Macroeconomics of Labour Markets: the Role of Modern Technologies and Search Frictions

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vorgelegt von Francesco Carbonero

Berichterstatter:

Prof. Dr. Enzo Weber, Universität Regensburg

Prof. Dr. Christian Merkl, Friedrich-Alexander-Universität Erlangen-Nürnberg

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Preface

I dedicate this work to the people that contributed professionally to my research career. Foremost, I wish to thank Enzo Weber and the precious guidance he provided to my research agenda. In particular, I'm grateful for his rigorous and clearcutting arguments as well as for the time and the responsiveness he offered. Moreover, I thank my second supervisor Christian Merkl because he has been an uncommon source of suggestions and stimulating discussions. A kind gratitude to Hermann Gartner, my mentor, who has always come up with fruitful ideas and has shared with me several political debates.

This research work would have not been the same without the support of two main actors. First, the Graduate Programme of the Institute for Employment Research (IAB) and the University of Erlangen-Nuremberg (GradAB). Second, the staff of the Forecasts and Macroeconomic Analyses and that of the Labour Market Processes and Institutions departments in the IAB. I am glad to have shared highly professional as well as non-professional relationships with all of them. I owe special thanks to Ekkehard Ernst and to the Research Department of the International Labour Organisation in Geneva for having hosted me in a great international atmosphere.

Finally, I want to thank my family, my grandpa in particular, for the moral support and the expectations on my accomplishment.

Introduction and Overview

This research work covers three essays that deal with the impact of technology on labour markets worldwide (chapter 1 and 3) and the macroeconomic role of search frictions (chapter 2 and 3). In what follows I provide a short summary and a brief discussion of the main contributions and scientific relevance of the essays.

Modern economies have witnessed a massive inflow of technology in the last decades of 20th century. Computers, software, communication technologies (henceforth ICT) have become a key capital asset in most sectors and have replaced a huge variety of human tasks. More recently, there has been a trend in automating part of, if not all, the production process that, together with the codifiable actions available with the use of ICT, ended up in a vaste wave of robotization and digital automation. On the one side, this has brought important productivity gains and contributed substantially to GDP growth. On the other side, it has raised several questions concerning the size and the heterogeneity of the impact of technology on the labour market. Indeed, while the rise of productivity generated by the technological change may push labour demand, the increasing tasks carried out by computers, robots and, in the near future, artificial intelligence, may displace workers and reduce labour demand.

Chapter 1 provides an analysis that contributes to the current discussion concerning automation and insists on the following highly debated questions: Do robots reduce employment? Does the impact of automation on labour market differ between developed and developing countries? Is the global value chain affected by the automation wave? Most of the literature so far has focused on developed countries (see Acemoglu and Restrepo, 2018; Chiacchio et al., 2018; Dauth et al., 2017; Graetz and Michaels, 2015), despite the increasing interest in the occupational consequences of automation in the developing world (World Bank, 2016). Moreover, a increasing bulk of research discusses the hypothesis that automation is bringing back to developed countries those economic activities that have been off-shored in countries where the cost of labour was low (UNCTAD, 2016; Cohen et al., 2016). First evidence provided by De Backer and Flaig (2017) shows that, indeed, the degree of off-shoring has diminished between 2000 and 2014. What remains unclear is to what extent this translates into employment loss in developing countries and in which sectors.

In chapter 1 I show that the worldwide impact of robots on employment is negative, largely driven by the effect in developing countries, for which I quantify a loss of employment of more then ten percent. This impact is relevant mainly for manufacturing sectors representing 85 percent of the data on robots. Sectoral spillovers turn out to be there, indeed I find positive effect from robots in manufacturing to employment outside manufacturing. These results are obtained with a novel instrumental variable capturing the degree of technological progress of robots at country level given by the range of tasks carried out by robots. I argue that these are endogenous to the stock of robots at sectoral level, but exogenous to overall employment. Looking at the re-shoring story, I confirm what (De Backer and Flaig, 2017) have found and provide a magnitude of the loss of employment in developing countries due to re-shoring. It is about 5%.

By looking at these results, it is clear that the nature of production, trade and, as a consequence, of the labour markets is changing rapidly. The changes come from the interdependent relations between these three environments, as well as from changes within each environment. Chapter 2 discusses an element belonging strictly to the labour market, namely, the presence of search costs, that will be exploited in chapter 3 for a second issue connected to the impact of technology on labour.

