled employment losses. Unskilled workers are partly reallocated from middle-paid routine jobs toward low-paid manual jobs that produce services easily substitutable with non-market services. Labor taxation alters this reallocation process by distorting the relative value of market services and non-market services. I use the calibrated model to compute the extent to which technological and labor taxation trends account for the overall decline in unskilled employment. I find that technological change induced significant unskilled employment losses in France between 1982 and 2008. They were enhanced by the high and increasing labor tax rates between 1982 and the mid-1990s while they have been mitigated by the implementation of payroll tax reduction policies targeted on low-paid worker since then. These policies have been especially effective in a context of job polarization as they interact with technological change; without them, unskilled employment losses would have more than doubled. Those findings highlight the need to acknowledge the biased nature of technological change when designing labor market policies.

Chapter 3, which is co-authored with Idriss Fontaine, investigates how employment reacts to technological change over the business cycle and measure the extent to which it molds aggregate fluctuations. The U.S. has experienced job polarization because technological change has been biased towards replacing routine labor. We ask if those observed shifts in the task composition of labor demand away from routine labor are accountable for the recessionary effect of technology shocks on hours worked initially observed by Galí (1999). We then assess whether technological shocks are able to generate recognizable business cycles. We proceed by building quarterly time series on hours worked, task premiums and relative hours from the IPUMS Current Population Survey. We estimate the effect of technological shocks by relying on a VAR model and identify structural shocks by combining long-run exclusion and sign restrictions derived from a Real Business Cycle model with capital-routine substitutability. Our results show that technology shocks identified as in Galí

(1999) are biased towards replacing routine labor. By disentangling neutral shocks from task-biased shocks, we find that most of the decline in total hours worked arising from the technology component is driven by routine-biased technology shocks. We then provide a wider picture of business cycle fluctuations. We argue that business cycles are driven by non-technology shocks when technological shocks are aggregated as in Galí (1999) while they are driven by task-biased technological shocks when they are disentangled. Those findings highlight the need to acknowledge the biased nature of technological change when exploring business cycle fluctuations.

While this thesis constitutes a step towards understanding the role of technological change and economic policies in shaping transatlantic employment performances, there are a promising avenue for further research in that direction. For instance, chapter 1 depicts transatlantic employment performances and some potential implications in terms of labor market policies stressing out the importance of the welfare state. Nevertheless, it does not provide explanatory models to grasp those differences or frameworks to make grounded policy recommendations. In order to determine whether those policies could improve employment outcomes and welfare in an era of increasing disturbances, there is a need to develop general equilibrium models to properly capture individual behaviors and determine how they are affected by those policies. Furthermore, those structural models would determine the effectiveness and the financial sustainability of those policies.

Chapter 2 provides some answers to the limitations of the previous chapter by providing a theorical model to assess the intertwined effects of technological change and labor taxation policies on unskilled employment outcomes in France. Nonetheless, labor taxation policies have often been implemented concomitantly with other labor market policies and rising trade competition. Yet, I voluntarily left out those features with the aim to highlight the importance of taking into account the task-biased nature of technological change when designing labor taxation policies. Hence, a proper evaluation of such policies should disentangle the effects of each policy from technological change and trade shocks by relying on a more complete general equilibrium model.

Finally, chapter 3 does not provide an exhaustive exploration of the determinants of business cycle fluctuations. Nonetheless, it stresses the importance of considering the biased nature of technological change. We do not however look at the asymmetries generated by technological change. This is particularly relevant since drops in routine employment appear in episodic events. Recessions might purge the economy from least profitable firms which probably rely intensively on routine labor. The asymmetric nature of business cycles is key to understand whether recessions generate waves of creative destruction. There is a need to empirically assess those asymmetries and to provide theoretical foundations for those asymmetries as the dynamics resulting from technological change over the business cycle appears particularly disruptive. Those issues are left for future research.

Appendix A

Appendix of chapter 1

A.1 Alternative measure of the employment deficit

Piketty (1998) uses an alternative methodology to estimate the French employment deficit but it delivers approximately the same results. In order to provide a measure of the French employment deficit, the author first constructs a counterfactual measure of employment. He asks what would be the employment level in France if it had the U.S. employment propensities. The counterfactual employment rate E^{fr}_{pro} is obtained as follows

$$E^{fr}_{pro} = \sum_{g=1}^{G} \theta^{fr}_{g,t} E^{us}_{g,t}. \tag{A.1}$$

Then, he obtains the employment deficit by taking the difference between the counterfactual level of employment and the observed French level of employment such that

$$E^{fr}_{pro} - E^{fr}_{obs} = \sum_{g=1}^{G} \left(E^{us}_{g,t} - E^{fr}_{g,t} \right) \theta^{fr}_{g,t}. \tag{A.2}$$

The only difference between this measure and the one used in this study is that the author uses the French socio-demographic shares $\theta^{fr}_{g,t}$ as weights instead of the average demographic shares of both countries, i.e. $(\theta^{us}_{g,t} + \theta^{fr}_{g,t})/2$. Normalizing weights allows to exactly decompose the transatlantic employment gap into a demographic component $G^{fr}_{dem,t}$ and a propensity component $G^{fr}_{pro,t}$ which provides a measure of the French employment deficit in this study.

	Employment per capita			Employment differences	
	E^{fr}_{obs}	E^{fr}_{pro}	E^{us}_{obs}	E^{fr}_{pro}-E^{fr}_{obs}	E^{us}_{obs}-E^{fr}_{obs}
1982	62.85	63.54	64.97	0.69	2.12
1998	60.32	71.41	72.56	11.09	12.24
2017	64.39	68.02	68.82	3.64	4.44

Table A.1 – Alternative measure of the French employment deficit over time
Notes: levels are in percentage and differences are in percentage points.

Table A.1 provides the French employment deficit using Piketty (1998)'s methodology. By comparing results from Tables A.1 and 1.2, it appears that both methods deliver similar results. For example, the employment deficit differential is of 0.04 pp in 1998 and in 2017.

A.2 Margin-error adjustment

There are discrepancies between observed and imputed stocks from the law of motion described by equation (1.1) when using observed transition probabilities. This occurs because stocks are computed over the full sample while transition probabilities rely only on linked observations between two surveys. Thus, linked samples suffer from a number of flaws such as attrition due to the rotating structure of surveys or movements in and out of the population (turning 15, immigration, death, etc.) among others. Elsby, Hobijn, and Şahin (2015) propose a correction procedure to make transition probabilities consistent with observed stocks. I follow their methodology.

I first rewrite the model. Since $N_t = 1 - A_t - R_t - M_t - U_t$, the five dimensional model can be rewritten into a four dimensional model

$$s_t = \begin{bmatrix} P_{AA} - P_{NA} & P_{RA} - P_{NA} & P_{MA} - P_{NA} & P_{UA} - P_{NA} \\ P_{AR} - P_{NR} & P_{RR} - P_{NR} & P_{RM} - P_{NR} & P_{UR} - P_{NR} \\ P_{AM} - P_{NM} & P_{RM} - P_{NM} & P_{MM} - P_{NM} & P_{UM} - P_{NM} \\ P_{AU} - P_{NU} & P_{RU} - P_{NU} & P_{MU} - P_{NU} & P_{UU} - P_{NU} \end{bmatrix}_{t-1} s_{t-1} + \begin{bmatrix} P_{NA} \\ P_{NR} \\ P_{NM} \\ P_{NU} \end{bmatrix}_{t-1} \tag{A.3}$$

with $s_t = [A\ R\ M\ U]'_t$ and $P_{ii} = 1 - \sum_{j \neq i} P_{ij}$. The change in stocks between $t-1$ and t can be written as

$$\Delta s_t = s_t - s_{t-1} = X_{t-1}\mathcal{P}_{t-1} \tag{A.4}$$

where $\mathcal{P}$ is the vector of the twenty stock-consistent transition probabilities and $X_{t-1} = [X_{A,t-1}\ X_{R,t-1}\ X_{M,t-1}\ X_{U,t-}$ a matrice where

$$X_{A,t-1} = \begin{bmatrix} -A & -A & -A & -A \\ A & 0 & 0 & 0 \\ 0 & A & 0 & 0 \\ 0 & 0 & A & 0 \\ 0 & 0 & 0 & A \end{bmatrix} \quad X_{R,t-1} = \begin{bmatrix} R & 0 & 0 & 0 \\ -R & -R & -R & -R \\ 0 & R & 0 & 0 \\ 0 & 0 & R & 0 \\ 0 & 0 & 0 & R \end{bmatrix}$$

$$X_{M,t-1} = \begin{bmatrix} M & 0 & 0 & 0 \\ 0 & M & 0 & 0 \\ -M & -M & -M & -M \\ 0 & 0 & M & 0 \\ 0 & 0 & 0 & M \end{bmatrix} \quad X_{U,t-1} = \begin{bmatrix} U & 0 & 0 & 0 \\ 0 & U & 0 & 0 \\ 0 & 0 & U & 0 \\ -U & -U & -U & -U \\ 0 & 0 & 0 & U \end{bmatrix}$$

$$X_{N,t-1} = \begin{bmatrix} N & 0 & 0 & 0 \\ 0 & N & 0 & 0 \\ 0 & 0 & N & 0 \\ 0 & 0 & 0 & N \\ -N & -N & -N & -N \end{bmatrix}$$

I then choose the vector of stock-consistent transition probabilities by using the weighted-restricted-least-squares adjustment method

$$\underset{\mathcal{P}}{Min}\, \frac{1}{2}(\mathcal{P} - \hat{\mathcal{P}})' W (\mathcal{P} - \hat{\mathcal{P}}), \quad \text{subject to} \quad \Delta s_t = X_{t-1}\mathcal{P} \tag{A.5}$$

where $\hat{\mathcal{P}}$ is the vector of observed transition probabilities. W is an efficient weighting matrix. It is computed as the inverse of the covariance matrix of $\hat{\mathcal{P}}$

$$W = \begin{bmatrix} \Omega_A & 0_{(4,4)} & 0_{(4,4)} & 0_{(4,4)} & 0_{(4,4)} \\ 0_{(4,4)} & \Omega_R & 0_{(4,4)} & 0_{(4,4)} & 0_{(4,4)} \\ 0_{(4,4)} & 0_{(4,4)} & \Omega_M & 0_{(4,4)} & 0_{(4,4)} \\ 0_{(4,4)} & 0_{(4,4)} & 0_{(4,4)} & \Omega_U & 0_{(4,4)} \\ 0_{(4,4)} & 0_{(4,4)} & 0_{(4,4)} & 0_{(4,4)} & \Omega_N \end{bmatrix}^{-1} \tag{A.6}$$

$$\Omega_S = \frac{diag(\hat{\mathcal{P}}_S) - \hat{\mathcal{P}}_S \hat{\mathcal{P}}_S'}{S_{t-1}} \tag{A.7}$$

with $S \in \{A, R, M, U, N\}$. The Lagrangian of the problem is

$$\mathcal{L} = \frac{1}{2}(\mathcal{P} - \hat{\mathcal{P}})' W (\mathcal{P} - \hat{\mathcal{P}}) + \mu'(X_{t-1}\mathcal{P} - \Delta s_t). \tag{A.8}$$

Finally, solving for the Lagrangian yields

$$\begin{bmatrix} \mathcal{P} \\ \mu \end{bmatrix} = \begin{bmatrix} W & X'_{t-1} \\ X_{t-1} & 0 \end{bmatrix}^{-1} \begin{bmatrix} W\hat{\mathcal{P}} \\ \Delta s_t \end{bmatrix} \tag{A.9}$$

which gives stock-consistent transition probabilities.

A.3 Additional Tables and Figures

	Tasks		
Classifications	Manual	Routine	Abstract
PCS 1982	CSE: 52 (except 5211, 5212, 5213, 5214, 5215), 53, 56	CSE: 21, 45, 46, 48, 54, 55, 62, 63 (except 6301, 6354), 64, 65, 67, 68 (except 6891), 69	CSE: 22, 23, 31, 33, 34, 35, 37, 38, 42, 43, 44, 47
	Other job codes: 6301, 6354, 6891	Other job codes: 5211, 5212, 5213, 5214, 5215	Other job codes: -
PCS 2003	CSE: 52 (except 521a, 521b, 522a, 523a, 524a), 53, 56	CSE: 21, 45, 46, 48, 54, 55, 62, 63 (except 631a, 636d), 64, 65, 67, 68 (except 684a), 69	CSE: 22, 23, 31, 33, 34, 35, 37, 38, 42, 43, 44, 47
	Other job codes: 631a, 636d, 684a	Other job codes: 521a, 521b, 522a, 523a, 524a	Other job codes: -

Table A.2 – Occupational codes and tasks

Note: This table describes the allocation of occupational codes across tasks for the PCS1982 and the PCS2003 classifications.

Group	France				U.S.			
	θ	E	U	N	θ	E	U	N
MxYxH	0.89	45.57	8.23	46.20	0.89	78.56	5.32	16.11
MxYxL	9.30	31.44	8.70	59.86	9.88	50.20	8.32	41.48
MxPxH	7.24	91.83	4.28	3.89	11.53	92.61	2.70	4.68
MxPxL	23.51	86.14	7.56	6.30	19.39	82.74	5.63	11.62
MxOxH	1.08	63.57	2.32	34.11	2.46	75.42	2.37	22.21
MxOxL	6.72	35.72	2.80	61.48	4.68	59.44	3.24	37.32
WxYxH	1.31	52.23	7.07	40.69	1.17	78.12	4.26	17.62
WxYxL	9.53	25.11	7.82	67.07	9.72	45.56	6.66	47.78
WxPxH	8.22	82.71	4.98	12.31	12.14	80.18	2.53	17.28
WxPxL	23.60	66.76	8.34	24.91	20.26	64.59	4.48	30.93
WxOxH	1.04	46.63	3.26	50.11	2.26	62.20	1.60	36.20
WxOxL	7.56	29.14	2.37	68.49	5.61	45.98	2.14	51.88

Table A.3 – Average composition and propensities by socio-demographic groups

Notes: men (M), women (W), 15-24 year-olds (Y), 25-54 year-olds (P), 55-64 year-olds (O), with at most a high school degree (L), with more than a high school degree (H). Values are in percentage of the stock considered.

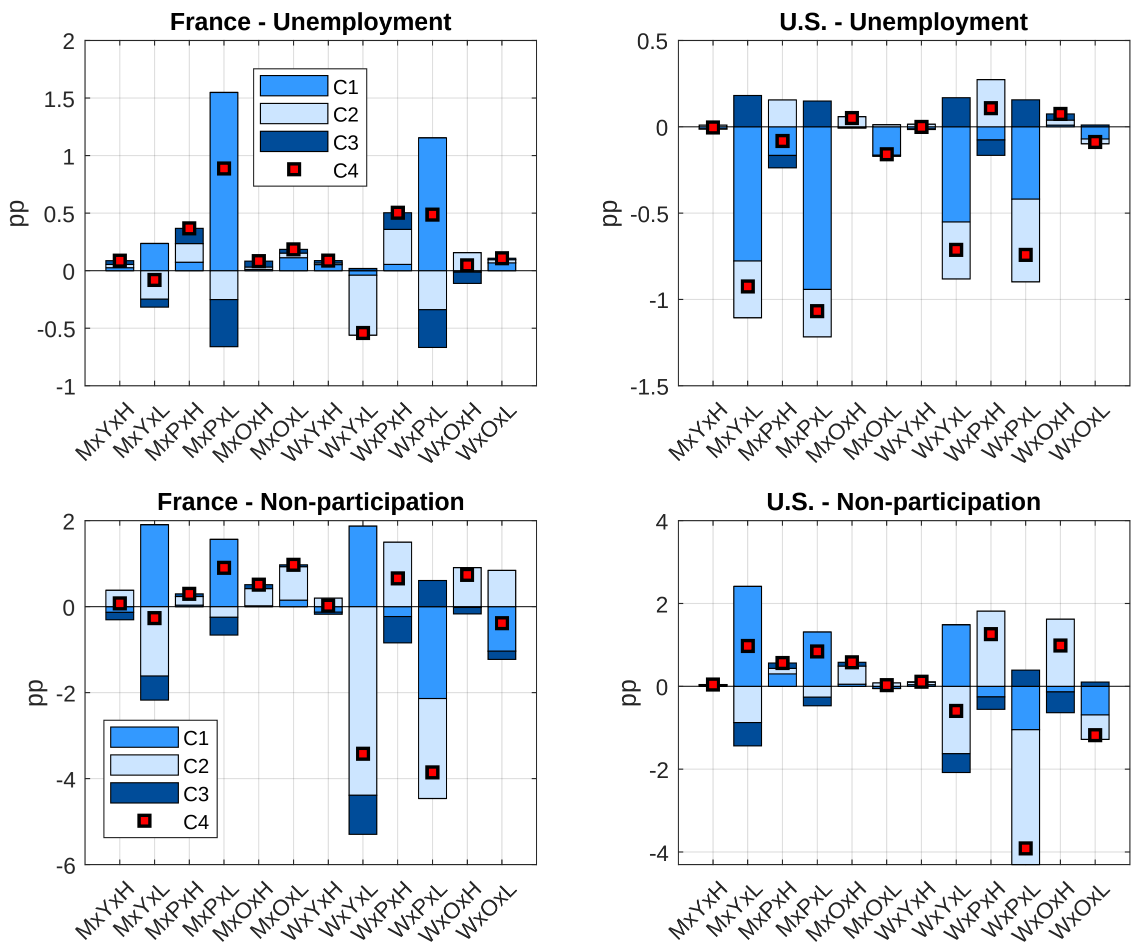

Figure A.1 – Non-employment changes by socio-demographic groups between 1982 and 2017

Notes: men (M), women (W), 15-24 year-olds (Y), 25-54 year-olds (P), 55-64 year-olds (O), with at most a high school degree (L), with more than a high school degree (H). C1, C2 and C3 are defined as the propensity, composition, interaction components, respectively, with $C4 = C1 + C2 + C3$. Values are in percentage points (pp).

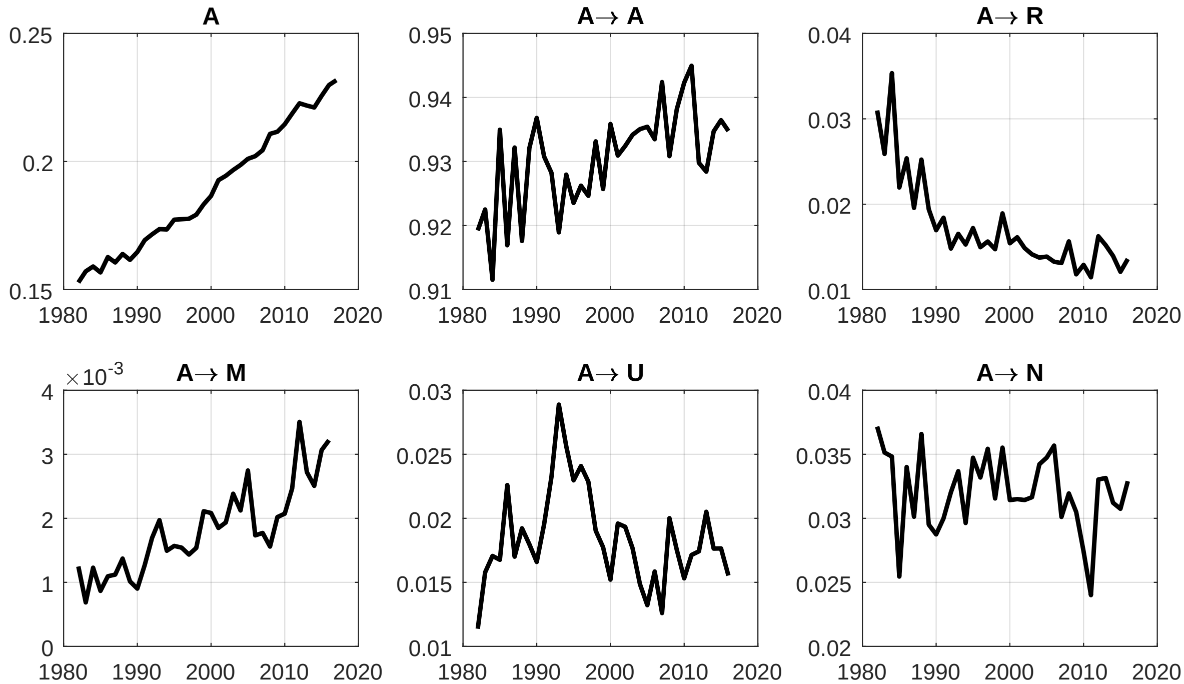

Figure A.2 – French transition probabilities from abstract jobs between 1982 and 2017
Notes: see section 1.2 for details on data construction.

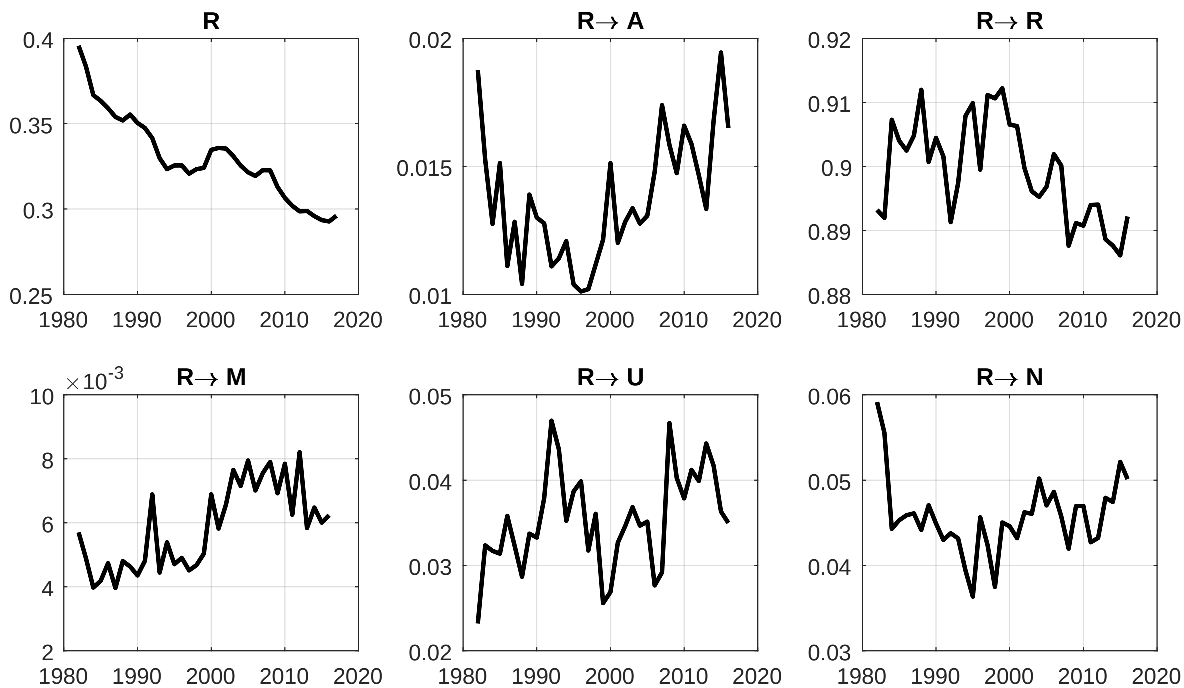

Figure A.3 – French transition probabilities from routine jobs between 1982 and 2017
Notes: see section 1.2 for details on data construction.