Search costs represent a key ingredient of modern micro- and macroeconomics of the labour markets. Economic models embedding the search process have been successful in explain several job market facts, such as the presence of frictional unemployment, the evolution of job creation and job destruction, the presence of employer's and employee's rent. However, the business cycle properties of search models proved to be poor. Shimer (2005) is the first to show that the volatility of vacancies and unemployment in the data was not hit by those in the model. This puzzle has generated an intense debate on the property of the matching function and on the possibility of using wage stickiness to reproduce the volatility in the data (see Hall, 2005; Hall and Milgrom, 2008). Pissarides (2009) has proposed a modification of the job creation condition that allows for a portion of search search cost being, namely, costs that do not vary with the duration of the vacancy.

This has important theoretical implications. Assuming that all search costs move one to one with search duration dampens the number of vacancies open by the firms in periods of expansion because of a sort of crowding out effect. Instead, if search costs are mainly fixed, firms are in the condition to open as much vacancies they want to adjust their labour force. Given the lack of data on search cost and search duration, Pissarides (2009) proposes a simulation where he builds on real data of labour market tightness, job finding rate and job separation and compute the elasticity of tightness with respect to the productivity shock, for different share of fixed costs. It turns out that search costs entirely fixed are able to generate the volatility of tightness observed in the data.

The analysis of chapter 2 aims at providing an empirical assessment to the hypothesis of Pissarides (2009). First, I document the existence of a volatility puzzle also in Germany (see also Gartner et al., 2009). Second, I use two waves of the German Job Vacancy Survey (2014 and 2015) containing novel information on the duration of the vacancy and the cost the employer bears to fill the vacancy (among others, headhunter, advertising, travel reimbursement for the interview). Together with precious data on plant and vacancy characteristics, the analysis assesses the dependence of search costs on search duration via an OLS and IV approach. In both cases, the search costs appear to be weakly, if not linked at all, with the duration of the vacancy. This result gives a first empirical validation to the hypothesis of Pissarides (2009).

The study goes further and simulate the German labour market computing the elasticity of labour market tightness with respect to productivity for different share of fixed search costs. The volatility observed in the data for Germany fits with a calibration where fixed costs represents at least 74% of total search costs. This result is highly consistent with the outcome of the empirical analysis. The study of chapter 2, apart from its contribution to the knowledge of the heterogeneity of search costs and search duration and the validation of the theoretical argument of Pissarides (2009), it consists in an innovative example of micro data usage to explore macroeconomic facts.

As anticipated before, this essay proposes to the reader a second analysis regarding the link between technology and labour market. The fear that technological capital might displace workers has attracted the attention of researchers on one of the so called "stylized facts" of macroeconomics. This is the constancy of the labour share, computed as the share of labour compensation in the GDP (Kaldor, 1955). Its constancy is not only the result of theoretical models but the evidence of extensive empirical literature. In the last years, however, the labour share has behaved far from being constant, instead it declined constantly in many countries (see OECD, 2012; Raurich et al., 2012; Arpaia et al., 2009). This has given rise to a flourishing debate on the elasticity of substitution between capital and labour as well as on the overall factors that may influence the labour share (see Autor et al., 2017; Antras, 2004).

The literature that used the stock of capital and labour did not find a role for the elasticity of substitution in lowering the labour share. Then, new contributions came up in the last years, that have exploited the variation in the price of inputs and the distinction between technological and non-technological equipment. These two elements turned out to be relevant. Indeed ICT equipment have witnessed a rapid decline in their cost since the 1980s, reflecting the improved performance in computation and memory storage. Conversely, non-technological capital has been trendless. Therefore some researcher started to look at the price of capital (Karabarbounis and Neiman, 2014) or at the impact of different type of capital (Eden and Gaggl, 2018).

Chapter 3 contributes to the literature by providing a theoretical equation for the labour share depending on the price of ICT capital. Moreover, given the rising interest in search frictions and the matching process, it provides the answer to the following question: in a context where technological capital becomes (at constant lower cost) substitute to labour, do labour market frictions play any role? Therefore, I propose a modification that adds the search costs as a further element in the standard profit maximization based on labour and capital costs. From the model, it follows that we may expect either an exacerbation of the substitution between capital and labour, or a dampening effect on the labour demand.

For eight European countries and the US, we estimate, first, the aggregate elasticity of substitution between capital and labour, then, the elasticity of substitution between ICT and labour. Both with and without the search costs. We find that the aggregate elasticity is unable to explain the decline in the labour share, as the majority of the estimates in the previous literature point to. Instead, the elasticity of substitution between ICT and labour is statistically larger than one and robust to a number of alternative specifications. According to our computation, this magnitude explains between one third and two third of the decline in the labour share.