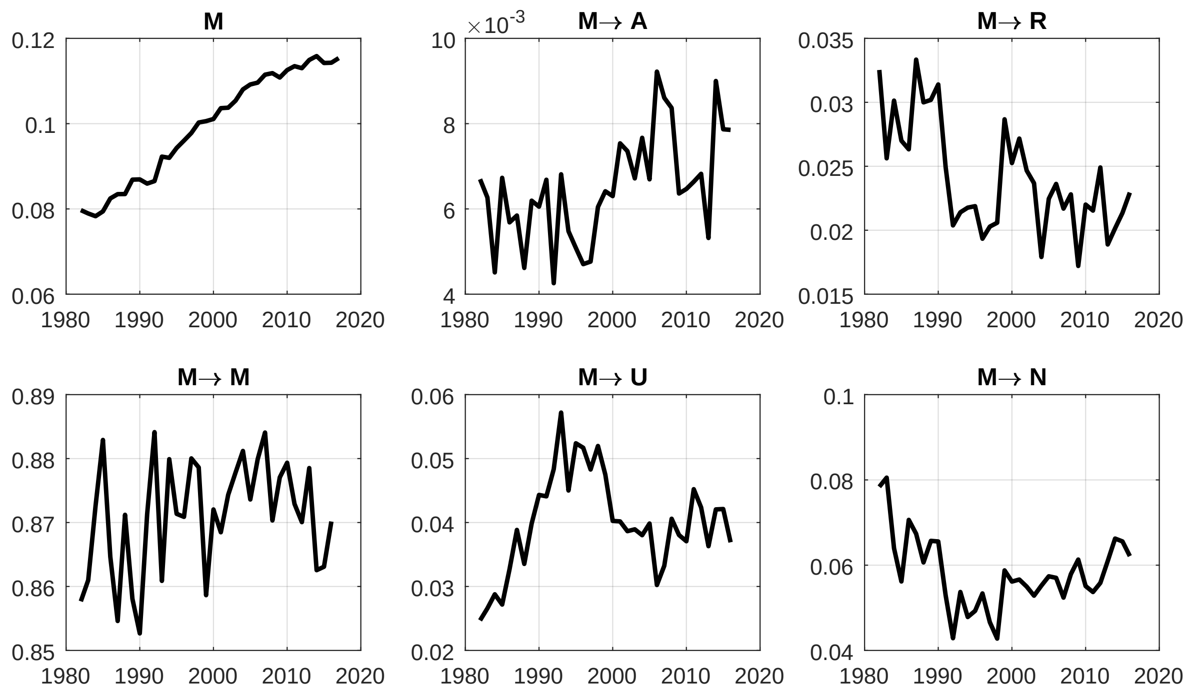

Figure A.4 – French transition probabilities from manual jobs between 1982 and 2017
Notes: see section 1.2 for details on data construction.

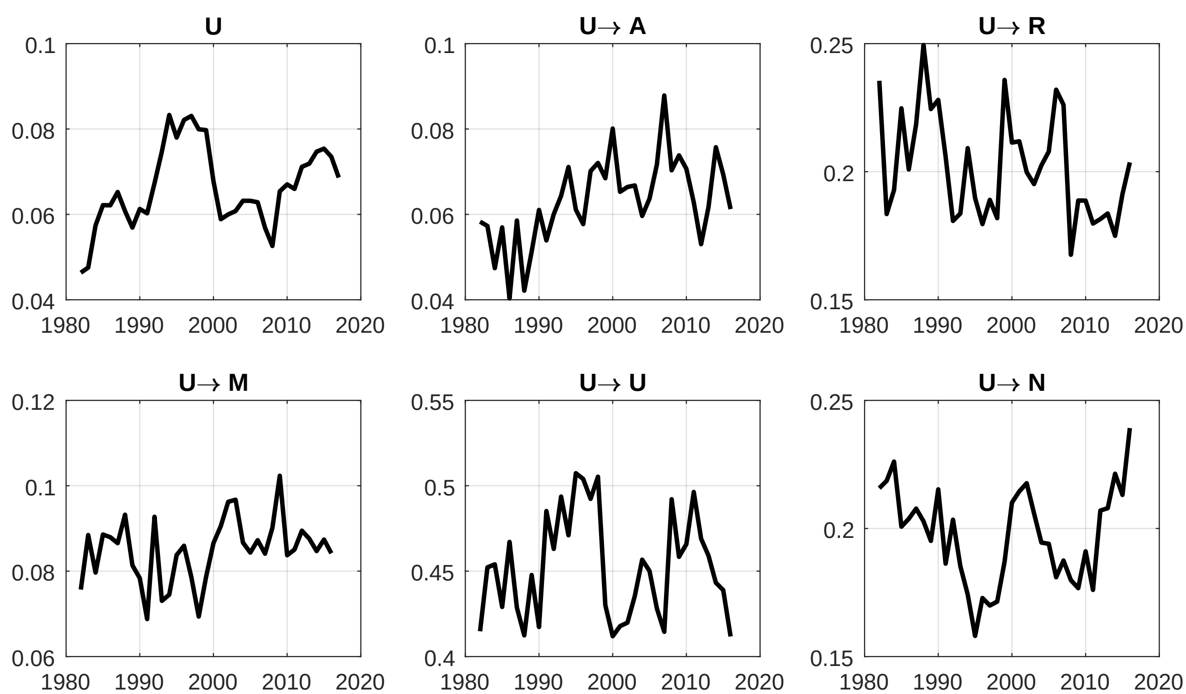

Figure A.5 – French transition probabilities from unemployment between 1982 and 2017
Notes: see section 1.2 for details on data construction.

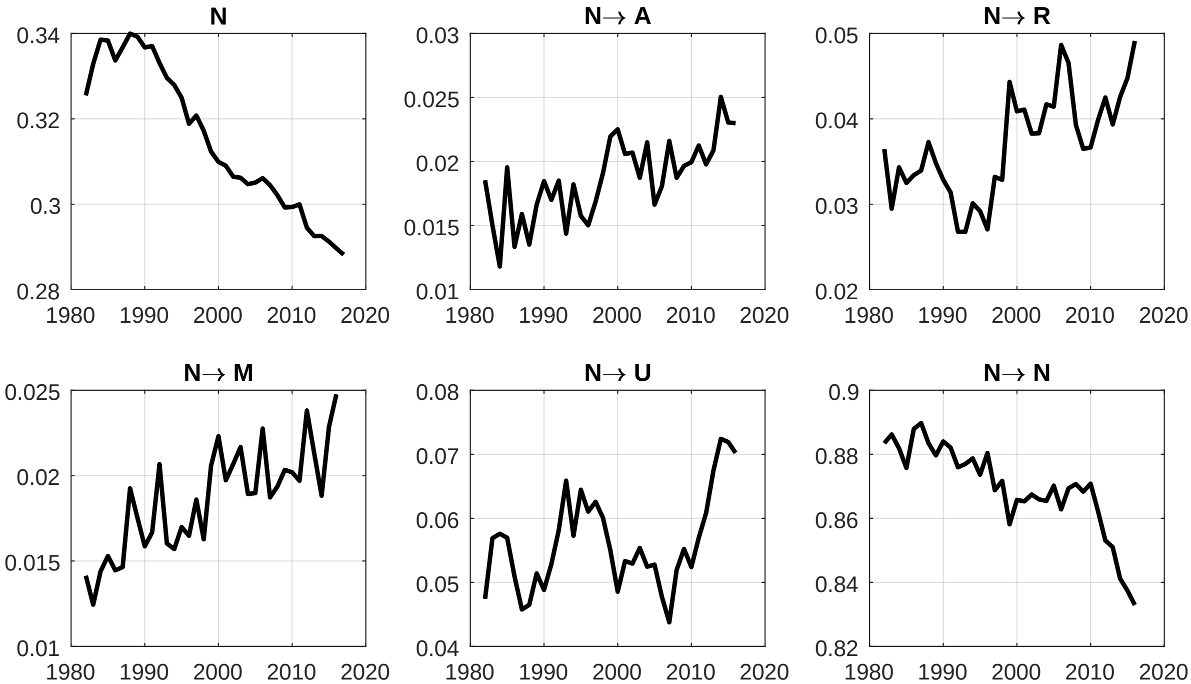

Figure A.6 – French transition probabilities from non-participation between 1982 and 2017
Notes: see section 1.2 for details on data construction.

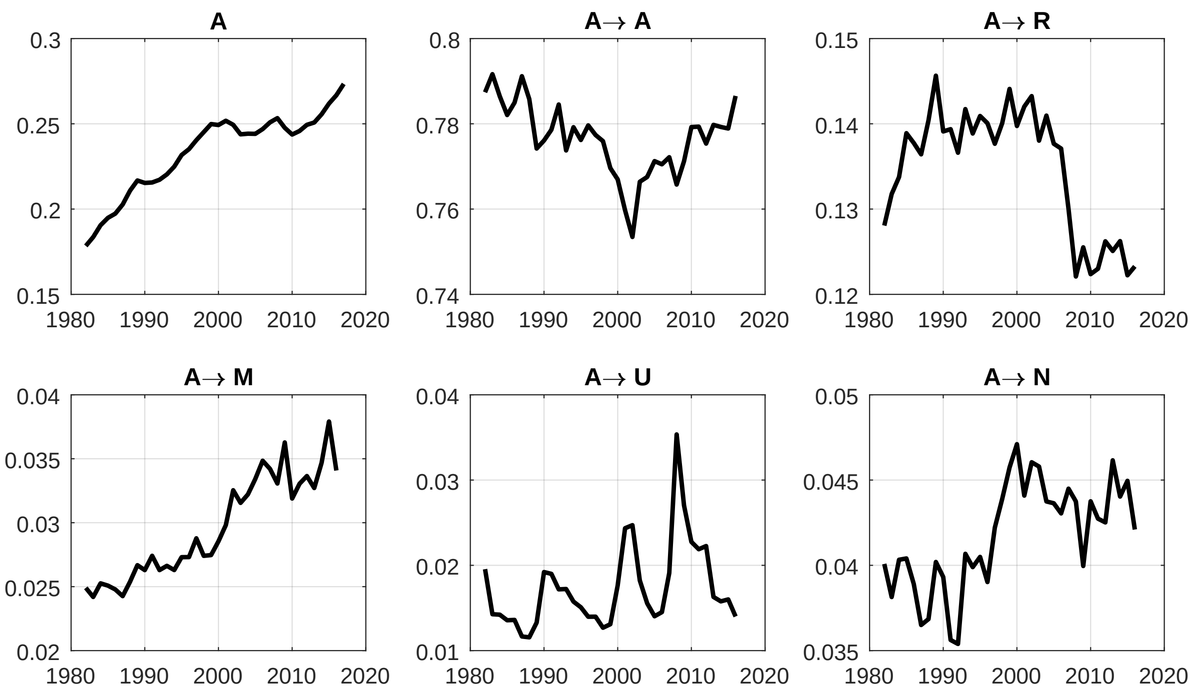

Figure A.7 – U.S. transition probabilities from abstract jobs between 1982 and 2017
Notes: see section 1.2 for details on data construction.

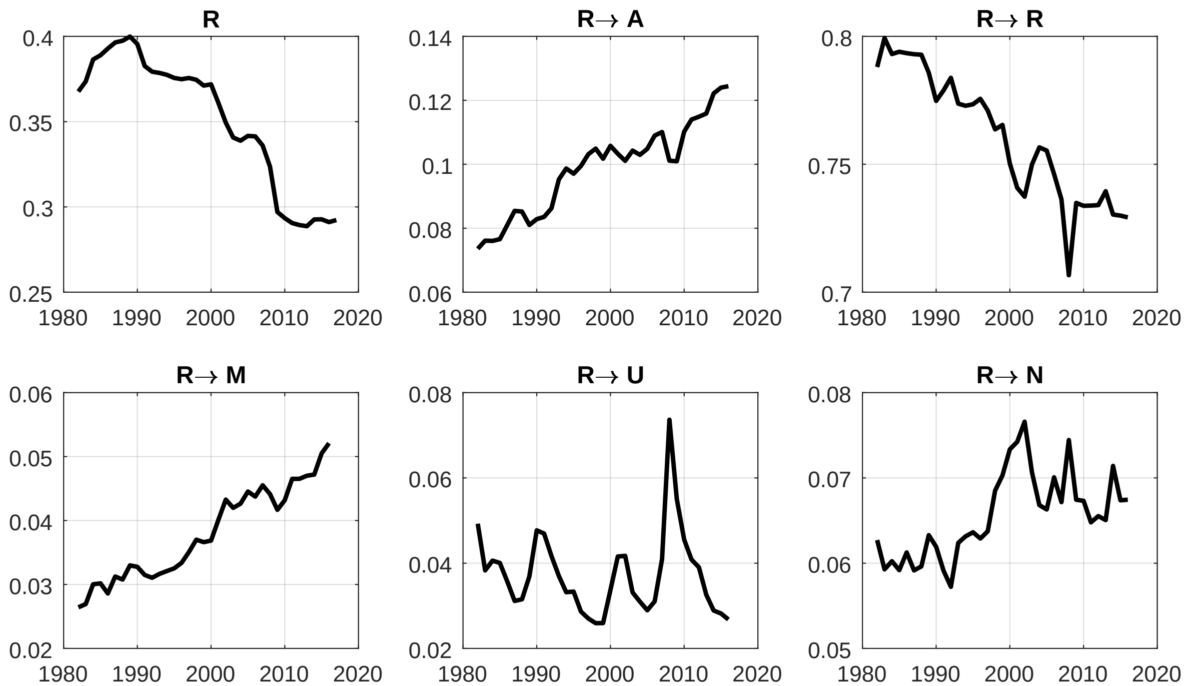

Figure A.8 – U.S. transition probabilities from routine jobs between 1982 and 2017
Notes: see section 1.2 for details on data construction.

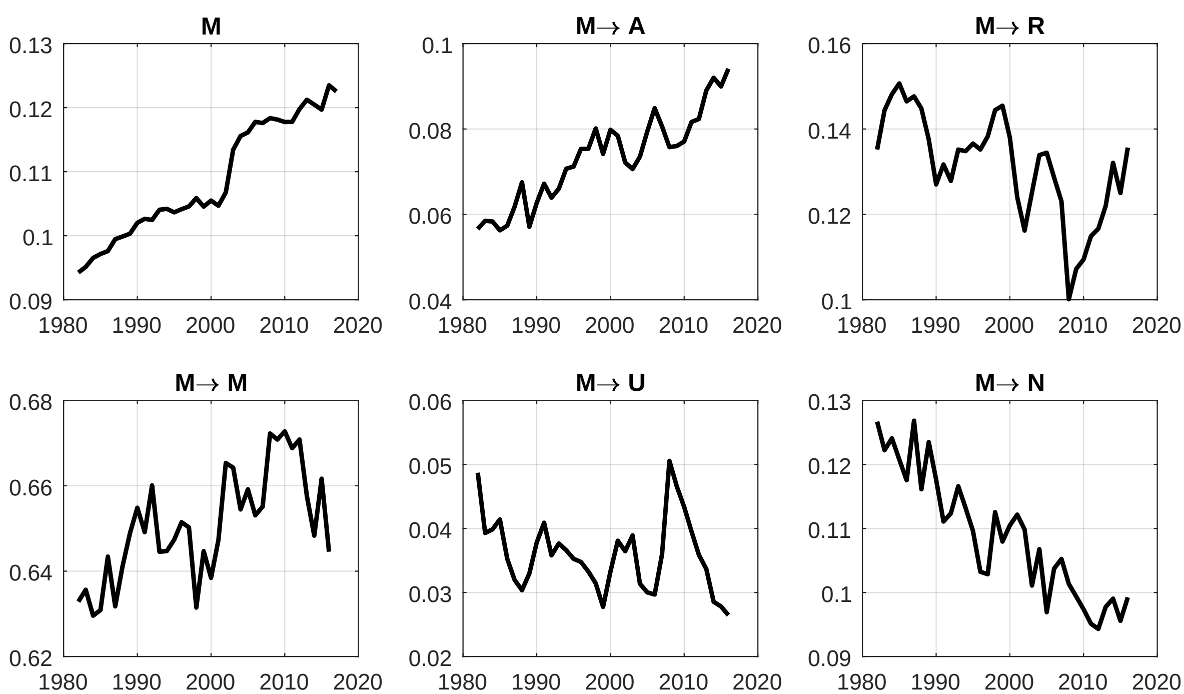

Figure A.9 – U.S. transition probabilities from manual jobs between 1982 and 2017
Notes: see section 1.2 for details on data construction.

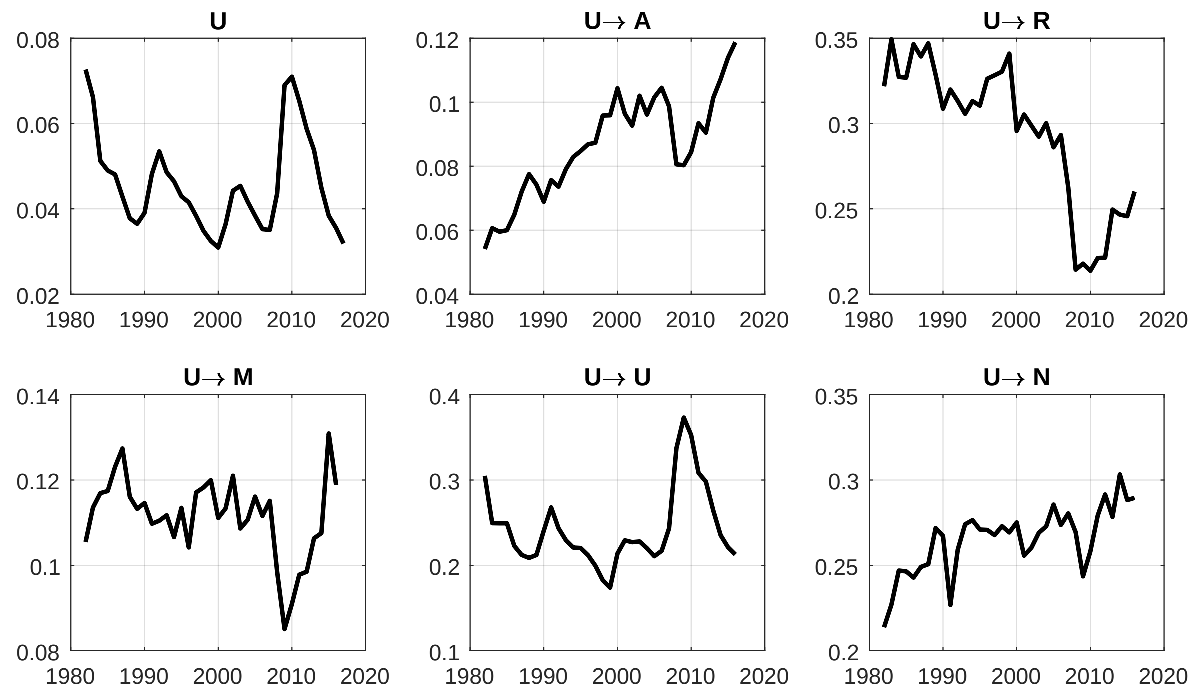

Figure A.10 – U.S. transition probabilities from unemployment between 1982 and 2017
Notes: see section 1.2 for details on data construction.

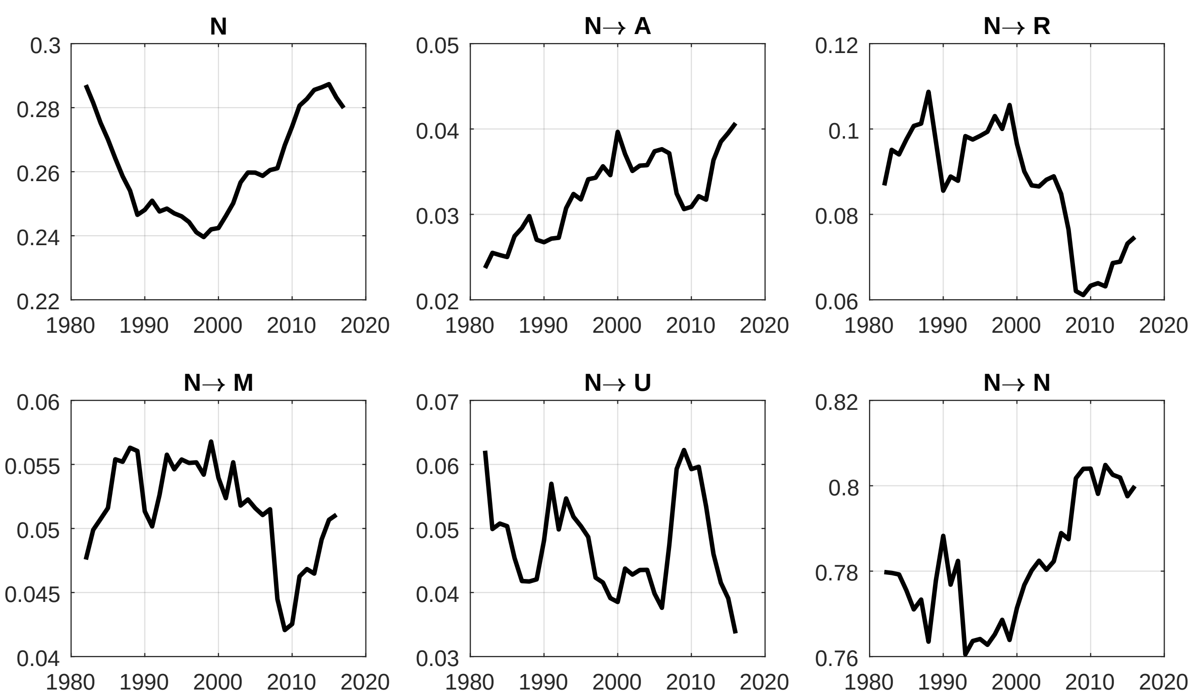

Figure A.11 – U.S. transition probabilities from non-participation between 1982 and 2017
Notes: see section 1.2 for details on data construction.

	France					U.S.				
	A	*R*	*M*	*U*	*N*	*A*	*R*	*M*	*U*	*N*
AR	-3.41	2.75	0.17	0.13	0.36	-3.41	2.75	0.17	0.13	0.36
AM	0.27	-0.02	-0.21	-0.01	-0.03	0.27	-0.02	-0.21	-0.01	-0.03
AU	1.43	-0.53	-0.25	-0.27	-0.38	1.43	-0.53	-0.25	-0.27	-0.38
AN	-1.22	0.24	0.14	0.08	0.76	-1.22	0.24	0.14	0.08	0.76
RA	1.39	-1.00	-0.12	-0.06	-0.20	1.39	-1.00	-0.12	-0.06	-0.20
RM	0.01	0.21	-0.21	-0.00	-0.01	0.01	0.21	-0.21	-0.00	-0.01
RU	-0.49	2.50	-0.56	-0.72	-0.73	-0.49	2.50	-0.56	-0.72	-0.73
RN	0.18	-2.24	0.28	0.10	1.68	0.18	-2.24	0.28	0.10	1.68
MA	-0.05	-0.00	0.05	0.00	0.00	-0.05	-0.00	0.05	0.00	0.00
MR	0.06	0.83	-0.82	-0.01	-0.06	0.06	0.83	-0.82	-0.01	-0.06
MU	-0.30	-0.42	1.17	-0.28	-0.17	-0.30	-0.42	1.17	-0.28	-0.17
MN	0.20	0.18	-1.24	0.04	0.82	0.20	0.18	-1.24	0.04	0.82
UA	-0.58	0.21	0.10	0.10	0.16	-0.58	0.21	0.10	0.10	0.16
UR	-0.26	1.44	-0.31	-0.44	-0.42	-0.26	1.44	-0.31	-0.44	-0.42
UM	0.12	0.18	-0.49	0.12	0.08	0.12	0.18	-0.49	0.12	0.08
UN	-0.08	-0.15	-0.04	0.19	0.08	-0.08	-0.15	-0.04	0.19	0.08
NA	-0.60	0.04	0.03	0.04	0.50	-0.60	0.04	0.03	0.04	0.50
NR	0.01	-1.09	0.06	0.04	0.98	0.01	-1.09	0.06	0.04	0.98
NM	0.16	0.17	-1.46	0.04	1.08	0.16	0.17	-1.46	0.04	1.08
NU	-0.21	-0.54	-0.19	-1.05	1.99	-0.21	-0.54	-0.19	-1.05	1.99

Table A.4 – Difference between observed and counterfactual stocks between 1982 and 2017
Notes: values are in percentage points. A, R and M refer to abstract, routine and manual employment per capita while U and N refer to unemployment and non-participation per capita.

Appendix B

Appendix of chapter 2

B.1 Additional Figures and Tables

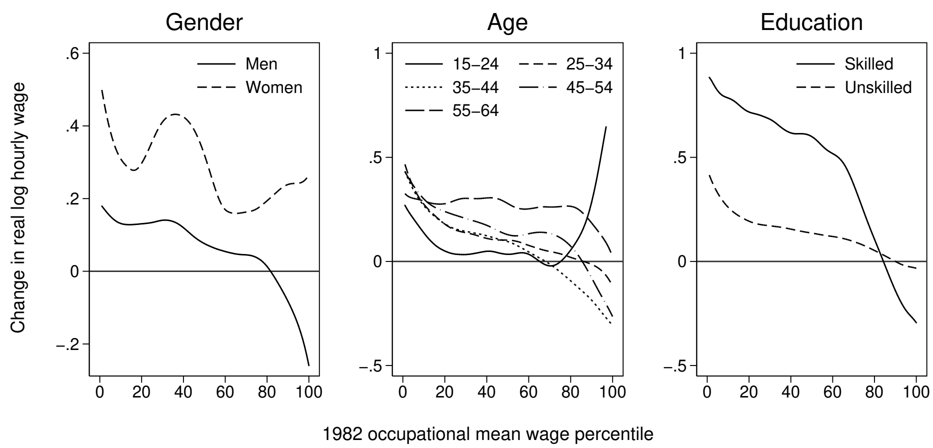

Figure B.1 – Counterfactual wage structure effects over 1982-2008

Notes: Data are constructed as described in appendix B.2. The methodology used to compute counterfactual wage structure effects is explained in appendix B.3.2. Changes are smoothed by using a locally linear model with a .5 bandwidth.

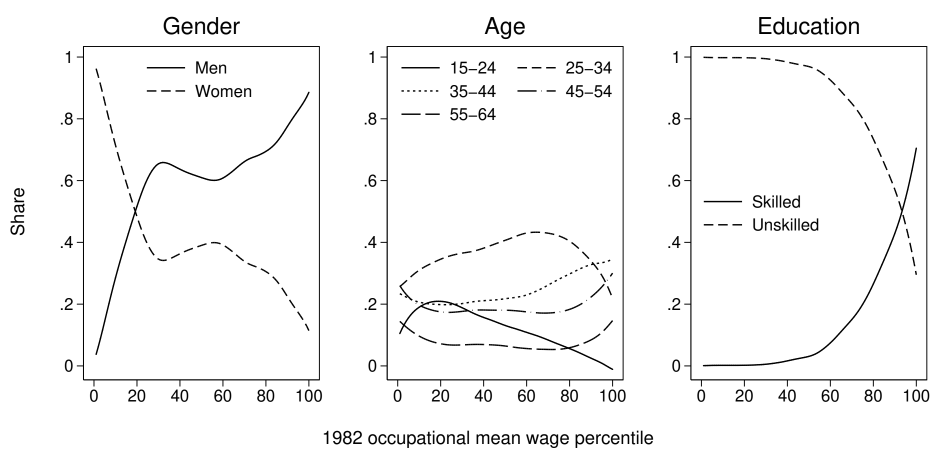

Figure B.2 – Socio-demographic composition of occupations in 1982

Notes: Data are constructed as described in appendix B.2. Values represent the share of workers with the corresponding characteristic in each occupation ranked by their 1982 occupational net wage. Shares are smoothed by using a locally linear model with a .5 bandwidth.

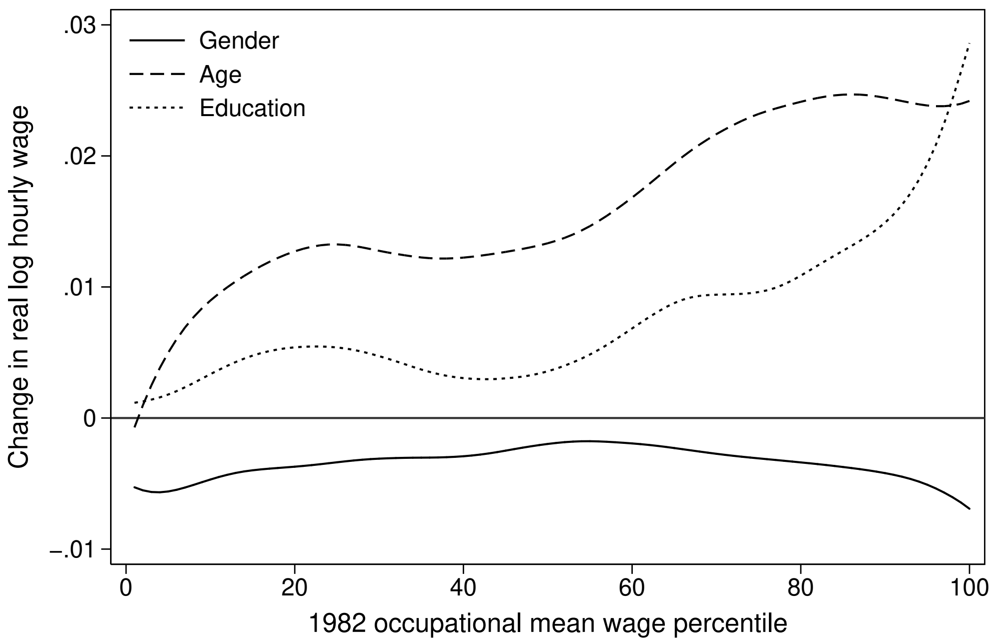

Figure B.3 – Detailed decomposition of the aggregate composition effect over 1982-2008
Notes: Data are constructed as described in appendix B.2. The methodology used to compute the detailed decomposition of the aggregate composition effect is explained in appendix B.3.2. Changes are smoothed by using a locally linear model with a .5 bandwidth.

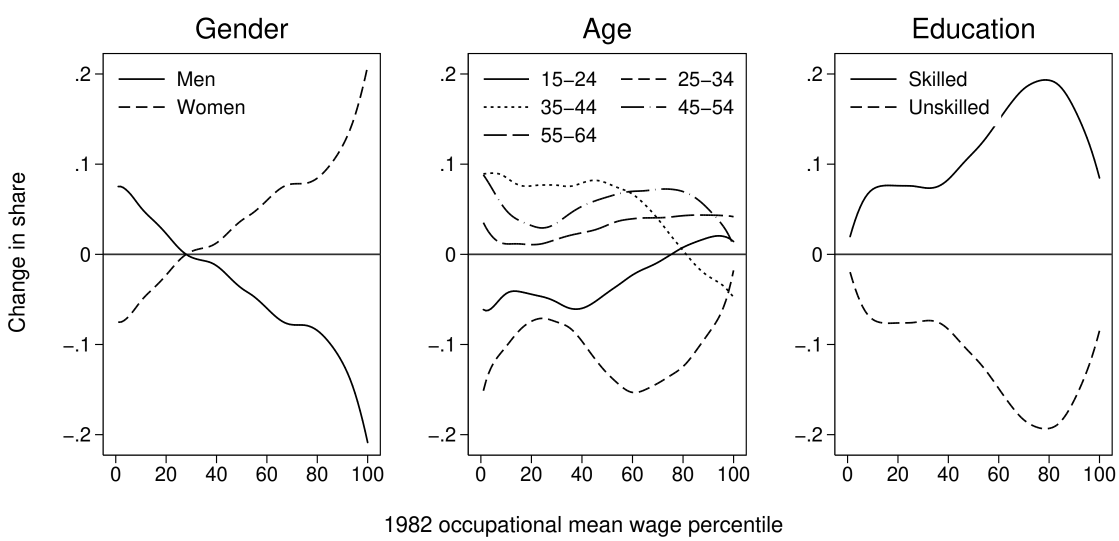

Figure B.4 – Change in the socio-demographic composition of occupations over 1982-2008
Notes: Data are constructed as described in appendix B.2. Values are in percentage points. They represent changes in the share of workers with the corresponding characteristic in each occupation ranked by their 1982 occupational net wage. Changes are smoothed by using a locally linear model with a .5 bandwidth.

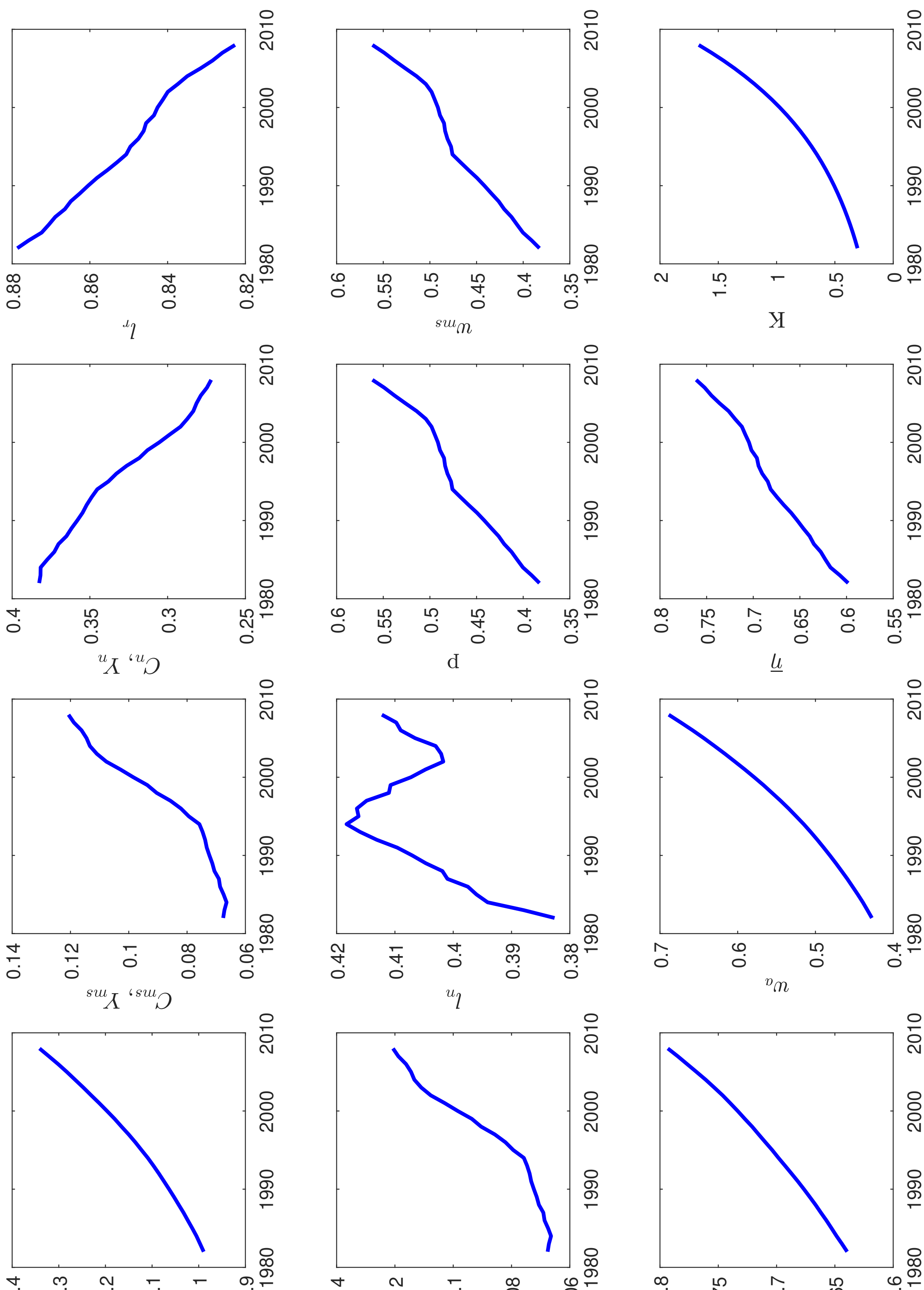

Figure B.5 – Model - Deterministic simulation with benchmark calibration

Notes: Time series are derived from a deterministic simulation of the calibrated model. The calibration is described in section 2.3.

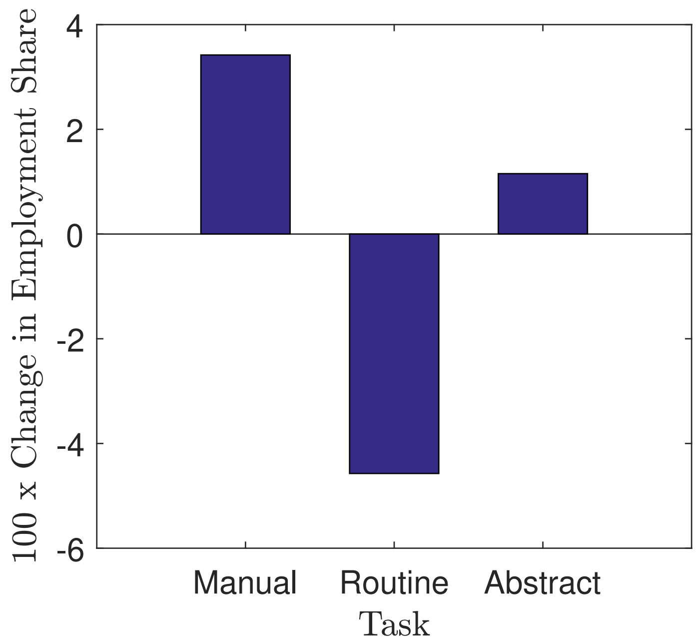

Figure B.6 – Model - Job polarization over 1982-2008

Notes: Values are in percentage points. They display simulated employment share changes by occupational groups.

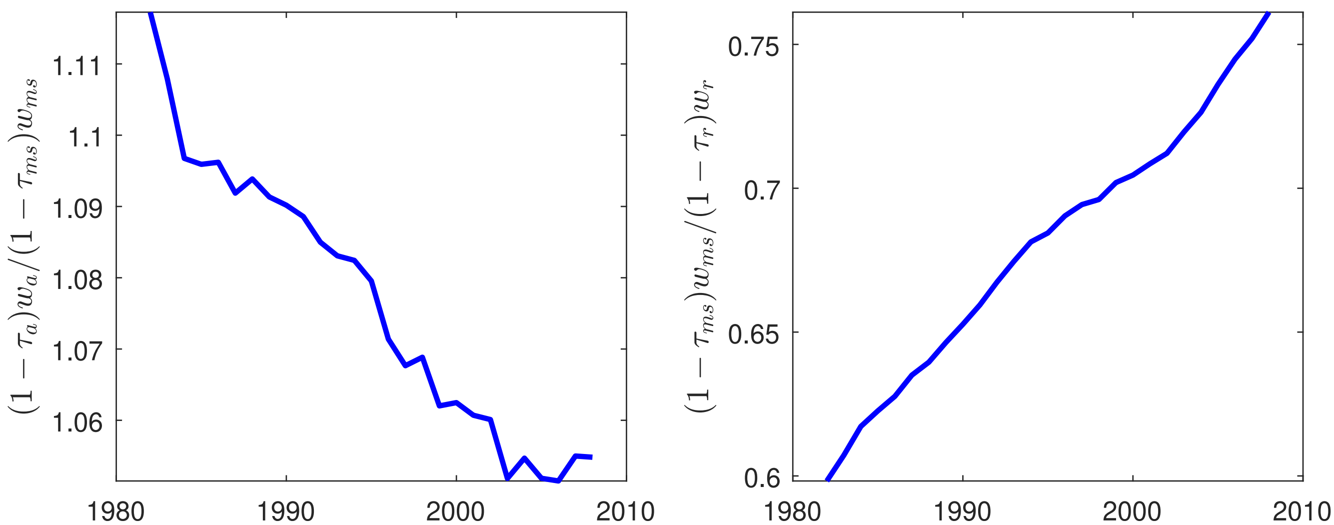

Figure B.7 – Model - Relative net wage changes over 1982-2008

Notes: Time series depict the dynamics of occupational net wage ratios derived from the deterministic simulation. The left panel displays the abstract to manual net wage ratio while the right panel displays the manual to routine net wage ratio.

15 Most Declining Occupations (ascending order)

675a	Unskilled production workers in textile and dressmaking, tanneries, and leather work
543d	Administrative employees of various companies
542a	Secretaries
543a	Financial or accounting service employees
542b	Typists, stenographers, (non secretarial) word processing operators
681a	Unskilled structural works construction workers
671b	Unskilled workers in public works, construction and extraction work, excluding state and local government
682a	Unskilled metalworkers, locksmiths, mechanical repairers
641a	Drivers and long-haul truck drivers (fully employed)
675b	Unskilled production workers in woodworking and furniture
421a	Primary school teachers
544a	Employees and operators of computer usage
524a	Civil Service administrative officials (including education)
672a	Unskilled workers in electricity and electronics
673b	Unskilled production workers for metal formation

15 Most Growing Occupations (ascending order)

423b	Continuing education trainers and facilitators
636d	Cooks and kitchen assistants
463d	Commercial and technical sales technicians, service representatives working with companies or professionals (excluding banking, insurance, IT)
461f	Supervisors and administrative technicians of other administrative services
479b	Expert fully-employed or independent technicians, various technicians
553a	Non-specialized vendors
451f	Class B administrative staff of local authorities and hospitals (except Education, Heritage)
525c	Civil service officials (outside of schools, hospitals)
523a	Deputy civil service administrators (including education)
341a	Professors specializing and certified in secondary education
431f	General care nurses, fully employed
526a	Caregivers (civil service or private sector)
388a	Engineers and research managers, research and development in computer science
563a	Childcare assistant, nannies, host families
563b	Home health aides, housekeepers, family workers

Table B.1 – Occupational employment share change rank 1982-2008

Notes: The sample includes individuals aged between 15 and 64 years during the survey year. It includes employed salary workers who are the only ones to report their wages consistently from 1982 to 2008. Most occupational label translations are taken from IPUMS international website: `https://international.ipums.org/international/`.

15 Least Paid Occupations (ascending order)	
683a	Baker, butcher apprentices
563a	Childcare assistants, nannies, host families
563b	Home health aides, housekeepers, family workers
564a	Janitors, caretakers
562b	Fully employed hairdressers
563c	Domestic workers
682a	Unskilled metalworkers, locksmiths, mechanical repairers
681b	Unskilled secondary construction workers
636b	Pork butchers (except meat industry)
684a	Cleaners
564b	Employees in various services
344c	Medical, odontology, and pharmacy interns
554a	Food vendors
675a	Unskilled production workers in textile and dressmaking, tanneries, and leather work
561a	Servers, restaurant assistants, waiters (bar, pub, cafe or restaurant)

15 Most Paid Occupations (ascending order)	
384a	Engineers and research managers, R&D in mechanics and metalworking
376c	Commercial bank executives
384b	Engineers and managers in manufacturing in mechanics and metalworking
344b	Non-hospital, affiliated doctors
385a	Engineers and research managers, R&D of processing industries (food, chemicals, metallurgy, heavy materials)
388d	Engineers and technical sales executives in IT and telecommunications
342a	Higher education instructors
386d	Engineers and managers in the production and distribution of energy, water
381a	Engineers and research and farming managers for agriculture, fisheries, water and forests
385b	Engineers and managers of manufacturing processing industries (food, chemicals, metallurgy, heavy materials)
383b	Engineers and managers in manufacturing of electrical, electronic materials
331a	Public service management personnel (State, local authorities, hospitals)
371a	Top administrative, finance and commercial management for large companies
333a	Magistrates
380a	Technical directors of large companies

Table B.2 – Occupational mean wage rank 1982

Notes: The sample includes individuals aged between 15 and 64 years during the survey year. It includes employed salary workers who are the only ones to report their wages consistently from 1982 to 2008. Most occupational label translations are taken from IPUMS international website: `https://international.ipums.org/international/`.

B.2 Data

B.2.1 French Labor Force Survey and samples

I use the FLFS to study the evolution of aggregate employment and its occupational employment structure from 1982 to 2008. The study starts in 1982 because pre-1982 FLFS lack in precision concerning some variables. On the other side, the study ends in 2008 because of the great recession. This event goes beyond the frame of this study.

I retain two separate samples to study changes in the occupational employment structure and the evolution of aggregate employment, respectively, because some variables are not always reported. In both samples, I focus on individuals aged between 15 and 64 years. I also drop military contingent.

In the first sample which is used to study changes in the occupational structure across the wage distribution, I focus on employed salary workers. I restrict the first sample to salary workers because wages or income earned by other types of workers are not reported in the FLFS. The survey only reports wages for employed workers under a labor contract.[1] Some occupational groups do not report their earnings or the number of observations for some occupational groups is too small to be considered as representative. Therefore, eight occupational groups are dropped which include artisans, wholesalers, heads of companies, agricultural, liberal, religious and related miscellaneous occupations.[2] All computations in sections 2.2.2 and 2.2.3 use the first sample data.

However, wages are not required to study the evolution of employment rates. This is why such restrictions are not necessary in the second sample. Furthermore, I need the entire working age population to compute employment rates. Therefore, non participants, unemployed workers and excluded occupations in the first sample are included in the second sample. All computations in section 2.2.5 use the second sample data.

B.2.2 Building variables

Yearly averages. In 2003 the FLFS has been subject to drastic changes. From 1982 to 2002, the survey was conducted on a yearly basis and the data was collected in March except in 1982 (April-

[1] Abowd, Kramarz, Margolis, and Philippon (2000) provide a precise description of the wage sample for pre-2003 FLFS.

[2] Occupational groups CSE 11, 12, 13, 21, 22, 23, 31, 44 and 69 are dropped when the study focuses on changes in the occupational employment structure over the wage distribution.

May), 1990 (January) and 1999 (January), while from 2003 onward the data has been collected on a quarterly basis. From 1982 to 2002, the data was directly taken as yearly, while from 2003 to 2008 I compute yearly averages.

Real hourly wage. The French Labor Force Survey reports the monthly net nominal wage of salary workers. Therefore, employer and employee social security contributions are already deduced but not the income tax. Before 1990, wages were not reported precisely but by wage groups. I deal with this issue by allocating to each observation the average wage of the reported category. From 1990 onward, precise monthly wages are reported. The real log hourly wage rate $w_{i,t}$ is then computed

$$w_{i,t} = ln\left(\frac{W_{i,t}}{h_{i,t}}\frac{12}{52}\frac{100}{p_t}\right)$$

with $W_{i,t}$ the nominal monthly wage, $h_{i,t}$ usual hours worked per week and p_t the basis year 2005 CPI in year t. Missing values for usual hours worked per week are imputed by allocating the average usual weekly hours worked within each usual weekly hours worked category captured by variables DU or DUHAB for respectively pre-2003 FLFS and post-2003 FLFS when available. Once the real log hourly wage is computed, one can obtain an occupational mean real log hourly wage $w_{occ,t}$ which is then used to rank occupations

$$w_{occ,t} = \sum_{i \in Occ} w_{i,t} \frac{\omega_{i,t}}{\sum\limits_{j \in Occ} \omega_{j,t}}$$

with Occ the set of observations for occupation Occ and $\omega_{t,j}$ the sample person weight.

Skill levels. In this study, education is a proxy for skills. Variable DDIPL which reports the highest diploma obtained by an individual is used to compute variables by skill levels. Before 1990, people had to explicitly write the name of their diploma while after 1990 they were asked to check a category of diploma. Therefore, the rate of non-reported answers is high especially for non-participants and unemployed survey participants. Those unreported answers induce breaks in computed time series. I solve this issue in two steps. In a first step I impute missing values for employed workers using an ordered logistic model with explanatory variables on age categories, gender and occupational groups (CSE).[3] However, most unreported values are coming from non-employed workers. This model can not be applied to non-participants since CSE relates to jobs. In order to neutralize the effect of remaining missing observations related to non-participants, I use in a second step a statistical break correction model.

Break correction. In order to deal with remaining breaks, I use a purely statistical break correction model which is a simplified version of the model used by the French national statistical institute (INSEE) to compute long run aggregated time series.[4] This break correction model works in two steps. First, time series are corrected for the 2003 break. I regress a sufficiently aggregated variable $\widetilde{\widetilde{y}}_t$ on a time trend and $ind2003_t$ an indicator variable that is equal to one when FLFS are pre-2003 surveys. The model is estimated on a restricted sample of five years that includes year 2001 to year 2005. Then I correct $\widetilde{\widetilde{y}}_t$ by subtracting the OLS estimated break coefficient $\hat{\beta}_1$ to the raw time series for pre-2003 years in order to obtain a first step corrected variable $\widetilde{y}_t$.

$$\begin{aligned}\widetilde{\widetilde{y}}_t &= \alpha_1 + \delta_1 t + \beta_1\, ind2003_t + \varepsilon_t \\ \widetilde{y}_t &= \widetilde{\widetilde{y}}_t - \hat{\beta}_1\, ind2003_t.\end{aligned}$$

Secondly, I correct the variable corrected in the first step for the second break that occurred in 1990 by applying the same type of model but this time the model is estimated on year 1988 to year 1992.

$$\begin{aligned}\widetilde{y}_t &= \alpha_2 + \delta_2 t + \beta_2\, ind1990_t + \varepsilon_t \\ y_t &= \widetilde{y}_t - \hat{\beta}_2\, ind1990_t.\end{aligned}$$

The resulting variable y_t is a usable variable considered to be corrected for all breaks.

Tasks. Tasks are defined by occupational codes. Table B.3 displays the crosswalk between occupational codes and task groups. Manual, routine and abstract occupational group definitions are based on Autor and Dorn (2013). In this study, I define manual occupations as *low-skilled manual service* occupations. This definition of manual jobs is restrictive but it captures as for the U.S. the bulk of

[3] The results obtained in this paper are not affected by such a method. In fact, I obtain almost the same results by only applying the statistical break correction model described in the next appendix without using the ordered logit imputation.

[4] `https://www.insee.fr/fr/statistiques/2388195?sommaire=2045174#documentation`

the employment growth at the bottom of the occupational mean wage distribution. Other manual occupations such as farmers (CSE11, 12 and 13) and drivers (CSE64) are included in the routine group even though they are manual. They are considered to be routine-manual occupations. Those occupations are not included in service occupations as in Autor and Dorn (2013). Thus, manual occupations include mostly personal service workers (CSE56) and some public service civil servants (CSE52). Routine jobs are located in the middle of the occupational mean wage distribution. They include occupations such as foremen (CSE48), business administrative personnel (CSE54), salespeople (CSE55), drivers (CSE64), maintenance, storage and transportation workers (CSE65), skilled industry and artisan laborers (CSE62 and 63), and unskilled industry and in construction finishing laborers (CSE67 and 68). A substantial portion of those jobs have been subject either to automation or computerization since the last three decades which explains why the middle class has been shrinking ever since. Abstract jobs include occupations that usually require a relatively high diploma because of the complexity of the cognitive tasks accomplished. They include occupations such as wholesalers (CSE22), head of companies (CSE23), liberal professions (CSE31), public service professionals (CSE33), professors and scientific professions (CSE34), business administration and commerce jobs (CSE37), technicians (CSE38), business engineers and technicians (CSE38), intermediate health and social work personnel (CSE43), technicians (CSE47), and so on and so forth.

	Tasks		
Classifications	Manual	Routine	Abstract
PCS 1982	CSE: 56, 52 (except 5211, 5212, 5213, 5214, 5215)	CSE: 11, 12, 13, 21, 48, 54, 55, 62, 63 (except 6301, 6354), 64, 65, 67, 68 (except 6891), 69	CSE: 22, 23, 31, 33, 34, 35, 37, 38, 42, 43, 44, 45, 46, 47, 53
	Other job codes: 6301, 6354, 6891	Other job codes: 5211, 5212, 5213, 5214, 5215	Other job codes: -
PCS 2003	CSE: 56, 52 (except 521a, 521b, 522a, 523a, 524a)	CSE: 11, 12, 13, 21, 48, 54, 55, 62, 63 (except 631a, 636d), 64, 65, 67, 68 (except 684a), 69	CSE: 22, 23, 31, 33, 34, 35, 37, 38, 42, 43, 44, 45, 46, 47, 53
	Other job codes: 631a, 636d, 684a	Other job codes: 521a, 521b, 522a, 523a, 524a	Other job codes: -

Table B.3 – Occupational codes and tasks

Notes: This table describes the allocation of occupational codes across tasks.

Conversion factors. One needs to observe the same jobs across time to observe changes in the occupational structure. The French occupational classification has changed once between 1982 and 2008. The FLFS used the PCS 1982 from 1982 and 2002, while it used the PCS 2003 from 2003 to 2008. In order to deal with this break I exploit a singularity of the 2003 survey which provides a variable (p1982) that reports the occupational code for each individual according to the 1982 classification. Therefore, it is possible to map several 2003 occupational codes for each 1982 occupational code. I compute the distribution of 2003 jobs for each 1982 job which gives conversion factors. As a result, I obtain data on 374 consistent occupations based on the 2003 occupational classification from 1982 to 2008. Results obtained by using conversion factors are robust as they reflect sub-periods and occupational group patterns that avoid classification inconsistencies. The conversion factors are used to produce figures in subsections 2.2.2 and 2.2.3. Figure B.8 illustrates this method through an example.

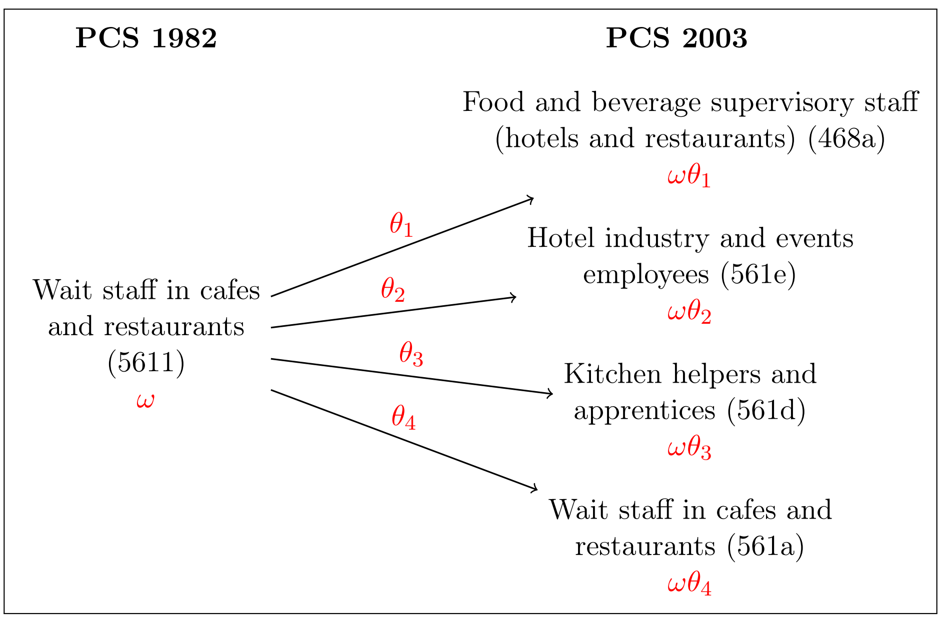

Figure B.8 – Conversion factors - An illustration

Notes: I denote by ω the PCS 1982 occupation's sample weight and θ_i the share of the PCS 1982 occupation's sample weight that is allocated into occupation i of PCS 2003 classification where the sum of θ_i equals one for each 1982 occupation.

B.3 Re-weigthing methods

B.3.1 Counterfactual employment structure

The polarization of the French occupational employment structure requires a counterfactual analysis to determine whether the rise in low-paid jobs employment shares is emanating from manual service occupations. In that respect, I use the same counterfactual re-weighting method as Autor and Dorn (2013). This method is analogous to the one developed by DiNardo, Fortin, and Lemieux (1996) and Fortin, Lemieux, and Firpo (2011) to decompose wage distributions. The sampling weight for the initial year $\omega_{i,t_0}^{t_0}$ is expressed as

$$\omega_{i,t_0}^{t_0} = f\left(x_i \mid T = t_0, Occ\right) P\left(Occ \mid T = t_0\right) \tag{B.1}$$

with $f\left(x_i \mid T = t_0, Occ\right)$ a scaling function that represents the observation x_i employment share in occupation Occ at the initial year and $P\left(Occ \mid T = t_0\right)$ the occupation Occ employment share observed at the initial year. I compute the counterfactual occupational employment structure in t_1 that would prevail if the share of occupation Occ remained at its initial level t_0 by re-weighting observations in t_1. The counterfactual weight $\omega_{i,t_0}^{t_1}$ is

$$\begin{aligned} \omega_{i,t_0}^{t_1} &= f\left(x_i \mid T = t_1, Occ\right) P\left(Occ \mid T = t_0\right) && \text{(B.2)} \\ &= \psi_i(Occ) f\left(x_i \mid T = t_1, Occ\right) P\left(Occ \mid T = t_1\right) && \text{(B.3)} \\ &= \psi_i(Occ)\omega_{i,t_1}^{t_1} && \text{(B.4)} \end{aligned}$$

where $\omega_{i,t_1}^{t_1}$ is the observed weight in period t_1 and $\psi_i(Occ)$ is the re-weighting factor. The re-weighting factor is rewritten using Bayes' theorem as

$$\begin{aligned} \psi_i(Occ) &= \frac{P\left(Occ \mid T = t_0\right)}{P\left(Occ \mid T = t_1\right)} && \text{(B.5)} \\ &= \frac{P\left(T = t_0 \mid Occ = Manual\right)}{1 - P\left(T = t_0 \mid Occ = Manual\right)} \frac{1 - P\left(T = t_0\right)}{P\left(T = t_0\right)}. && \text{(B.6)} \end{aligned}$$

The propensity score $P\left(T = t_0 \mid Occ = Manual\right)$ is the weighted share of initial year observations in manual occupations. Factor $\psi_i(Occ)$ is computed by estimating a probit or a logit model on observations pooled from both periods, from which predicted probabilities are then retrieved. I compute observed and counterfactual occupational employment shares for each occupation by using corresponding weights. Then, occupational employment shares are ranked by their respective observed 1982 occupational net wage. This allows to obtain observed S^p_{1982} and counterfactual S^p_C occupational employment share for each percentile p. The difference between the two statistics delivers the counterfactual change in the occupational employment structure

$$\Delta S^p_C = S^p_C - S^p_{1982}. \tag{B.7}$$

B.3.2 Wage change decompositions

Aggregate decomposition

The decline in occupational net wage inequalities across occupations between 1982 and 2008 justifies a decomposition analysis. The aim of this inquiry is to assess whether those changes in occupational net wages are accounted for by shifts in the composition of workers or if they are due to shifts in occupational net wage schedules. DiNardo, Fortin, and Lemieux (1996) and Fortin, Lemieux, and Firpo (2011) develop an aggregate decomposition method for distributional statistics such as occupational net wage percentiles. This method decomposes observed changes in occupational net wage percentiles ΔW^p_O into a composition effect ΔW^p_X and a wage structure effect ΔW^p_S as described by equation (2.2).

The procedure requires three main steps. First, it necessitates the computation of counterfactual occupational net wage distributions using re-weighting factors as in appendix B.3.1. Second, relevant distributional statistics, i.e. occupational net wage percentiles as in Autor and Dorn (2013), are computed using both observed and counterfactual distributions. Third, the wage structure effect and the composition effect are then derived from observed and counterfactual occupational net wage percentiles.

Let $X \in \mathcal{X}$ be a vector of K covariates capturing socio-demographics characteristics where $\mathcal{X}$ is the support of X. In this paper, we consider three covariates that captures gender, age and educational characteristics. For each observation i at time t, the occupational net wage $W_{i,t}$ and socio-demographic characteristics X_i are observed. The joint distribution of occupational net wages and socio-demographic characteristics at time t is denoted by $F_{W_t,X_t}(.,.) : \mathbb{R}\times\mathcal{X} \rightarrow [0,1]$. The distribution of occupational net wages at time t can be defined by integrating the conditional distribution of occupational net wages over the observed socio-demographic characteristics such as

$$F_{W_t}(w) = \int_{\mathcal{X}} F_{W_t|X_t}(w|X)dF_{X_t}(X) \tag{B.8}$$

for $t = 1982, 2008$. The counterfactual distribution of occupational net wages is denoted as $F_{W_C}(w)$. It is the distribution of occupational net wages that would prevail in 2008 if the distribution of socio-demographic characteristics of workers remained as in 1982

$$F_{W_C}(w) = \int_{\mathcal{X}} F_{W_{2008}|X_{2008}}(w|X)dF_{X_{1982}}(X). \tag{B.9}$$

An efficient way to compute the counterfactual distribution is by re-weighting the observed 2008 distribution of occupational net wages by a factor $\psi(X)$ such that

$$F_{W_C}(w) = \int_{\mathcal{X}} F_{W_{2008}|X_{2008}}(w|X)\psi(X)dF_{X_{2008}}(X). \tag{B.10}$$

The re-weighting factor is the ratio of multivariate marginal distribution functions of socio-demographic covariates

$$\Psi(X) = \frac{dF_{X_{1982}}(X)}{dF_{X_{2008}}(X)} \tag{B.11}$$

where $dF_{X_t}(X) = P(X|T = t)$. By using Bayes' theorem, this factor is computed as

$$\Psi(X) = \frac{P\left(T = 1982 \mid X\right)}{1 - P\left(T = 1982 \mid X\right)} \frac{1 - P\left(T = 1982\right)}{P\left(T = 1982\right)}. \tag{B.12}$$

It is obtained by estimating a probability model $P\left(T = 1982 \mid X\right)$ from which predicted probabilities are retrieved to compute the relevant re-weighting factor for each observation. Then, I compute observed as well as the counterfactual average net wages for each occupation. I rank occupations according to their observed 1982 net wage and compute 1982 occupational net wage percentiles as Autor and Dorn (2013) do. The composition effect and the wage structure effect are then computed as differences between observed W_t^p and counterfactual W_C^p occupational net wage percentiles for percentiles $p = 1, ..., 100$ such that

$$\Delta W_X^p = W_{2008}^p - W_C^p \tag{B.13}$$

$$\Delta W_S^p = W_C^p - W_{1982}^p. \tag{B.14}$$

Detailed decomposition

The aggregate decomposition only determines whether observed changes in occupational net wages are emanating from compositional shifts or changes in wage schedules. It does not provide the contribution of each covariate to the aggregate composition and wage structure components. Thus, I assess the contribution of each socio-demographic characteristic by providing a detailed decomposition when possible or by producing counterfactual experiments.

Composition effect. I follow Fortin, Lemieux, and Firpo (2011) who provide a method to conduct a detailed decomposition of the aggregate composition effect by re-weighting observations.[5] As previously, the detailed decomposition of the composition effect relies on the computation of counterfactual wage distributions. Let X_k be a covariate that captures socio-demographic characteristic k (i.e. gender, age or education) and X_{-k} the vector of covariates representing all socio-demographic characteristics except for characteristic k. For each covariate X_k, I compute the distribution of occupational net wages in 2008 that would prevail if the distribution of characteristics X_{-k}, conditional on feature X_k, was as in 1982

$$\begin{aligned} F_{W_{C,k}}(w) &= \int_{\mathcal{X}_k}\int_{\mathcal{X}_{-k}} F_{W_{2008}|X_{2008}}(w|X) dF_{X_{1982}}(X_{-k}|X_k) dF_{X_{2008}}(X_k) \\ &= \int_{\mathcal{X}_k}\int_{\mathcal{X}_{-k}} sF_{W_{2008}|X_{2008}}(w|X)\Psi_{X_{-k}|X_k}(X) dF_{X_{2008}}(X_{-k}|X_k) dF_{X_{2008}}(X_k) \\ &= \int_{\mathcal{X}} F_{W_{2008}|X_{2008}}(w|X)\Psi_{X_{-k}|X_k}(X) dF_{X_{2008}}(X). \end{aligned} \tag{B.15}$$

[5] Their reference period is different from the one used in this study which explains why the re-weighting factors formulas are not exactly the same.

Those counterfactual distributions are obtained by using re-weighting factors $\Psi_{X_{-k}|X_k}(X)$ that can be expressed as a ratio of factors

$$\begin{aligned}\Psi_{X_{-k}|X_k}(X) &= \frac{dF_{X_{1982}}(X_{-k}|X_k)}{dF_{X_{2008}}(X_{-k}|X_k)} \\ &= \frac{dF_{X_{1982}}(X)/dF_{X_{1982}}(X_k)}{dF_{X_{2008}}(X)/dF_{X_{2008}}(X_k)} \\ &= \Psi(X)/\Psi_k(X_k). \end{aligned} \tag{B.16}$$

In addition to the aggregate decomposition re-weighting factor $\Psi(X)$, they require the computation of the factor $\Psi_k(X_k)$ for each individual covariate X_k. By using Bayes' theorem, the factor $\Psi_k(X_k)$ is written as

$$\begin{aligned}\Psi_k(X_k) &= \frac{P\left(X_k \mid T = 1982\right)}{P\left(X_k \mid T = 2008\right)} \\ &= \frac{P\left(T = 1982 \mid X_k\right)}{1 - P\left(T = 1982 \mid X_k\right)} \frac{1 - P\left(T = 1982\right)}{P\left(T = 1982\right)}. \end{aligned} \tag{B.17}$$

It is obtained by estimating a probability model $P\left(T = 1982 \mid X_k\right)$ from which predicted probabilities are retrieved. Then, I compute occupational net wages using $\Psi_{X_{-k}|X_k}(X)$ as weight. As previously, I rank occupations by their observed 1982 net wage to obtain occupational net wage percentiles $W^p_{C,k}$ for each covariate k. The estimated contribution of covariate k to the aggregate composition effect $\Delta W^p_{X,k}$ is derived as

$$\Delta W^p_{X,k} = W^p_{C,k} - W^p_C. \tag{B.18}$$

where W^p_C is the counterfactual occupational net wage percentile obtained from the aggregate decomposition. The contribution of each covariate approximately sums up to the aggregate composition effect such that

$$\Delta W^p_X \approx \sum_{k=1}^{K} \Delta W^p_{X,k}. \tag{B.19}$$

The residual difference between the aggregate composition effect and the sum of contributions captures an interaction effect between covariates. The detailed decomposition of the aggregate composition effect is depicted in Figure B.3.

Wage structure effect. There is no straightforward method to provide a detailed decomposition of the aggregate wage structure effect through standard re-weighting procedures.[6] Nevertheless, I produce counterfactual experiments to determine whether the wage structure effect is widespread across socio-demographic groups or whether it is group specific. In that respect, I compute the wage structure effect that would prevail if all workers had subsequently the same gender, age and educational level. Each socio-demographic characteristic X_k (i.e. gender, age and education) encompasses different subgroups indexed by g. There is a total of nine subgroups depending on gender (men and women), age (15-24, 25-34, 35-44, 45-54 and 55-64 years of age) and education (skilled and unskilled). The occupational net wage distribution among workers of type X_{k_g} is denoted as

$$F_{W_t}(w|X_{k_g}=1) \quad = \quad \int_{\mathcal{X}_{-k}} F_{W_t|X_t}(w|X_{k_g}=1, X_{-k})dF_{X_t}(X_{-k}|X_{k_g}=1). \tag{B.20}$$

I rely on re-weighted wage distributions in order to control for compositional differences both across time and across socio-demographic groups. Thus, observations are re-weighted such that other characteristics X_{-k} are the same as for the entire workforce in 1982. I get the following counterfactual occupational net wage distribution

$$F_{W_{S,t}}(w|X_{k_g}=1) \quad = \quad \int_{\mathcal{X}_{-k}} F_{W_t|X_t}(w|X_{k_g}=1, X_{-k})\Psi_{k_g,t}dF_{X_t}(X_{-k}|X_{k_g}=1) \tag{B.21}$$

where $\Psi_{k_g,t}$ is the re-weighting factor of period t observations when all workers are considered to be of type X_{k_g}. Occupational weights are computed differently depending on the period considered since the aim is to control for compositional differences both across time and socio-demographic groups. Practically, I proceed in two subsequent steps. First, I re-weight the 1982 occupational net wage distribution of subgroup X_{k_g} so that the conditional distribution of other covariates X_{-k} remains the same as for the entire workforce in 1982. Second, I re-weight the 2008 occupational net

[6]Though, there are some regression-based methods that explicitly estimate the subcomponents of the aggregate wage structure effect. Mata and Machado (2005) provide a method which relies on quantile regressions in addition to a simulation procedure. Firpo, Fortin, and Lemieux (2018) use recentered influence function (RIF) regressions in the spirit of Oaxaca-Blinder decompositions.

wage distribution of subgroup X_{k_g} such that the conditional distribution of other covariates X_{-k} is the same as for the entire workforce in 1982. Consequently, re-weighting factors for 1982 and 2008 observations are respectively

$$\Psi_{k_g,1982}(X_{-k}) = \frac{P(X_{k_g}=1|T=1982)}{P(X_{k_g}=1|X_{-k},T=1982)} \tag{B.22}$$

$$\Psi_{k_g,2008}(X_{-k}) = \frac{P\left(T=1982 \mid X_{-k},X_{k_g}=1\right)}{1-P\left(T=1982 \mid X_{-k},X_{k_g}=1\right)}\frac{1-P\left(T=1982|X_{k_g}=1\right)}{P\left(T=1982|X_{k_g}=1\right)}. \tag{B.23}$$

The first factor is estimated only by using 1982 observations while the second is estimated by using pooled observations from 1982 and 2008. Finally, I compute occupational net wages using $\Psi_{k_g,1982}(X_{-k})$ and $\Psi_{k_g,2008}(X_{-k})$ as weights for respectively 1982 and 2008 observations. As previously, I rank occupations by their observed 1982 net wage to obtain the relevant counterfactual occupational net wage percentiles $W^p_{S,k_g,t}$ for each subgroup X_{k_g}. The wage structure effect that would prevail if all workers were of type X_{k_g} is derived as

$$\Delta W^p_{S,k_g} = W^p_{S,k_g,2008} - W^p_{S,k_g,1982}. \tag{B.24}$$

Those counterfactual wage structure effects are depicted in Figure B.1.

B.4 Labor taxation policies

B.4.1 Labor taxation time series

McDaniel (2007) imputes tax rate time series for several countries including France based on OECD national accounts publications. Based on those time series, I compute an average labor tax rate $\tau = \tau_{SS} + \tau_{inc}$ with τ_{SS} the average social security tax rate and τ_{inc} the household average income tax rate. Since differentiated labor tax rate time series do not exist for France over the time span studied, I use McDaniel (2007)'s tax time series and the June 2009 social security report (CCSS, 2009) to compute benchmark labor taxation parameters.[7] I apply the tax reform from 1994. Despite the fact that the first reform was implemented in July 1993, the LFS data were collected in March 1993 which means that the effect of the reform can not be observed in 1993. I assume for simplicity

[7] I refer to section 7-2 on the evolution of the labor cost since 1980 of the June 2009 social security report (CCSS, 2009). This report is available on the following website: `http://www.securite-sociale.fr/Rapports-2009`.

that payroll tax rates were the same across the wage distribution from 1982 to 1993. Therefore, I set all tax parameters to McDaniel (2007)'s average labor tax rate time series from 1982 to 1993. From 1994 to 2008, France relied massively on payroll tax reduction policies on low-paid workers to increase employment. In order to proxy payroll tax rate reductions by task group, I use the social security report (CCSS, 2009) which provides average payroll tax rate reduction by sector for 2008. The personal service sector was subject to a 10 pp payroll tax rate reduction while high skilled sectors such as the energy or the financial sectors had near zero payroll tax rate reduction. Manufacturing and construction sectors benefited from payroll tax rate reductions that ranged from 2 pp to 8 pp for an average of 5 pp. Furthermore, the bulk of the drop in payroll tax rates and labor cost on the minimum wage occurred mainly from 1994 to 2003 according to the social security report (CCSS, 2009). Based on those information, I apply a linear decline of 10 pp to the manual labor tax rate from 1994 to 2003 while the routine labor tax rate is subject to a 5 pp decline. In contrast, I assume that the abstract labor tax rate followed the McDaniel (2007) average labor tax rate without any labor tax rate reduction. The time series obtained display dynamics that are close to those obtained by Bozio, Breda, and Guillot (2016) by decile across the wage distribution.

B.4.2 A brief history of labor taxation policies

In Figure B.9, I display payroll tax rate reductions for some major policies. Payroll tax rate reductions were implemented in two main steps. From 1993 to 1998, successive governments implemented those policies with the explicit aim of boosting unskilled employment and containing the labor cost of low-paid workers that was inflating due to the rise of the minimum wage. The Balladur and the Juppé laws progressively implemented a 18.2 pp digressive payroll tax rate reduction for workers paid at the minimum wage that cancels out at 1.3 minimum wage.[8] From 1998 to 2007, additional payroll tax reductions were implemented in order to counter the increase in the labor cost induced by the 35-hour workweek policies implemented by the Aubry I and II laws.[9] The Aubry I law introduced a lump-sum financial aid independent of worker's salary for firms that implemented directly the working time reduction policy. The Aubry II law introduced an additional payroll tax reduction targeted

[8] The Balladur law of July 1st, 1993 suppressed family social contributions (-5.4 pp) for workers paid at the minimum wage to 1.1 minimum wage and suppressed half of them for those paid from 1.1 to 1.2 minimum wage. The Juppé tax cuts were introduced by the law of October 1st, 1996 and the law of January 1st, 1998.

[9] Respectively the law of June 13, 1998 and the law of January 19, 2000. Those laws are also well known under the name of "thirty five hour laws".

Figure B.9 – Payroll tax rate reduction policies

Notes: * applies only for firms that implemented the 35-hour working time reductions (GMR). ** also applies for firms with more than 19 employees after the 2007 reform. *** applies only for firms with less than 20 employees. *Sources*: Legislation and Ourliac and Nouveau (2012).

on low-paid workers for firms that implemented the 35-hour working time reduction policy.[10] Instead of benefiting from the Juppé payroll tax reduction, those firms benefited from a reduction by 26 pp of the payroll tax rate for the minimum wage that declined until 1.7 minimum wage. Above this threshold, employers received a 609.79 euros lump-sum financial aid in 2000 independent of worker's salary. The Fillon law progressively unified and generalized the digressive payroll tax reductions to reach a 26 pp payroll tax rate reduction for the minimum wage that canceled out at 1.6 minimum wage for all firms.[11] In 2007, a slight modification was introduced.[12] The payroll tax rate reduction was of 26 pp for the minimum wage for firms with more than nineteen employees and of 28.1 pp for the minimum wage for firms with less than twenty employees and canceled out at 1.6 minimum wages.

[10] In order to benefit from additional payroll tax reductions, firms that implemented the 35-hour working time reduction reform had to pay minimum wage workers a monthly wage equal to what they would have received before the reform. This is called the monthly guarantee of remuneration (GMR).

[11] Law of January 17, 2003. The payroll tax rate reduction was implemented progressively and took its final form with the reform of July 1st, 2005.

[12] Law of July 1st, 2007.

B.5 Asymptotic equilibrium

As in Autor and Dorn (2013), I now turn to asymptotic wage inequality and allocation of labor in order to grasp their long run determinants. The computation of asymptotic wage inequality and labor allocation also allows to get a preliminary idea of the parameter values that one should obtain during the calibration.

B.5.1 Preliminary computations

One cannot use the social planner program. Because of distortionary taxation, this exercise has to rely on the decentralized equilibrium. In this section, I focus mainly on the role played by the diffusion of ICT capital. The growth device of the model is perfectly deterministic. As time passes, the price of capital falls and the capital stock increases because capital and routine labor are substitutes (i.e $\mu \in [0;1]$)

$$\underset{t\to+\infty}{lim} p_k = 0 \tag{B.25}$$

$$\underset{t\to+\infty}{lim} K = +\infty. \tag{B.26}$$

Indeed, as time passes, the price of capital tends to zero because of capital diffusion. Therefore, capital is less expensive and goods producers buy more capital. Since routine labor is bounded and is substitutable with capital, producers progressively substitute capital for routine labor.[13] Therefore, the production of routine tasks $X = [((1-\alpha_k)l_r)^{\mu} + (\alpha_k K)^{\mu}]^{\frac{1}{\mu}}$ is asymptotically determined by capital[14]

$$X \sim \alpha_k K. \tag{B.27}$$

According to the definition of Y_g and equation (2.20), the asymptotic production of the goods sector is defined by

$$Y_g \sim (\alpha_k K)^{\beta}. \tag{B.28}$$

[13]Indeed, we have $l_r = (1+\overline{\eta})\, e^{-\overline{\eta}}$ with $\overline{\eta} \in [0;+\infty[$ and therefore $l_r \in [0;1]$.

[14]$x \sim y$ and $\underset{t\to+\infty}{lim} \frac{x}{y} = 1$ are two equivalent notations.

Using equation (2.8),the price of capital is equal to

$$p_k = \beta\alpha_k^{\mu}K^{\mu-1}X^{\beta-\mu}. \tag{B.29}$$

This implies that asymptotically

$$p_k \sim \beta\alpha_k^{\beta}K^{\beta-1} \tag{B.30}$$

$$p_kK \sim \beta\left(\alpha_kK\right)^{\beta}. \tag{B.31}$$

Given the definition of good consumption $C_g = Y_g - p_kK$, I obtain the asymptotic consumption of market goods

$$C_g \sim (1-\beta)\left(\alpha_kK\right)^{\beta}. \tag{B.32}$$

In order to find asymptotic wages and allocation of labor, some of the equilibrium conditions and variables have to be rewritten. Employment for each task and sector can be written as a function of market service employment. According to equation (2.29)

$$l_n = \Theta l_{ms} \tag{B.33}$$

with $\Theta = \left(\frac{A_{ms}}{A_n}\right)^{\frac{\nu}{\nu-1}}\left[\frac{a_s(1-\tau_{ms})}{1-a_s}\right]^{\frac{1}{\nu-1}}$. Variables l_s, $\overline{\eta}$, l_r are also written as a function of l_{ms} by using equations (2.17), (2.18) and (2.19)

$$l_s = (1+\Theta)\,l_{ms} \tag{B.34}$$

$$\overline{\eta} = -ln\left(1-(1+\Theta)\,l_{ms}\right) \tag{B.35}$$

$$l_r = \left[1-ln\left(1-(1+\Theta)\,l_{ms}\right)\right]\left[1-(1+\Theta)\,l_{ms}\right]. \tag{B.36}$$

B.5.2 Asymptotic wages

One needs asymptotic wages to compute the asymptotic allocation of labor. The asymptotic routine wage is computed by using equations (2.6), (B.27) and (B.36)

$$\begin{aligned} w_r &= \beta(1-\alpha_k)^{\mu} l_r^{\mu-1} X^{\beta-\mu} \\ w_r &\sim \beta(1-\alpha_k)^{\mu} \left[1 - ln\left(1-l_s\right)\right]^{\mu-1} \left[1-l_s\right]^{\mu-1} \left(\alpha_k K\right)^{\beta-\mu} \end{aligned} \tag{B.37}$$

with $l_s = (1+\Theta)\, l_{ms}$. For the abstract wage, I obtain

$$\begin{aligned} w_a &= (1-\beta)\, X^{\beta} \\ w_a &\sim (1-\beta)\left(\alpha_k K\right)^{\beta}. \end{aligned} \tag{B.38}$$

Equations (2.12) and (2.29) give the asymptotic manual wage

$$w_{ms} = \Omega^{-1} l_{ms}^{\varepsilon-1} C_g^{1-\varepsilon} \tag{B.39}$$

$$w_{ms} \sim \Omega^{-1} l_{ms}^{\varepsilon-1} \left(1-\beta\right)^{1-\varepsilon} \left(\alpha_k K\right)^{\beta(1-\varepsilon)} \tag{B.40}$$

with $\Omega = \frac{a_g}{a_s(1-a_g)} A_{ms}^{-\nu} \left[a_s A_{ms}^{\nu} + (1-a_s)\left(A_n \Theta\right)^{\nu}\right]^{\frac{\nu-\varepsilon}{\nu}}$. By using (2.16), (B.35) and (B.37), the asymptotic manual wage rate can be rewritten as

$$w_{ms} = -ln\left(1-l_s\right) w_r \tag{B.41}$$

$$w_{ms} \sim -ln\left(1-l_s\right) \beta(1-\alpha_k)^{\mu} \left[\left(1-ln\left(1-l_s\right)\right)\left(1-l_s\right)\right]^{\mu-1} \left(\alpha_k K\right)^{\beta-\mu} \tag{B.42}$$

with $l_s = (1+\Theta)\, l_{ms}$.

B.5.3 Asymptotic allocation of labor

By rearranging equation (B.39), I obtain a relation that links manual employment in the market sector with the manual wage rate

$$l_{ms}^{\varepsilon-1} = \Omega C_g^{\varepsilon-1} w_{ms}. \tag{B.43}$$

Therefore, asymptotic manual employment in market services $\underset{t\to+\infty}{lim} l_{ms}(t)$ is the solution to

$$\left(\frac{l_s}{1+\Theta}\right)^{\varepsilon-1} = -\Omega\beta(1-\alpha_k)^{\mu}(1-\beta)^{\varepsilon-1} ln(1-l_s)\left[(1-ln(1-l_s))(1-l_s)\right]^{\mu-1}(\alpha_k K)^{\beta\varepsilon-\mu}$$

with $l_s = (1+\Theta)\,l_{ms}$. By using the previous equation, one can solve the asymptotic level of l_s and thus l_{ms} and l_n. As in Autor and Dorn (2013), the allocation of unskilled labor between manual and routine tasks depends upon the relative magnitudes of the consumption and production elasticities, scaled by the share of the routine aggregate in goods production

$$\underset{t\to+\infty}{lim} l_s = \begin{cases} 1 & \text{if } \varepsilon < \frac{\mu}{\beta} \\ ]0;1[& \text{if } \varepsilon = \frac{\mu}{\beta}. \\ 0 & \text{if } \varepsilon > \frac{\mu}{\beta} \end{cases} \tag{B.44}$$

The asymptotic level of routine labor is recovered by combining equations B.36 and B.44

$$\underset{t\to+\infty}{lim} l_r = \begin{cases} 0 & \text{if } \varepsilon < \frac{\mu}{\beta} \\ ]0;1[& \text{if } \varepsilon = \frac{\mu}{\beta}. \\ 1 & \text{if } \varepsilon > \frac{\mu}{\beta} \end{cases} \tag{B.45}$$

In contrast to Autor and Dorn (2013), because of the existence of the non-market sector, the allocation of unskilled labor in market services is obstructed. The extent of the allocation of unskilled labor to market services is affected notably by labor taxation. This finding is obtained by combining equations (B.34) and (B.44) such that

$$\underset{t\to+\infty}{lim} l_{ms} = \begin{cases} \frac{1}{1+\Theta} & \text{if } \varepsilon < \frac{\mu}{\beta} \\ \frac{1}{1+\Theta} l_s & \text{with } l_s \in \,]0;1[\text{ if } \varepsilon = \frac{\mu}{\beta} \\ 0 & \text{if } \varepsilon > \frac{\mu}{\beta} \end{cases} \tag{B.46}$$

$$\lim_{t\to+\infty} l_n = \begin{cases} \frac{\Theta}{1+\Theta} & \text{if } \varepsilon < \frac{\mu}{\beta} \\ \frac{\Theta}{1+\Theta} l_s & \text{with } l_s \in]0;1[\text{ if } \varepsilon = \frac{\mu}{\beta} \\ 0 & \text{if } \varepsilon > \frac{\mu}{\beta} \end{cases} \tag{B.47}$$

with $\Theta = \left(\frac{A_{ms}}{A_n}\right)^{\frac{\nu}{\nu-1}} \left[\frac{a_s(1-\tau_{ms})}{1-a_s}\right]^{\frac{1}{\nu-1}}$. The asymptotic allocation of employment to the market service sector and the non-market sector depends on ε, β and μ, but also on ν, τ_{ms}, a_s, A_{ms} and A_n. It replicates the observed rise in market service employment and the decline in routine employment when $\varepsilon < \frac{\mu}{\beta}$. Furthermore, since market services and non-market produced goods are substitutes ($\nu < 0$), Θ and l_n are increasing functions of τ_{ms} and A_n while l_{ms} is a decreasing function of those variables.

B.5.4 Asymptotic wage inequality

Finally, I compute the asymptotic wage ratios. When those are indeterminate, I compute the asymptotic relative labor share. The manual to routine wage ratio is computed from equation (B.41) and (B.44)

$$\lim_{t\to+\infty} \frac{w_{ms}}{w_r} = \begin{cases} +\infty & \text{if } \varepsilon < \frac{\mu}{\beta} \\ -ln\,(1-l_s) & \text{if } \varepsilon = \frac{\mu}{\beta}. \\ 0 & \text{if } \varepsilon > \frac{\mu}{\beta} \end{cases} \tag{B.48}$$

The asymptotic abstract to manual wage ratio is computed by combining (B.38) and (B.40)

$$\lim_{t\to+\infty} \frac{w_a}{w_{ms}} = \Omega\,(1-\beta)^{\varepsilon}\,(\alpha_k K)^{\beta\varepsilon}\, l_{ms}^{1-\varepsilon}. \tag{B.49}$$

The asymptotic economy replicates the observed rise in market service employment and relative wage as for the decline in routine employment when $\varepsilon < \frac{\mu}{\beta}$. Therefore, I focus on the case where $\varepsilon < \frac{\mu}{\beta}$ which means that $l_{ms} = \frac{1}{1+\Theta}$. In fact, three sub-cases are distinguishable depending on the value of ε:

$$\lim_{t\to+\infty} \frac{w_a}{w_{ms}} = \begin{cases} +\infty & \text{if } \varepsilon > 0 \\ \frac{\Omega}{1+\Theta} & \text{if } \varepsilon = 0. \\ 0 & \text{if } \varepsilon < 0 \end{cases} \tag{B.50}$$

According to Rogerson (2008) and Autor and Dorn (2013), the empirically relevant case that replicates the process of structural transformation and labor market polarization occurs when $\varepsilon < 0$ such that goods and manual services are complementary. In such case, the abstract wage grows less rapidly than the market service wage as observed in the data. On the contrary, when $\varepsilon > \frac{\mu}{\beta}$, $\varepsilon \in [0;1]$ and $l_{ms} = 0$ given A_n. Therefore, the asymptotic abstract to manual relative labor share tends to zero

$$\lim_{t\to+\infty} \frac{l_a w_a}{l_{ms} w_{ms}} = 0. \tag{B.51}$$

The abstract to routine wage ratio is then computed

$$\lim_{t\to+\infty} \frac{w_a}{w_r} = \frac{(1-\beta)(\alpha_k K)^{\mu}}{\beta(1-\alpha_k)^{\mu} [1 - ln(1-l_s)]^{\mu-1} [1-l_s]^{\mu-1}}. \tag{B.52}$$

When $\varepsilon < \frac{\mu}{\beta}$, $l_s = 1$ and the abstract to routine relative labor share tends to zero

$$\lim_{t\to+\infty} \frac{l_a w_a}{l_r w_r} = 0. \tag{B.53}$$

When $\varepsilon \geq \frac{\mu}{\beta}$, $l_s \in [0;1[$. Since $\mu \in [0;1]$, the abstract to routine wage ratio tends to infinity

$$\lim_{t\to+\infty} \frac{w_a}{w_r} = +\infty. \tag{B.54}$$

Appendix C

Appendix of chapter 3

C.1 Comparative statics analysis

		Percent deviation from SS0		
Relative variables	SS0	Z_t	$\zeta_{a,t}$	$\zeta_{r,t}$
Y/H	0.6185	0.2611	-0.0652	0.0594
H_a/H_r	0.9338	0.1771	-0.2893	0.2934
H_r/H_m	6.0471	-0.1768	0.0410	-0.2926
W_a/W_r	1.5413	0.3544	0.4165	-0.4082
W_r/W_m	1.4364	-0.3532	0.0819	0.4099
Aggregate variables				
Output	0.6046	0.2426	-0.2152	-0.0990
Consumption	0.5282	0.2219	-0.1938	-0.1222
Investment	0.0764	0.3860	-0.3635	0.0614
Capital	3.0565	1.3899	-0.3635	0.0614
Rental rate	0.0351	-0.9901	-0.0000	-0.0000
Total hours	0.9775	-0.0185	-0.1502	-0.1583
Abstract hours	0.4349	0.0658	-0.3075	-0.0190
Routine hours	0.4657	-0.1111	-0.0183	-0.3115
Manual hours	0.0770	0.0658	-0.0592	-0.0190
Abstract wage	0.6444	0.3537	0.1852	-0.1601
Routine wage	0.4181	-0.0007	-0.2303	0.2492
Manual wage	0.2911	0.3537	-0.3120	-0.1601

Table C.1 – Comparative statics analysis

Notes: SS0 provides the initial steady state values for which all shocks are normalized to one. The other columns display percentage deviations of the new steady state values from the initial values following a positive one percent permanent change in corresponding shocks.

Variable	ADF test H_0 : unit root	KPSS test H_0 : stationarity
Levels		
AR premium	Not rejected	Rejected
Labor productivity	Not rejected	Rejected
Total hours	Not rejected	Rejected
AR relative hours	Not rejected	Rejected
RM relative hours	Not rejected	Rejected
First differences		
AR premium	Rejected	Not rejected
Labor productivity	Rejected	Not rejected
Total hours	Rejected	Not rejected
AR relative hours	Rejected	Not rejected
RM relative hours	Rejected	Not rejected

Table C.2 – Unit root tests

Notes: Results of unit root tests are based on a degree of significance of five percent. Unit root tests for variables in level are done with and without trend. Unit root tests for first differences are done with and without constant. Results of unit root tests are insensitive to other alternatives.

C.2 Univariate time series analysis

C.2.1 Unit root tests

C.2.2 Robustness of business cycle moments

		Correlation				
	SD	W_r/W_m	H_a/H_r	H_r/H_m	Y/H	H
W_a/W_r	1.2395	-0.1340	0.1513	-0.1934*	0.2110*	-0.1303
W_r/W_m	2.2739	-	0.0344	0.0844	0.0983	0.0299
H_a/H_r	2.3862	-	-	-0.1392	-0.0027	-0.4098*
H_r/H_m	3.2604	-	-	-	-0.1128	0.0187
Y/H	0.6160	-	-	-	-	-0.2576*
H	0.7961	-	-	-	-	-

Table C.3 – Business cycle moments

Notes: SD stands for standard deviation. Data are constructed as described in subsection 3.3.1. Variables are in first difference of their logarithm. Significance of at least five percent ($*$).

C.3 VAR algorithm

We combine long-run exclusion and sign restrictions in order to identify structural shocks. In our case, this approach is challenging because the structural model is not block-recursive.

When combining both types of restrictions, sign restrictions need to be applied on candidate long-run impulse responses that satisfy long-run exclusion restrictions. In other words, we need to draw a rotation matrix Q conditional on zero restrictions. Otherwise, the probability of drawing a rotation matrix for which candidate long-run impulse responses satisfy the exclusion restrictions is near zero. This would invalidate the impulse responses as well as decompositions of forecast error variance. When the model has a block-recursive form, we can use sub-rotation matrices as in Balleer and van Rens (2013). In our case, the structural model is not block-recursive. We tackle this issue by relying on a solution proposed by Arias, Ramirez, and Waggoner (2014). We summarize the algorithm as followed.

Step 1 We draw N sets (B,Ω) from the posterior distribution of reduced-form parameters.[1]

Step 2 For each of the N draws, we compute $\Xi = \left(I_N - \sum_{k=1}^{p} B_k\right)^{-1} L_0$ where $L_0 = chol(\Omega)$. This allows us to obtain long-run impulse responses of orthogonalized shocks which are not yet structural shocks as they might not fulfill the identifying restrictions.

Step 3 For each of the N draws, we draw one orthogonal matrix Q such that the candidate long-run impulse response $\widetilde{LR} = \Xi Q$ satisfies the long-run zero restrictions. We obtain a candidate structural model. In order to do so, we draw Q conditional on exclusion restrictions by using a Gram-Schmidt orthogonalization process. This allows us to build a matrix Q iteratively that is orthogonal and that fulfills the exclusion restrictions.

Step 4 We retain from those N candidate structural models only those for which long-run impulse responses $\widetilde{LR}$ satisfy long-run sign restrictions. Therefore, we obtain the posterior distribution of structural models that satisfy both kinds of long-run restrictions.

[1]We set $N = 1000$ in specification I and $N = 50000$ in specification II and III.

C.4 Additional results

C.4.1 Impulse responses

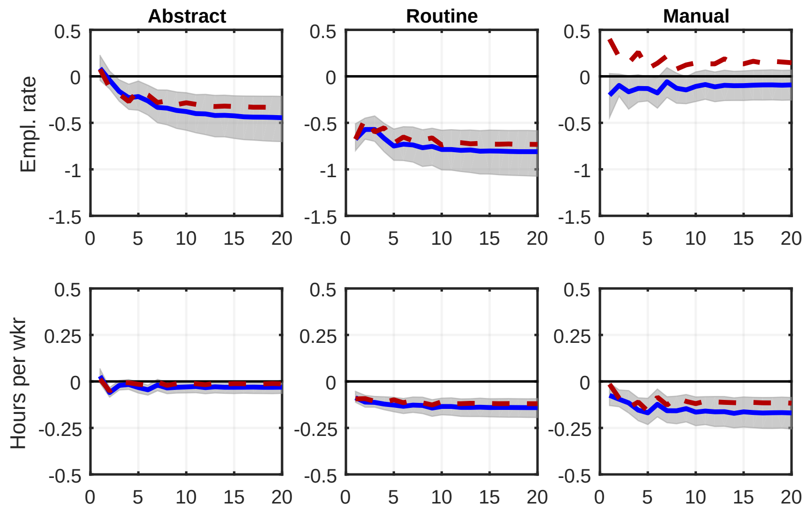

Figure C.1 – Impulse response functions to RBTC shocks - Extensive vs intensive margins

Notes: Impulse responses to a one-standard deviation shock are reported. Solid lines represent the median of impulse responses. Grey areas correspond to the 68% of the posterior distribution. Dashed lines capture the median-target responses as defined by Fry and Pagan (2011).

C.4.2 Forecast error variance decompositions

Horizon	1	4	8	16	32
AR Premium	1.08	15.46	19.69	23.15	25.56
	[0.17,2.70]	[10.17,21.40]	[12.51,28.68]	[13.55,35.85]	[13.88,40.14]
Productivity	79.35	89.37	95.16	97.90	99.04
	[61.21,91.33]	[78.56,95.84]	[89.76,98.08]	[95.63,99.17]	[98.09,99.61]
Total hours	24.29	22.87	23.73	24.13	24.01
	[10.98,42.91]	[9.76,42.11]	[8.74,42.49]	[7.76,43.70]	[6.97,44.00]
AR rel. hours	1.04	2.35	2.44	2.48	2.45
	[0.09,4.11]	[0.84,6.89]	[0.90,6.75]	[0.83,6.98]	[0.64,7.66]
RM rel. hours	8.81	16.07	18.92	20.75	21.45
	[4.72,13.88]	[7.96,27.02]	[8.28,33.09]	[8.23,37.32]	[7.97,39.97]

Table C.4 – Forecast error variance decomposition with Gali's shock
Notes: We report the median and in brackets 68% Bayesian confidence bands from the posterior distribution.

Horizon	1	4	8	16	32
Abstract hours	10.20	23.44	28.86	30.72	31.53
	[6.25,15.41]	[12.51,36.14]	[13.95,44.81]	[14.32,48.83]	[13.90,50.86]
Routine hours	11.22	15.41	15.99	16.61	17.08
	[3.48,23.26]	[5.62,31.45]	[4.66,33.16]	[3.88,35.35]	[3.52,36.22]
Manual hours	0.79	1.77	2.01	2.10	2.19
	[0.11,2.23]	[0.69,4.10]	[0.93,5.04]	[0.81,6.55]	[0.60,8.15]

Table C.5 – Forecast error variance decomposition with Gali's shock - Hours by task
Notes: We report the median and in brackets 68% Bayesian confidence bands from the posterior distribution.

Horizon	1	4	8	16	32
AR Premium					
Supply	4.61	9.97	9.78	9.55	8.92
	[0.39,27.72]	[3.90,28.52]	[3.27,28.85]	[2.61,31.09]	[1.96,32.04]
RBTC	13.77	27.40	37.14	45.55	49.91
	[4.28,36.16]	[15.89,47.22]	[23.16,57.22]	[28.10,65.20]	[31.04,70.56]
Neutral	5.73	4.48	2.88	1.58	0.81
	[0.63,20.69]	[1.40,12.41]	[1.00,7.66]	[0.55,4.12]	[0.29,2.15]
Productivity					
Supply	41.18	43.24	41.39	40.00	39.23
	[5.86,78.40]	[6.03,79.27]	[6.29,78.29]	[6.16,76.98]	[5.81,76.48]
RBTC	7.66	12.54	19.16	22.77	24.68
	[0.69,26.46]	[1.67,33.37]	[3.19,41.25]	[4.41,47.53]	[5.23,50.40]
Neutral	32.31	32.07	29.09	27.61	26.73
	[3.84,65.15]	[4.09,64.49]	[3.87,60.55]	[3.70,57.58]	[3.49,56.39]
Total hours					
Supply	6.63	7.43	7.36	7.33	7.26
	[0.57,25.79]	[0.83,27.21]	[0.79,27.45]	[0.86,27.97]	[0.84,27.75]
RBTC	46.40	39.05	39.76	39.87	39.71
	[22.39,69.10]	[17.34,62.95]	[17.05,63.02]	[16.83,62.83]	[16.59,63.01]
Neutral	6.15	6.07	6.03	6.02	5.99
	[0.50,25.15]	[0.71,26.29]	[0.63,27.10]	[0.60,26.92]	[0.52,26.79]
AR rel. hours					
Supply	8.95	8.64	9.55	10.31	11.48
	[0.79,37.18]	[1.43,34.79]	[1.46,37.32]	[1.45,40.56]	[1.34,42.30]
RBTC	48.95	50.90	50.14	47.86	46.41
	[24.73,77.38]	[25.15,76.72]	[23.94,76.11]	[22.14,75.31]	[20.52,74.76]
Neutral	18.66	18.71	19.92	20.75	21.55
	[1.57,54.49]	[2.73,52.32]	[2.67,54.06]	[2.67,56.29]	[2.56,58.16]
RM rel. hours					
Supply	6.42	8.46	8.50	8.04	8.03
	[0.64,27.43]	[2.04,27.16]	[1.78,27.83]	[1.32,28.30]	[1.09,28.47]
RBTC	10.15	18.87	23.82	26.84	28.30
	[2.06,23.36]	[6.97,36.29]	[9.04,43.78]	[10.27,49.00]	[10.85,51.99]
Neutral	5.57	7.17	6.81	6.49	6.27
	[0.37,30.58]	[1.72,30.75]	[1.58,30.02]	[1.20,29.65]	[0.92,29.78]

Table C.6 – Forecast error variance decomposition with abstract supply, RBTC and neutral technology shocks

Notes: We report the median and in brackets 68% Bayesian confidence bands from the posterior distribution.

Horizon	1	4	8	16	32
Abstract hours					
Supply	25.27	20.85	17.75	16.46	16.06
	[4.59,55.49]	[4.54,48.34]	[3.37,45.79]	[2.54,45.31]	[2.09,45.00]
RBTC	5.50	10.19	12.31	14.63	16.08
	[0.55,23.26]	[5.29,21.30]	[4.02,30.75]	[3.09,37.32]	[2.74,39.63]
Neutral	21.31	14.57	11.63	9.30	8.63
	[2.32,53.55]	[4.16,35.25]	[3.13,33.35]	[2.01,32.34]	[1.45,31.75]
Routine hours					
Supply	4.61	5.66	5.26	5.55	5.58
	[0.45,21.02]	[1.33,21.09]	[1.04,21.08]	[0.92,21.04]	[0.74,20.94]
RBTC	65.71	57.39	55.64	54.35	53.59
	[37.93,84.34]	[31.61,75.19]	[29.20,74.06]	[27.50,73.42]	[26.42,73.14]
Neutral	11.60	9.55	8.77	8.59	8.08
	[1.18,39.54]	[1.87,30.98]	[1.38,30.31]	[1.09,29.90]	[0.92,29.79]
Manual hours					
Supply	9.08	10.32	10.08	10.02	9.96
	[1.13,31.04]	[2.64,29.83]	[2.57,30.07]	[2.28,30.05]	[1.78,30.90]
RBTC	5.23	7.22	8.13	8.70	8.95
	[0.58,15.55]	[1.86,18.62]	[1.96,21.61]	[1.79,24.48]	[1.49,25.72]
Neutral	11.06	12.66	12.99	13.03	13.06
	[0.91,37.82]	[2.93,36.45]	[2.81,37.12]	[2.31,39.12]	[1.87,39.85]

Table C.7 – Forecast error variance decomposition with abstract supply, RBTC and neutral technology shocks - Hours by task

Notes: We report the median and in brackets 68% Bayesian confidence bands from the posterior distribution.

C.4.3 Historical decompositions

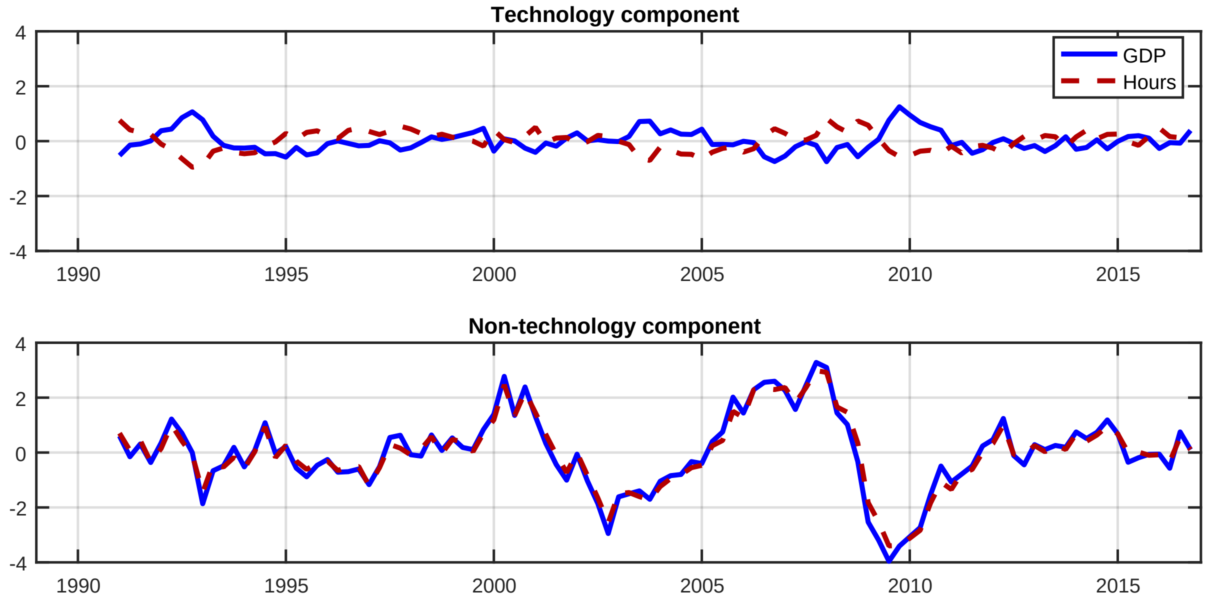

Figure C.2 – Specification I - Historical decomposition of GDP and total hours
Notes: We retrieve the cumulative contribution of each shock to (log) output and (log) hours worked time series from the estimated structural VAR identified using specification I restrictions. We use the HP-filter ($\lambda = 1600$) on the resulting time series to isolate business cycle fluctuations.

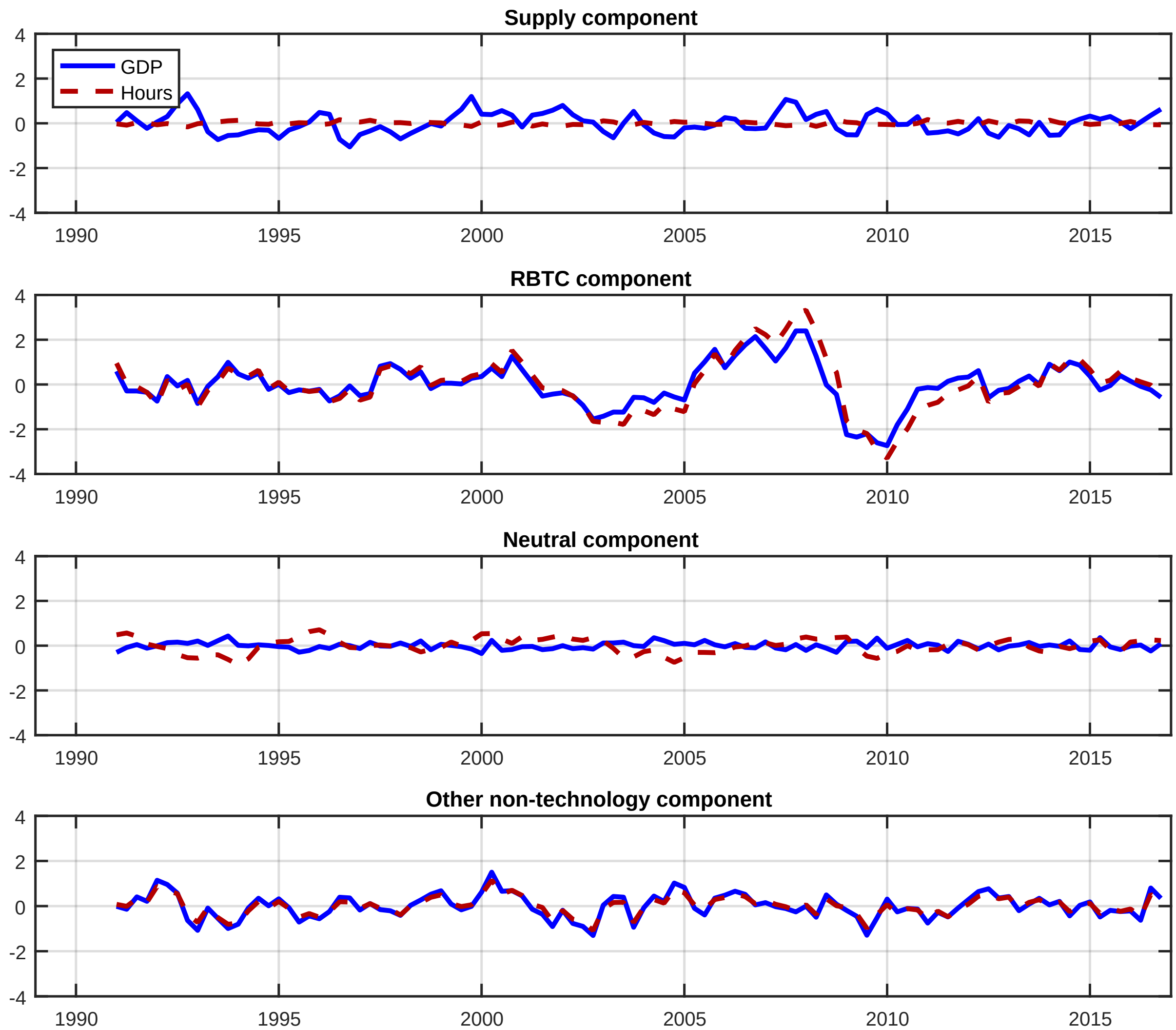

Figure C.3 – Specification I - Historical decomposition of GDP and total hours

Notes: We retrieve the cumulative contribution of each shock to (log) output and (log) hours worked time series from the estimated structural VAR identified using specification II restrictions. We use the HP-filter ($\lambda = 1600$) on the resulting time series to isolate business cycle fluctuations.

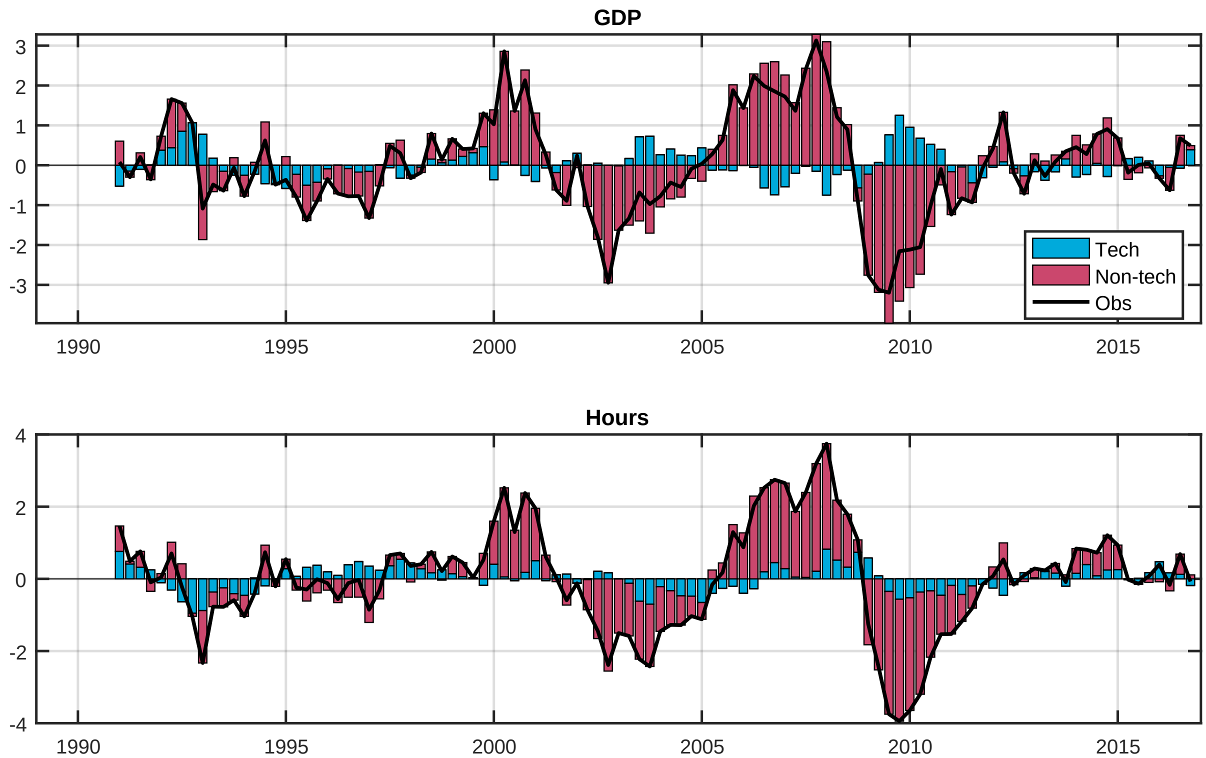

Figure C.4 – Specification I - Historical decomposition of GDP and total hours

Notes: We retrieve the cumulative contribution of each shock to (log) output and (log) hours worked time series from the estimated structural VAR identified using specification I restrictions. We use the HP-filter (λ = 1600) on the resulting time series to isolate business cycle fluctuations.

C.5 Empirical robustness

In order to establish whether our results are robust, we run an array on robustness check. All alternative specifications are based on specification II, namely the one that separately identifies RBTC from task-supply shocks and neutral technology shocks. Figures C.5 and C.6 report results obtained from our alternative specifications. For the sake of clarity, we report only median impulse responses. Complete results, with all confidence intervals, remain available upon request.

Alternative measures of labor productivity. In our baseline specification, we use the labor productivity measure from Ohanian and Raffo (2012). To test the sensitivity of our results to this initial choice, we run two alternative models. In the first one, the labor productivity variable is replaced by the utilization-adjusted Total Factor Productivity (TFP) computed by Fernald (2012). In the spirit, the computation is close to the one conducted by Basu, Fernald, and Kimball (2006) but the resulting time series are derived on a quarterly rather than an annual basis. In the second one, we use a labor productivity variable based on our measure of total hours derived from the CPS. Corresponding median impulse responses are displayed in blue squares in the first case and in sky-blue crosses in the second case.

Alternative Bayesian specifications. Another important robustness check is to establish if results are affected when we change modeling choices related to the Bayesian environment of the VAR model. In our baseline specification, we rely on a Minnesota prior incorporating a fixed residual variance and a lag decay, so that eight lags could be included in the model. Our baseline model is different from specifications using a flat prior (OLS equivalent) or a Normal Inverted-Wishart prior as developed by Kadiyala and Karlsson (1997). Consequently, we consider four robustness checks. First, we keep the baseline structure but the VAR lag length is reduced to two. Second, we conserve the Minnesota prior and the generous lag length of the baseline specification but we use a linear decay rather than a harmonic one. Third, we use an OLS equivalent flat prior with only two lags. Fourth, we relax the fixed residual variance assumption by using the prior developed by Kadiyala and Karlsson (1997). As in our baseline model, this prior uses the same average values for the VAR coefficients but it generalizes the Minnesota prior by providing an estimation of the residual variance. Results obtained with those alternative specifications are respectively depicted in Figures C.5 and C.6 using orange triangles, green circles, pink diamonds and red inverted triangles.

Shorter sample period. It remains possible that our results are an artefact due to our sample period and the inclusion of the post Great Recession period. To deal with this issue, we estimate the same VAR as in the baseline but with a shorter sample ending in 2006Q4. IRFs obtained from such a model are displayed in brown crosses.

Comments. As shown in Figures C.5 and C.6, results are quite insensitive to our set of robustness checks both from a qualitative and a quantitative point of view. Each time, estimated IRFs closely follow those obtained in the baseline specification (depicted in black). We observe the same weak responses of relative hours and hours by task after task-supply and neutral technology shocks. By contrast, RBTC unambiguously declines total hours. It also increases abstract to routine hours while it decreases routine to manual hours. Those patterns are then translated into a fall in hours by task. As found in our baseline specification, the fall of routine hours is by far the largest after RBTC.

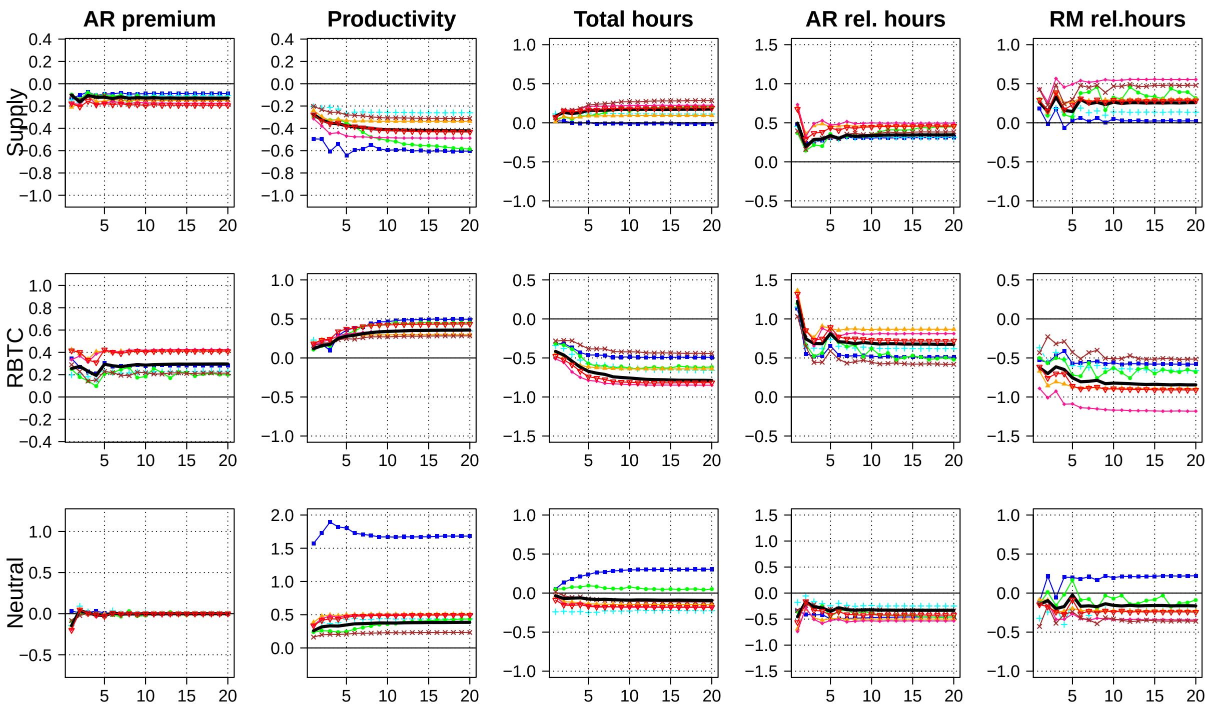

Figure C.5 – Impulse response functions to task-supply, RBTC, and neutral technology shocks - Robustness

Notes: Impulse responses to a one-standard deviation shock are reported. Blue square lines correspond to the model estimated with the TFP variable of Fernald (2012) rather than with labor productivity. Sky-blue cross lines correspond to the model estimated with our measure of labor productivity based on CPS data. Green circle lines correspond to the model estimated with eight lags and a linear decay. Pink diamond lines correspond to the model estimated with two lags and a flat prior. Red inverted triangles lines correspond to the model estimated with the prior of Kadiyala and Karlsson (1997). Orange triangle lines correspond to the model estimated with two lags. Brown cross lines correspond to the model estimated for the sample 1989Q1-2006Q4 and black solid lines correspond to the baseline specification of subsection 3.5.2.

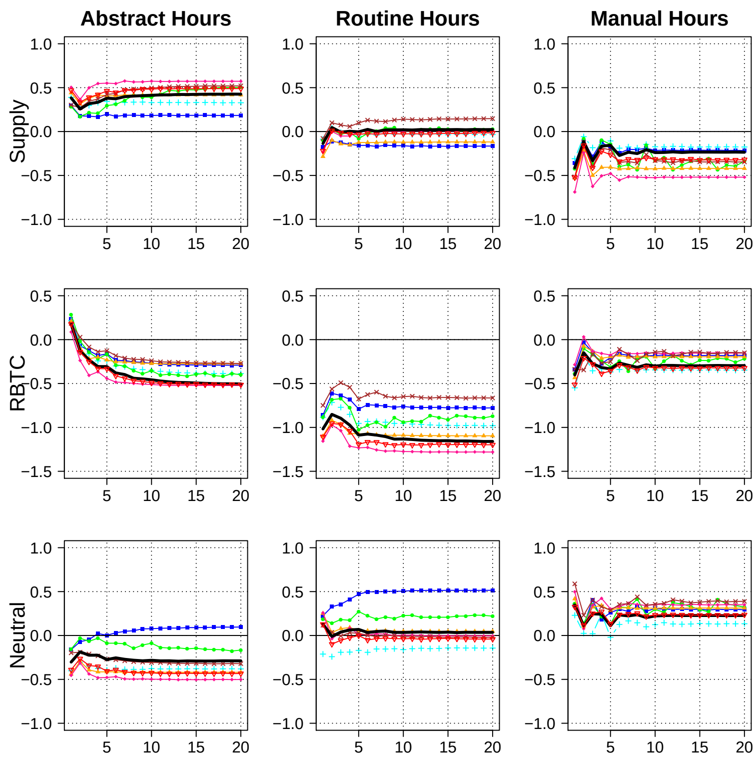

Figure C.6 – Median impulse response functions of hours by task to task-supply, RBTC, and neutral technology shocks - Robustness

Notes: Impulse responses to a one-standard deviation shock are reported. Blue square lines correspond to the model estimated with the TFP variable of Fernald (2012) rather than with labor productivity. Sky-blue cross lines correspond to the model estimated with our measure of labor productivity based on CPS data. Green circle lines correspond to the model estimated with eight lags and a linear decay. Pink diamond lines correspond to the model estimated with two lags and a flat prior. Red inverted triangles lines correspond to the model estimated with the prior of Kadiyala and Karlsson (1997). Orange triangle lines correspond to the model estimated with two lags. Brown cross lines correspond to the model estimated for the sample 1989Q1-2006Q4 and black solid lines correspond to the baseline specification of subsection 3.5.2.

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Résumé français

Au cours des quatre dernières décennies, le progrès technique a façonné en profondeur les pays développés ainsi que leur marché du travail. Les bouleversements qu'il a induits ont à la fois suscité de l'enthousiasme et généré de la peur dans le débat public car ils affectent la croissance et la répartition des richesses. D'une part, le progrès technique joue un rôle déterminant dans la croissance économique sur le long terme comme le souligne Solow (1956). Il permet d'accroître collectivement le revenu des individus en augmentant la capacité de production de l'économie : les consommateurs en profitent car leur niveau de vie augmente. D'autre part, ce changement a un fort impact sur la répartition des richesses. Il génère des inégalités et donc des perdants et des gagnants car il touche à la fois aux inégalités de salaires et aux perspectives d'emploi.

La réallocation du travail issue du progrès technique génère souvent de l'inquiétude quant aux performances de l'emploi. L'histoire nous fournit plusieurs exemples où ce progrès a détériorer les conditions de travail et de vie des travailleurs, favorisant l'éruption de soulèvements populaires. Ainsi, au XIXe siècle, l'Angleterre vit l'émergence du luddisme. Le secteur du textile était confronté à de profonds bouleversements technologiques et structurels dus à l'introduction de machines qui effectuaient le travail auparavant accompli par des ouvriers qualifiés. Les adeptes de ce mouvement protestaient contre la mécanisation de leur secteur en détruisant les métiers à tisser qui faisaient disparaître leurs perspectives d'emploi. De même, en 1830, le mouvement des "Swing Riots", toujours en Angleterre, vit le soulèvement des ouvriers agricoles. Ils se rebellaient contre la mécanisation de l'agriculture et des conditions de travail extrêmement dures, là encore en détruisant des machines et en brûlant des champs, entre autres.

Les travailleurs ne sont pas les seuls à redouter l'impact négatif du progrès technique sur l'emploi, on retrouve également cette crainte dans la pensée économique. Par exemple, bien que David Ricardo loue le bienfait collectif du progrès technique, il partage certaines inquiétudes quant à ses effets délétères sur le bien-être des travailleurs. Il envisage la possibilité que l'essor des machines dans le processus de production puisse entraîner une détérioration de l'emploi. Ricardo (1821) déclare ainsi :

> *"la demande de bras diminuera nécessairement, la population deviendra excessive et les classes ouvrières entreront dans une période de détresse et d'angoisses."*
>
> *Des principes de l'économie politique et de l'impôt*, 3e édition (1821).

Au XXe siècle, Keynes (1930) souligne également les effets potentiellement néfastes du progrès technique mais il insiste sur leur nature transitionnelle. Il les considère comme des défis à court terme.

> *"Nous sommes actuellement affligés d'une maladie nouvelle dont certains lecteurs peuvent bien ignorer encore le nom, mais dont ils entendront beaucoup parler dans les années à venir, et qui est le chômage technologique. Il faut entendre par là le chômage qui est dû au fait que nous découvrons des moyens d'économiser de la main d'œuvre à une vitesse plus grande que nous ne savons trouver de nouvelles utilisations du travail humain. [...] Mais ce n'est là qu'une période passagère d'inadaptation."*
>
> *Perspectives économiques pour nos petits enfants (1930)*

Un siècle plus tard, les défis décrits par Keynes sont toujours d'actualité. Les progrès techniques récents ont provoqué une réallocation massive de la main d'œuvre entraînant simultanément de pertes et des gains d'emplois. En effet, le progrès technique a façonné en profondeur la structure professionnelle des économies développées telles que la France et les États-Unis au cours des quatre dernières décennies. L'essor des nouvelles technologies a déclenché un processus de réallocation de la main d'œuvre qui a conduit à une polarisation de l'emploi. Ce processus s'est produit parce que le progrès technique s'est effectué sur la base d'un remplacement des tâches routinières. Il est lié à la nature du progrès technique qui est biaisé en défaveur des tâches routinières. Les emplois moyennement rémunérés comportent des tâches routinières répétitives et codifiées qui peuvent être en partie exécutées par les nouvelles technologies. Par opposition, les emplois faiblement rémunérés se composent de tâches manuelles exigeant des interactions en face à face ou une dextérité manuelle qui ne sont pas facilement substituables par ces mêmes technologies. De même, les emplois à haut salaire impliquent des tâches abstraites de nature décisionnelle ou cognitive qui leurs sont généralement complémentaires. Ainsi, la proportion des emplois à bas et haut salaires a augmenté de manière significative tandis que la proportion des emplois moyennement rémunérés a diminué entraînant le déclin de la classe moyenne et engendrant en fin de compte de la détresse sociale. A cet égard, Frey and Osborne (2017) soulignent qu'environ la moitié des emplois actuels aux États-Unis a une forte probabilité de disparaître du fait de l'automatisation des processus de production.

La présente thèse va plus loin en mettant en évidence les conséquences de la nature du progrès technique sur les économies française et américaine. Elle fournit également des modèles explicatifs qui tiennent compte des spécificités du marché du travail. Il n'existe pas de consensus sur la manière dont la polarisation de l'emploi se traduit en termes de performances d'emploi. Rien ne garantit que les gains d'emplois issus du processus de réallocation compensent les pertes. Par exemple, bien que la France et les États-Unis aient subi des mutations similaires dans la structure professionnelle de leur emploi, ils présentent des différences marquantes quant aux inégalités de salaires et aux performances d'emploi entre 1982 et 2017. De plus, on en sait peu sur les effets à court terme des chocs technologiques biaisés et leur impact sur le cycle économique et pourtant ils ont modifié considérablement la structure professionnelle de l'emploi au cours des quarante dernières années.

Cette thèse est composée des trois chapitres suivants : performances d'emploi transatlantiques, polarisation de l'emploi et déclin du travail non qualifié en France, et progrès technique routinier et heures travaillées au cours du cycle économique. Ils peuvent être lus indépendamment les uns des autres.

Chapitre 1 - Performances d'emploi transatlantiques

Au cours des quatre dernières décennies, l'économie française a été caractérisée par des performances en matière d'emploi inférieures à celles des États-Unis. Les économistes soutiennent que ces écarts mettent en évidence un éventuel dysfonctionnement du marché du travail français. À cet égard, Piketty (1998) propose une analyse structurelle à long terme pour identifier les secteurs où l'emploi fait défaut en France par rapport aux États-Unis. Bien que ces pays aient tous deux enregistré un déclin de l'emploi agricole et manufacturier, il soutient que la France n'a pas développé son secteur des services dans la même mesure que les États-Unis. Le coût élevé du travail semble avoir entravé la réallocation de la main d'oeuvre entre les différents secteurs.

Nonobstant ces différences, les deux pays ont connu des mutations similaires dans leur structure professionnelle. Ils ont tous deux subi une polarisation de l'emploi, comme le montrent Autor, Katz, and Kearney (2006) et Goos, Manning, and Salomons (2009). La structure professionnelle de l'emploi a évolué, passant d'emplois moyennement rémunérés qui se composent des tâches routinières à des emplois fortement et faiblement rémunérés comportant respectivement des tâches abstraites et manuelles. Ce processus reflète avant tout les effets du progrès technique et de la mondialisation. Néanmoins, les gains et les pertes d'emploi résultant de ce processus de réallocation semblent se produire à des moments différents pour chaque pays. En conséquence, l'omission des caractéristiques professionnelles de la réallocation du travail ne permet de comprendre que partiellement le fossé transatlantique qui s'est créé en matière d'emploi.

Ce premier chapitre réévalue l'analyse structurelle de long terme initiée par Piketty (1998) en examinant dans quelle mesure l'évolution des structures professionnelles et sociodémographiques façonne le fossé transatlantique en matière d'emploi. Je démontre que le processus de polarisation est au cœur de la dynamique de l'emploi dans les deux pays et que des groupes sociodémographiques spécifiques capturent la majorité du déficit d'emploi français. Par conséquent, ce déficit ne reflète pas seulement un marché du travail déficient mais également le processus réallocation du travail qui s'est opéré au cours des quatre dernières décennies et qui affecte les perspectives d'emploi et les décisions de participation de groupes sociodémographiques spécifiques.

Je procède en construisant des séries chronologiques sur de longues périodes pour la France et les États-Unis entre 1982 et 2017 à partir de l'Enquête Emploi pour la France et des Current Population Surveys pour les États-Unis. Ces séries comprennent des informations sur l'emploi agrégé, l'emploi par catégorie professionnelle, la composition sociodémographique de la population, ainsi que les transitions des travailleurs entre les différents états du marché du travail pour les deux pays. Les deux principaux défis rencontrés lors de la construction des données sont les suivants : le traitement des incompatibilités internationales et celui des incohérences temporelles inhérentes aux données d'enquête. Tout d'abord, les enquêtes ont été soumises à d'importants remaniements au cours de la période 1982-2017, ce qui entraîne des ruptures dans les séries chronologiques obtenues. Ensuite, les pays collectent les données d'enquête selon des règles et des méthodologies différentes, ce qui rend les comparaisons internationales encore plus fastidieuses. Je m'attaque aux ruptures des séries en appliquant des procédures de correction, et aux incohérences internationales en utilisant des tables de concordances et en trouvant des compatibilités dans les définitions des variables. Les séries chronologiques qui en résultent sont ensuite exploitées pour décrire de manière approfondie les performances d'emploi transatlantiques à la lumière de l'évolutions des structures professionnelles et sociodémographiques.

L'analyse empirique montre que l'écart transatlantique en matière d'emploi reflète un déficit d'emplois routiniers et manuels français, avec une surreprésentation des jeunes et des séniors peu qualifiés qui ont une plus grande propension à la non-participation et au chômage. Néanmoins, l'écart transatlantique en matière d'emploi évolue de manière significative dans le temps. Il se creuse d'abord par une poussée de l'emploi aux États-Unis et une baisse de l'emploi en France entre 1982 et 1998. Il se contracte ensuite par une hausse de l'emploi en France et une baisse de l'emploi aux États-Unis entre 1998 et 2017. Les travailleurs peu qualifiés sont au cœur de ce processus de réallocation car ils représentent la majeure partie des pertes d'emploi. Ces évolutions se traduisent par une augmentation de la mobilité professionnelle et des transitions de participation au marché du travail aux États-Unis alors qu'elles passent en France par une diminution de la mobilité professionnelle ainsi que par des transitions de chômage et de participation au marché du travail.

Ces résultats ont plusieurs conséquences en termes de politiques pour l'emploi. Premièrement, l'emploi peu qualifié devrait être davantage soutenu. En effet, la France a commencé depuis le milieu des années 1990 à mettre en œuvre des politiques de réduction du coût du travail ciblées sur les bas salaires. Néanmoins, la pérennité des gains en matière d'emploi en découlant reste en partie menacée par de nouvelles évolutions technologiques et du commerce international. Deuxièmement, les politiques pour l'emploi devraient également intégrer des incitations à la participation au marché du travail. En effet, la majeure partie du fossé transatlantique en matière d'emploi est imputable à des groupes sociodémographiques qui sont confrontés à des décisions importantes en matière de participation ainsi qu'à la détérioration de leurs perspectives d'emploi. Enfin, ces politiques devraient promouvoir la mobilité et la formation professionnelles car elles pourraient atténuer les pertes d'emploi en permettant aux travailleurs licenciés de transiter vers des professions en forte demande.

Ce travail approfondie la littérature sur les performances de l'emploi transatlantique en déterminant le rôle joué par les facteurs professionnels et sociodémographiques dans le déficit d'emploi français. En ce sens, cette analyse comparative s'appuie sur Piketty (1998), Cahuc and Debonneuil (2004), Passet (2015) et Catherine, Landier, and Thesmar (2015) qui ont tous mené des analyses contrefactuelles similaires pour documenter le déficit d'emploi français. Cette étude se distingue en ce qu'elle repose sur une décomposition de ce déficit par catégories professionnelles et sociodémographiques, ce qui a de nouvelles implications en termes de politiques économiques. Elle est également étroitement liée à Cohen, Lefranc, and Saint-paul (1997) qui compare les marchés du travail français et américain. En revanche, ces auteurs se focalisent sur le chômage car ils considèrent qu'il s'agit d'un indicateur pertinent pour saisir les inefficacités du marché du travail. Contrairement à eux, je me concentre sur l'emploi puisque l'écart transatlantique est dû à la fois aux différences de taux de chômage et de non-participation. En outre, si la dynamique de l'emploi reflète l'évolution du chômage en France, elle semble plutôt se traduire par la non-participation aux États-Unis. Ainsi, le chômage ne fournit qu'une image fragmentée du marché du travail, qui ne parvient pas à expliquer la détérioration des performances du marché du travail américain. Néanmoins, la constatation que le déficit d'emploi français proviendrait d'un décalage dans la survenance des gains et des pertes d'emploi rejoint le point de vue des auteurs selon lequel les écarts de taux chômage n'émaneraient pas du comportement des chômeurs ou des institutions qui sous-tendent leurs décisions.

Une deuxième contribution de cette analyse tient à ce qu'elle décrit de manière approfondie la dynamique de l'emploi en France et aux États Unis au fil du temps. Elle détermine dans quelle mesure l'écart transatlantique en matière d'emploi est causé par l'amélioration ou la détérioration des performances d'emploi dans chaque pays. Elle quantifie le rôle joué par les changements de composition sociodémographique ou de propension à l'emploi dans les dynamiques d'emploi. Cette étude identifie également les groupes sociodémographiques qui se trouvent au cœur de ce processus de réallocation professionnelle. À cet égard, elle approfondit l'analyse de Cortes, Jaimovich, and Siu (2017) qui étudient la dynamique de l'emploi routinier aux États-Unis. Ces auteurs fournissent une description précise ainsi que des pistes d'explications de ces tendances par le biais d'un modèle néoclassique du marché du travail. Dans cet esprit, Albertini, Hairault, Langot, and Sopraseuth (2017) proposent un modèle avec frictions sur le marché du travail permettant de quantifier les gains et les pertes d'emploi résultant du progrès technique biaisé, des politiques du marché du travail et de l'augmentation du niveau de qualification en France, en Allemagne et aux États-Unis. Dans ce chapitre, je présente une évaluation empirique des performances de l'emploi transatlantique en déterminant le rôle joué par les composantes professionnelles et sociodémographiques dans les écarts d'emploi entre pays.

Enfin, cette analyse empirique contribue à approfondir nos connaissances sur les transitions de statut des travailleurs qui sous-tendent les performances observées en matière d'emploi. Elle permet de déterminer si la polarisation des emplois résulte de la mobilité professionnelle ou des transitions par le chômage et la non-participation à long terme. Cortes, Jaimovich, Nekarda, and Siu (2014) étudient également les flux de travailleurs et l'évolution de la structure professionnelle de l'emploi mais ils se concentrent principalement sur la disparition des emplois routiniers aux États-Unis. Ils quantifient également la mesure dans laquelle les facteurs démographiques expliquent les changements dans les principaux taux de transition responsables du déclin de l'emploi routinier. Charlot, Fontaine, and Sopraseuth (2019) fournissent une étude comparative plus approfondie sur les flux de travailleurs en France et aux États-Unis. Cependant, ils se focalisent sur la contribution des transitions du marché du travail aux fluctuations du chômage, ainsi que sur l'influence de la polarisation sur le dualisme du marché du travail. Dans la présente analyse, je m'attache à décrire comment les flux de travailleurs affectent la dynamique de l'emploi par catégories professionnelles sur le long terme.

Chapitre 2 - Polarisation de l'emploi et déclin du travail non qualifié en France

Au cours des quatre dernières décennies, l'évolution technologique a profondément façonné la structure professionnelle des économies développées, y compris la France. La part des emplois à bas et haut salaires a augmenté concomitamment, tandis que celle des emplois moyennement rémunérés a diminué. L'automatisation des emplois routiniers a provoqué une contraction de la classe moyenne. Autor, Levy, and Murnane (2003), Goos, Manning, and Salomons (2009) et Oesch (2013) décrivent d'abord ce changement de la structure professionnelle aux États-Unis et en Europe comme une polarisation des emplois. Autor and Dorn (2013) font valoir en outre que le progrès technique a réorienté les perspectives d'emploi des travailleurs peu qualifiés vers des emplois de services manuels qui ne sont pas substituables par les nouvelles technologies. En effet, ces emplois requièrent des compétences en matière d'interaction sociale et une dextérité manuelle que les nouvelles technologies ne permettent pas encore. Ainsi, les travailleurs peu qualifiés ont connu une diminution des perspectives d'emploi dans les emplois routiniers, compensée par une augmentation des emplois de services manuels. À première vue, ces résultats suggèrent que le progrès technique restructurerait plutôt que réduirait les perspectives d'emploi non qualifié.

Malgré un processus de réallocation similaire, les pays européens ont enregistré des performances différentes en matière d'emploi, notamment par rapport aux États-Unis. Par exemple, Prescott (2004) affirme que les pays européens présentent des niveaux d'offre de travail plus faibles qu'aux États-Unis. Il souligne que la plupart des écarts constatés dans l'offre de travail s'expliquent par les taux d'imposition élevés dans les pays européens, qui ont un effet dissuasif sur l'offre de travail en réduisant la valeur de celui-ci. Rogerson (2008) approfondit l'analyse initiée par Prescott (2004) en se concentrant sur la réallocation sectorielle du travail induite par le changement technologique. Malgré le rattrapage de productivité réalisé par rapport aux États-Unis, les pays européens n'ont pas procédé à une réallocation sectorielle aussi importante, ce qui a entraîné une baisse des performances d'emploi. Il affirme que la réallocation sectorielle du travail a été entravée par les taux d'imposition élevés en Europe. En effet, ces forts taux ont généré une incitation à exercer de nombreuses activités économiques dans le secteur non marchand plutôt que dans le secteur des services marchands. Néanmoins, on sait peu de choses sur le lien entre polarisation et performances de l'emploi. On en sait encore moins sur la répercussion des politiques économiques sur les performances d'emploi résultant de ce processus de réallocation du travail.

Ce deuxième chapitre réexamine la manière dont les politiques fiscales interagissent avec le progrès technique et évalue dans quelle mesure elles influencent les performances d'emploi non qualifié en France entre 1982 et 2008.[2] Il approfondit notre compréhension de l'impact du progrès technique et des politiques de taxation du travail sur les performances d'emploi en considérant la nature biaisée par les tâches de ce progrès ainsi que le caractère redistributif de ces politiques. Le cas français est particulièrement pertinent. La France a connu à la fois une polarisation de l'emploi due au progrès technique et des variations importants en termes d'emploi non qualifié. Une caractéristique frappante du marché du travail français est que l'augmentation des emplois manuels n'a pas été suffisante pour

[2] La période étudiée commence en 1982 car les données au niveau professionnel ne sont pas disponibles dans l'enquête française sur les forces de travail (EFT) avant cette date. Elle se termine en 2008 afin d'éviter l'influence de la grande récession qui dépasse le cadre de cette étude.

contrebalancer la baisse des emplois routiniers reflétant la détérioration des perspectives d'emploi des travailleurs non qualifié. Néanmoins, ce processus ne s'est pas déroulé de manière linéaire dans le temps et il a coïncidé avec des changements importants de politiques de taxation du travail. Plus précisément, l'emploi non qualifié a diminué entre 1982 et 1994 alors qu'il s'est stabilisé entre 1994 et 2008. Dans le même temps, la France a appliqué des taux d'imposition du travail élevés et croissants au cours de la première sous-période, tandis qu'elle a mené des politiques d'imposition du travail redistributives au cours de la deuxième sous-période. La conjonction de ces événements fait de la France un candidat approprié pour étudier les effets conjugués des politiques économiques et du progrès technique.

Afin de comprendre comment le progrès technique et les politiques de taxation du travail façonnent les performances de l'emploi non qualifié, ce chapitre s'appuie sur un modèle d'équilibre général parcimonieux avec choix professionnel endogène construit sur la base des modèles de Rogerson (2008), Acemoglu and Autor (2011), et Autor and Dorn (2013). Le modèle est calibré pour tenir compte de la baisse globale de l'emploi non qualifié en France de 1982 à 2008. Ensuite, je présente une analyse contrefactuelle pour déterminer comment les politiques de taxation du travail affectent les performances d'emploi dans une ère de progrès technique. J'utilise également le modèle pour étudier dans quelle mesure ce progrès et ces politiques façonnent la dynamique de l'emploi non qualifié. Pour ce faire, je quantifie la contribution des tendances de progrès techniques et de la fiscalité du travail au déclin de l'emploi non qualifié en France entre 1982 et 2008.

Trois principaux résultats découlent de cette approche. Premièrement, le progrès technique a induit des pertes significatives d'emplois non qualifiés en France entre 1982 et 2008. Il a déplacé les travailleurs non qualifiés des emplois routiniers vers les emplois manuels et le travail non marchand, entraînant une polarisation de l'emploi. L'augmentation de l'emploi manuel non qualifié n'a pas été suffisante pour contrebalancer le déclin de l'emploi non qualifié routinier. Deuxièmement, les pertes d'emplois non qualifiés induites par le progrès technique ont été amplifiées par les taux d'imposition du travail élevés et croissants entre 1982 et le milieu des années 1990. Troisièmement, depuis le milieu des années 1990, la tendance à la baisse de l'emploi non qualifié a été atténuée par la mise en œuvre de politiques de réduction des charges sociales ciblées sur les emplois à bas salaires. Ces politiques ont été particulièrement efficaces dans un contexte de polarisation de l'emploi en raison de leur interaction avec le processus de réallocation du travail ; sans elles, les pertes d'emplois non qualifiés auraient plus que doublé.

Cette approche apporte un nouvel éclairage sur les effets du progrès technique et des politiques fiscales sur les performances en matière d'emploi en examinant conjointement trois caractéristiques essentielles : la structure polarisante de l'emploi induite par la nature du progrès technique, l'aspect redistributif des politiques de taxation du travail et la substituabilité des services manuels par des services non marchands. Ces caractéristiques interagissent les unes avec les autres. Le progrès technique réoriente les travailleurs non qualifiés des emplois routiniers qui sont fortement substituables par le capital vers des emplois manuels qui produisent des services marchands eux-mêmes substituables par des services non marchands, ce qui, en fin de compte, détériore les performances de l'emploi non qualifié. Dans le cadre de ce processus de réallocation, les politiques fiscales affectent les performances de l'emploi non qualifié à la fois du fait de la substituabilité des services marchands et non marchands et du choix professionnel des travailleurs non qualifiés. D'une part, le niveau de taxation du travail impacte les performances de l'emploi non qualifié en altérant l'incitation à produire des services manuels de manière marchande ou non marchande. Par conséquent, la fiscalité du travail interagit avec le progrès technique en modifiant la valeur relative de l'emploi non qualifié par rapport au non-emploi. Au fur et à mesure de l'évolution technologique, ce canal prend de l'importance car les travailleurs non qualifiés sont plus nombreux à devoir choisir entre le travail marchand et non marchand, d'où une détérioration potentielle de leurs perspectives d'emploi. D'autre part, les politiques fiscales redistributives affectent le choix professionnel des travailleurs non qualifiés. Elles modifient la structure professionnelle ; les travailleurs non qualifiés sont ainsi plus ou moins contraints à un choix entre le travail marchand et le travail non marchand, selon la politique considérée. Le progrès technique module l'efficacité de ces politiques en termes de performances d'emploi.

La principale contribution de cette analyse est de relier les transformations de la structure de l'emploi initialement décrites par Autor and Dorn (2013) aux variations du niveau de l'emploi non qualifié en France en abordant la question de l'interaction entre les politiques de taxation du travail et le progrès technique. Elle souligne l'importance de prendre en compte le processus de réallocation du travail induit par le progrès technique biaisé lors de la conception des politiques de taxation du travail. La nature redistributive de ces politiques est cruciale puisque les emplois de services manuels sont situés au bas de la distribution des salaires professionnels. Les travailleurs non qualifiés qui occupent ces emplois sont généralement soumis à des taux d'imposition plus faibles que les travailleurs mieux rémunérés qui occupent des emplois routiniers et abstraits. Oesch (2009) examine également comment certaines institutions et politiques économiques affectent les performances de l'emploi non qualifié dans les pays européens et anglo-saxons entre 1991 et 2006. Il constate que les perspectives d'emploi non qualifié sont améliorées par des politiques actives du marché du travail et des politiques monétaires qui exploitent pleinement le potentiel de croissance des économies. Cependant, il ignore le progrès technique et les politiques de taxation du travail. Oesch (2013) fait la lumière sur les facteurs déterminants qui ont façonné la structure professionnelle en Grande-Bretagne, au Danemark, en Allemagne, en Espagne et en Suisse entre 1990 et 2008. Il se concentre sur cinq forces motrices sous-jacentes, à savoir la technologie, la mondialisation, l'éducation, les migrations et les institutions. Il fournit également une comparaison plus approfondie entre le Royaume-Uni et l'Allemagne, car ces deux pays ont procédé à d'importantes modifications dans leurs institutions salariales, mais dans des directions opposées. Cet auteur recommande aux gouvernements de prendre des mesures aux deux extrémités de la répartition professionnelle pour tirer profit de ces mutations structurelles de l'emploi. Les gouvernements devraient investir dans l'enseignement supérieur afin de fournir aux entreprises des travailleurs hautement qualifiés qui leur permettent de tirer parti des progrès techniques. Il préconise aussi de promouvoir la formation professionnelle et d'établir un salaire minimum pour inciter les entreprises à investir dans la productivité des travailleurs. Albertini, Hairault, Langot, and Sopraseuth (2016) étudient également les effets du progrès technique biaisé et des politiques du marché du travail sur l'emploi mais il souligne l'importance du salaire minimum en France. L'approche exposée dans ce chapitre se concentre sur l'interaction entre le progrès technique et la fiscalité du travail par le biais du travail non marchand.

Une contribution secondaire consiste à approfondir l'analyse initiée par Prescott (2004) et Rogerson (2008) d'au moins trois manières. Premièrement, ce chapitre étudie la réallocation professionnelle du travail induite par un progrès technique biaisé plutôt que la réallocation sectorielle connue sous le nom de changement structurel. En effet, Prescott (2004) constate que les différences de taux d'imposition du travail expliquent les écarts d'heures totales travaillées entre les pays tandis que Rogerson (2008) remarque que les taux d'imposition élevés en Europe ont empêché un développement correct du secteur des services. Dans le cas spécifique de la France, Piketty (1998) et Cahuc and Debonneuil (2004) identifient les secteurs sous-développés. Ils affirment que si la France avait le même taux d'emploi dans le secteur du commerce et de l'hôtellerie que les États-Unis, il devrait y avoir 2,8 millions de travailleurs supplémentaires en 1996 et 3,4 millions en 2001. Ce dernier chiffre représente approximativement le nombre de chômeurs en France en 2015. Si les effets du changement structurel sur les performances d'emploi ont été largement traités, peu d'études ont été consacrées à la manière dont le progrès technique biaisé les affecte. Dans cette analyse, nous apportons un éclairage sur cette question. Ensuite, ce chapitre ne se focalise pas sur l'emploi sectoriel mais sur l'emploi non qualifié qui est au cœur de la détérioration des performances d'emploi et de la conception des politiques du marché du travail en France. Bien que le progrès technique affecte tous les types d'emplois, il détériore particulièrement les perspectives de l'emploi non qualifié. Le fait de ne considérer que le niveau sectoriel masque les groupes d'individus les plus touchés. Il limite ainsi notre compréhension de l'impact des politiques fiscales sur la réallocation du travail induite par le progrès technique. Troisièmement, ce chapitre souligne l'importance du caractère redistributif des politiques fiscales. Étant donné que la polarisation de l'emploi réoriente les emplois moyennement rémunérés vers les emplois à bas salaires, les politiques fiscales redistributives du travail interagissent avec ce processus de réallocation en affectant le choix professionnel des individus. Par conséquent, les études utilisant des taux d'imposition agrégés omettent un aspect crucial de la complexité de la situation en France.

Chapitre 3 - Progrès technique routinier et heures travaillées au cours du cycle économique

En collaboration avec Idriss Fontaine

L'un des principaux objectifs de la macroéconomie est de comprendre le cycle économique. À cet égard, la macroéconomie moderne fournit deux théories dominantes : la théorie du cycle économique réel (RBC) et la théorie néo-keynésienne (NK). Pour les distinguer, la littérature utilise des modèles vectoriels autorégressifs (VAR) permettant d'évaluer les effets des chocs technologiques sur le facteur travail. Galí (1999) présente un résultat probant selon lequel les chocs technologiques ont des effets récessifs sur les heures travaillées, confortant ainsi la théorie néo-keynésienne plutôt que celle du RBC. Dans ce chapitre, coécrit avec Idriss Fontaine, nous réexaminons ce débat en réévaluant les résultats obtenus par Gali à la lumière du progrès technique biaisé en défaveur des tâches routinières (RBTC) : un type spécifique de développement technologique.

Le progrès technique a façonné de manière spectaculaire le marché du travail des économies développées au cours des quatre dernières décennies. Il est clairement établi, notamment par Autor and Dorn (2013) et Goos, Manning, and Salomons (2014), qu'une polarisation du marché du travail s'est produite dans la plupart des économies avancées. Les emplois moyennement rémunérés disparaissent massivement tandis que les emplois à bas et haut salaires se développent, générant une montée des inégalités salariales, en particulier aux États-Unis. La principale hypothèse avancée pour expliquer cette polarisation est celle du progrès technique biaisé en défaveur des tâches routinières. Elle véhicule l'idée selon laquelle le progrès technique, qui se manifeste par l'essor des nouvelles technologies de l'information, de la communication et de la robotique, favorise le remplacement du travail routinier. Dans ce contexte, le progrès technique modifie considérablement la composition de la demande de main d'oeuvre. Elle s'éloigne des emplois à salaire moyen car ils comportent principalement des tâches routinières facilement automatisables. Au contraire, les emplois à haut salaires impliquent des capacités cognitives et les emplois à bas salaires une dextérité manuelle et des interactions en face à face, qui se prêtent moins à l'automatisation. Bien que le RBTC ait été largement considéré comme un processus graduel de long terme, des recherches récentes soutiennent que ces changements dans la composition de la demande de main d'oeuvre se produisent principalement pendant les périodes de ralentissement économique (Jaimovich and Siu, 2018). À cet égard, le RBTC et donc l'hétérogénéité du facteur travail seraient essentiels pour démêler l'impact controversé des chocs technologiques sur les heures travaillées au cours du cycle économique.

En revanche, les théories standards du RBC et NK traitent le travail comme un facteur homogène. Dans ce cadre, le modèle RBC prédit qu'un choc technologique positif induit un effet expansionniste sur les heures travaillées.[3] Le marché de l'emploi est essentiel. Les chocs technologiques modifient la demande de travail, ce qui augmente les salaires, et produisent un effet de substitution qui incite les ménages à augmenter leurs heures travaillées. Au contraire, la théorie NK prédit que ce type de choc a un effet récessif sur les heures travaillées.[4] Les rigidités nominales sont cruciales car elles

[3] Parmi d'autres, on peut citer Kydland and Prescott (1982), King, Plosser, and Rebelo (1988), Plosser (1989) et King and Rebelo (1999).

[4] Par exemple, Smets and Wouters (2007), Galí (2008), Walsh (2005), Trigari (2009) et Galí (2010).

contraignent les entreprises à s'adapter à la demande de biens. Par conséquent, un choc technologique positif augmente la performance des facteurs de production. Les entreprises ajustent alors les heures travaillées à la baisse pour s'adapter à la faiblesse de la demande. Moins d'intrants sont nécessaires pour atteindre la même quantité de production.

Les résultats fournies par Galí (1999) en faveur de la théorie NK reposent sur un modèle vectoriel autorégressif structurel (SVAR). Cette approche lui permet d'interpréter la corrélation négative observée entre les heures travaillées et la productivité du travail. Il décompose les chocs structurels en composantes technologiques et non technologiques. Ainsi que l'ont initialement établi Blanchard and Quah (1989), l'identification du choc technologique dépend des restrictions d'exclusion de long terme. Gali soutient que le choc technologique agrégé est la seule perturbation qui a un effet permanent sur la productivité du travail. Il constate que les chocs technologiques ont une répercussion négative sur les heures travaillées et qu'ils ne génèrent pas des cycles économiques reconnaissables. Ces résultats paraissent difficiles à concilier avec la théorie RBC et semblent étayer la théorie NK.

Dans ce chapitre, nous réexaminons les résultats de Galí (1999) pour savoir si les changements dans la composition de la demande de travail induits par le RBTC peuvent expliquer l'effet récessif des chocs technologiques. À la lumière de ce processus, nous réévaluons ensuite l'importance des chocs technologiques dans la détermination des fluctuations cycliques. Considérer le RBTC et donc le travail comme un facteur hétérogène pourrait fragiliser la conclusion de Galí (1999) en questionnant sa stratégie d'identification. La prise en compte du RBTC implique que le choc technologique qu'il a identifié comporte des perturbations distinctes qui ont un impact permanent sur la productivité du travail. Ces perturbations ont sans doute des implications très différentes pour notre compréhension de l'effet des chocs technologiques sur les heures travaillées au cours du cycle économique. Par exemple, le RBTC pourrait générer un processus de réallocation brutal découlant de changements importants dans la composition des tâches de la demande de main d'oeuvre. Ce phénomène pourrait entrainer une diminution des heures travaillées. Cette baisse serait due non seulement à des rigidités nominales - comme le soutient la théorie NK - mais aussi à l'effet réel d'un processus de réallocation vigoureux induit par le progrès technique.

Nous traitons essentiellement cette question d'identification en décomposant le choc technologique de Gali en deux composantes principales. La première affecte la demande de main d'oeuvre de manière uniforme à long terme, quelle que soit la tâche effectuée. Nous la définissons comme un choc technologique neutre. La seconde composante affecte le contenu en tâches des heures travaillées à long terme. Elle comprend deux éléments qui modifient la composition en tâches de la demande et de l'offre de travail. Nous les avons définis de respectivement comme le RBTC et un choc d'offre de tâches. Nous procédons tout d'abord à la construction de séries chronologiques trimestrielles sur les heures travaillées et les salaires relatifs en utilisant les groupes de rotation sortants provenant de la Current Population Survey entre 1989 et 2017. Nous définissons les groupes professionnels abstraits, routiniers et manuels comme dans Cortes, Jaimovich, Nekarda, and Siu (2014). Comme le suggère Autor, Katz, and Kearney (2008), les salaires relatifs sont contrôlés pour tenir compte du biais de composition, et les heures relatives travaillées sont calculées en unités d'efficacité pour tenir compte de l'hétérogénéité démographique et des compétences. Ensuite, nous estimons un modèle SVAR pour démêler les effets des chocs technologiques neutres de ceux des chocs biaisés. Nous identifions ces perturbations en dérivant les restrictions d'exclusion et de signe de long terme d'un modèle d'équilibre général avec substituabilité des facteurs capital et routine construit sur la base d'un large éventail de la littérature sur le progrès technique biaisé. L'estimation d'un SVAR soumis à des restrictions combinées d'exclusions et de signes de long terme est une tâche complexe que nous entreprenons en utilisant une approche récemment développée par Arias, Ramirez, and Waggoner (2014).

Nos principaux résultats suggèrent que le choc technologique agrégé identifié comme dans Galí (1999) capture de fortes variations dans la composition des tâches de la demande de travail ainsi qu'une diminution des heures travaillées. Cette observation valide notre thèse selon laquelle le RBTC est important et justifie notre décomposition des chocs technologiques en composantes neutres et biaisées par rapport aux tâches. Ce faisant, nous constatons que les heures travaillées et surtout les heures routinières diminuent après un choc RBTC. Les chocs neutres et ceux liés à l'offre de tâches n'ont pas d'effets concluants sur les heures travaillées, si ce n'est de faible ampleur. Ainsi, nous soutenons que la majeure partie de la baisse des heures travaillées est due à un changement dans la composition des tâches de la demande de travail résultant du RBTC. En outre, il est essentiel de démêler les chocs technologiques pour évaluer les facteurs déterminants des fluctuations économiques. Les chocs technologiques ne sont pas capables de générer des cycles économiques reconnaissables lorsque nous

nous appuyons sur les restrictions d'identification de Galí (1999) alors qu'ils génèrent l'essentiel des fluctuations économiques par le biais du RBTC lorsque nous les distinguons. Ces résultats soulignent la nécessité de prendre en compte la nature biaisée du progrès technique lorsque l'on étudie les cycles économiques.

Une implication significative de nos résultats est que la prise en compte de l'hétérogénéité des tâches est importante pour l'étude des cycles économiques. En ce sens, notre travail contribue principalement à la littérature dédiée aux cycles économiques. En étudiant l'effet du RBTC sur les heures travaillées, nous réévaluons les résultats de Galí (1999) sur l'effet des chocs technologiques sur les heures travaillées à la lumière de l'hétérogénéité de la main-d'œuvre. De cette manière, nous nous rapprochons de Balleer and van Rens (2013). Ces auteurs analysent les effets des chocs technologiques biaisés en faveur de la qualification et de l'investissement sur les heures travaillées au cours du cycle économique. Nous nous distinguons d'eux d'au moins deux façons. Premièrement, nous étudions le progrès technique biaisé selon les tâches plutôt qu'en fonction du niveau d'éducation. Nous soutenons que les groupes professionnels abstraits, routiniers et manuels réagissent différemment face au progrès technique, tant à long terme que sur l'ensemble du cycle économique. Il est donc pertinent d'étudier l'hétérogénéité du travail du point de vue des tâches. Deuxièmement, nous nous différencions en ce qui concerne notre schéma d'identification. En utilisant la stratégie empirique de Arias, Ramirez, and Waggoner (2014), nous sommes en mesure de démêler les chocs technologiques structurels neutres des chocs technologiques biaisés. Dans leur spécification, Balleer and van Rens (2013) ne distinguent pas les chocs technologiques neutres de ceux biaisés par l'éducation. Par conséquent, notre stratégie empirique nous permet de décomposer les chocs technologiques en chocs affectant le travail de manière uniforme et de manière différenciée selon les tâches.

Nous contribuons également à la littérature sur la polarisation d'au moins deux façons. Tout d'abord, des travaux de référence tels que Autor, Levy, and Murnane (2003), Autor and Dorn (2013) et Goos, Manning, and Salomons (2014) affirment que la polarisation de l'emploi est principalement générée par le progrès techniques affectant les tâches routinières à long terme. Par ailleurs, Barany and Siegel (2018) étudient les déterminants de la réallocation de l'emploi entre les secteurs et les professions dans le cadre d'un modèle d'équilibre général. Ils constatent que le progrès technique biaisé routinier est de loin le facteur le plus important des tendances de productivité et de réallocation de l'emploi.

Cependant, rien ne garantit que ces chocs déterminent les fluctuations du cycle économique en termes d'emploi. En décomposant les perturbations de la productivité en une composante neutre et une composante biaisée par les tâches, nous sommes en mesure de dire si le progrès technique affecte le travail de manière uniforme ou différenciée selon les groupes de tâches au cours du cycle économique. L'une des limites de notre approche est que nous ne fournissons pas une décomposition plus exhaustive des perturbations. Cette question sort du cadre de notre analyse.

Deuxièmement, nous pensons être les premiers à tenter d'identifier l'impact du RBTC au cours du cycle économique dans le cadre d'un SVAR. Certaines études se concentrent principalement sur les épisodes récessifs plutôt que sur l'ensemble du cycle économique. Par exemple, Cortes, Jaimovich, Nekarda, and Siu (2014) affirment que la contraction de l'emploi routinier se produit durant ces périodes. L'effondrement de l'emploi routinier par habitant s'explique principalement par les flux d'entrées et de sorties entre ce type d'emploi et le non-emploi et non par les tendances démographiques. Jaimovich and Siu (2018) établit en outre un lien entre les récentes reprises économiques faibles en emplois et la polarisation. D'autres études examinent les propriétés cycliques de l'emploi par groupe professionnel mais ne s'intéressent pas explicitement au RBTC. Par exemple, Foote and Ryan (2015) allèguent que l'emploi des professions moyennement qualifiées est de nature plus cyclique que les autres, en partie parce qu'il se trouve dans des industries plus volatiles. Ils arguent également que ces emplois sont ceux qui disparaissent le plus rapidement lorsqu'une récession se produit en raison de leurs faibles perspectives à long terme. Charlot, Fontaine, and Sopraseuth (2019) quant à eux font valoir que la moitié des variations du chômage provient des entrées et sorties de l'emploi routinier. Ainsi, la disparition des emplois routiniers a une influence non négligeable sur les fluctuations conjoncturelles du chômage. À notre connaissance, Shim and Yang (2016) sont les seuls à étudier les fluctuations de l'emploi par groupes professionnels en utilisant un SVAR.[5] Ces auteurs évaluent l'effet d'un choc technologique agrégé sur les heures travaillées identifié comme dans Galí (1999). L'essentiel de notre approche consiste à démontrer que cette stratégie d'identification agrège des chocs qui ont des implications différentes sur les heures travaillées au cours du cycle économique.

[5] Breidemeier, Juessen, and Winkler (Forthcoming) étudient aussi la dynamique de l'emploi par catégorie professionnelle mais dans un contexte de chocs fiscaux.

Transatlantic employment performances and job polarization

Abstract

This thesis explores the implications of technological change and labor taxation for employment performances in France and the U.S. over the past four decades. Chapter 1 delves into transatlantic employment performances. It measures the extent to which cross-country discrepancies in socio-demographic and occupational structures account for the transatlantic employment gap over time. The French employment deficit does not only reflect a disfunctioning labor market but also the occupational reallocation of labor that affects the employment prospects and participation decisions of specific socio-demographic groups. Chapter 2 investigates the determinants of unskilled employment outcomes in France between 1982 and 2008. Technological change and labor taxation policies are pivotal to grasp the deterioration of unskilled employment. The reallocation of unskilled labor from routine jobs towards manual jobs induced by technological change is partly obstructed by the presence of a non-market sector. Labor taxation interacts with technological change by distorting the value of unskilled jobs with respect to non-market work. Chapter 3 studies the implications of routine-biased technological shocks for aggregate fluctuations between 1989 and 2017 in the U.S. It assesses the effects of technological shocks by estimating a structural VAR model with long-run exclusion and sign restrictions. Routine-biased technology shocks account for the recessionary effects of technological shocks on hours worked. These shocks appear quantitatively relevant and generate recognizable business cycle fluctuations.

Keywords : Labor market, Employment, Job polarization, Economic policies, Business cycle

Performances transatlantiques et polarisation de l'emploi

Résumé

Cette thèse explore les implications du progrès technique et de la fiscalité du travail sur les performances de l'emploi en France et aux États-Unis au cours des quatre dernières décennies. Le chapitre 1 évalue dans quelle mesure les différences de structures sociodémographiques et professionnelles entre pays expliquent le déficit d'emploi français. Ce déficit ne reflète pas seulement un marché du travail déficient, mais aussi une réallocation du travail qui affecte les perspectives d'emploi et les décisions de participation de groupes sociodémographiques spécifiques. Le chapitre 2 étudie les déterminants des performances d'emploi non qualifié en France entre 1982 et 2008. Le progrès technique et les politiques de taxation du travail sont essentiels pour appréhender la détérioration de l'emploi non qualifié. La réallocation de la main-d'œuvre non qualifiée des emplois de routiniers vers les emplois manuels induite par le progrès technique est en partie entravée par la présence du secteur non marchand. La fiscalité du travail interagit avec le progrès technique en modifiant la valeur des emplois non qualifiés par rapport au travail non marchand. Le chapitre 3 étudie les implications des chocs technologiques routiniers sur les fluctuations économiques entre 1989 et 2017 aux États-Unis. Il évalue leur impact en estimant un modèle VAR structurel. Les chocs technologiques biaisés en défaveur des tâches routinières expliquent les effets récessifs des chocs technologiques sur les heures travaillées. Ces chocs apparaissent quantitativement pertinents et génèrent des fluctuations reconnaissables du cycle économique.

Mots-clés : Marché du travail, Emploi, Polarisation, Politiques économiques, Cycle économique