When we account for the presence of search costs in the labour market, we find that the ICT-labour substitution is still key for the decline in the labour share, but that search costs acts also in this sense by decreasing labour demand. The channels through which labour share is declining turn out to be two: the drop in ICT price and the rise of search costs, the first through displacing workers the second by depressing labour demand.

In the second part of the essay, I assess the link of the displacement effect with the structure of the labour market and its institutions. It turns out that institutions do not seem to be relevant (as already found by Elsby et al., 2013) while the elasticity correlates significantly, and with similar magnitudes, with the share of routine workers (positively) and the share of high-skill workers (negatively).

1 Robots Worldwide: the Impact of Automation on Employment and Trade

Abstract. The impact of robots on employment and trade is a highly discussed topic in the academic and public debates. Particularly, there are concerns that automation may threat jobs in emerging countries given the erosion of the labour cost advantage. We provide evidence on the effects of robots on worldwide employment, including emerging economies. To instrument the use of robots, we introduce an index of technical progress, defined as the ability of robots to carry out different tasks. Robots turn out to have a significantly negative impact on worldwide employment. While it is small in developed countries, for emerging economies it amounts to a drop of employment by 11% between 2005 and 2014. However, here, there appear positive spillovers especially from robotization in manufacturing on employment outside manufacturing. Furthermore, we assess cross-country effects, finding that robots in developed countries decrease off-shoring just as employment in emerging economies.
This study has seen the collaboration of my coauthors, Enzo Weber and Ekkehard Ernst.

1.1 Introduction

The debate on the diffusion of robots is flourishing, with the number of studies rising constantly. Scholars particularly focused on the impact of robots on employment. We can summarize the approaches used to tackle this research question in two classes. Those using an industry-country panel setting (Graetz and Michaels, 2015; De Backer et al., 2018) and those looking at local labour markets (Acemoglu and Restrepo, 2017; Dauth et al., 2017; Chiacchio et al., 2018). Despite the high diffusion of robots in developing countries, however, research has focused mainly on developed countries. In the following paper we use the first approach to shed light on the role of robots in emerging economies and to analyse the impact of automation on the global organisation of production.

The evidence of the impact of robots on employment is ambiguous, both within and between the two approaches. Graetz and Michaels (2015) find no link between robots and overall employment in developed countries, while De Backer et al. (2018) show a positive correlation between robot investment and employment within MNEs in developed countries. Acemoglu and Restrepo (2017) show that one more robot per thousand workers negatively affects the US employment-to-population ratio by 0.37 percentage points , while Chiacchio et al. (2018) find a size of 0.16-0.20 pp in the EU. With a similar exercise, Dauth et al. (2017) find no detrimental role of robots for overall employment, while they see a compositional effect, namely, jobs lost in manufacturing are offset by new jobs in the service sector.

This paper contributes to the literature in two ways. First, we are the first to present evidence on the impact of robots on employment in emerging economies. The key point is that while the diffusion of automation in middle- and low-income countries has been as pronounced as in high-income countries, developing countries display several labour market weaknesses - such as limited labour market institutions, high informality, large share of employment in agriculture - that can be connected to larger adverse effect on employment in these countries.

Second, attention has been increasing as regards the tendency of bringing production back home to advanced economies, also known as re-shoring. Indeed, increasing labour cost and the need of a shorter and more agile supply chain are among the factors that reduce the advantage of off-shoring the production in developing countries. In this regard, firms in developed countries may find it cheaper to automate certain processes instead of running the production abroad (see UNCTAD, 2016). The implication would be a further detrimental effect on employment in middle- and low-income countries. In this paper we assess to what extent robots affect off-shoring in high-income countries and whether this matters for employment in middle- and low-income countries.

We find the following results. First, robots have a detrimental effect on employment growth at the global level, more than eleven times stronger in emerging economies than in developed economies. Second, the impact of robots on employment is not affected by the level of labour intensity in developed economies, while the evidence on such non-monotonic effects is mixed for emerging economies. We get these results using an OLS approach applied to the long-run trend of the variables as well as with an IV approach intended to capture the endogeneity between employment and robots. For that purpose, we propose a new instrument for the stock of robots that measures the degree of technological progress based on the capability of robots to carry out different tasks. Overall, our estimates point to a long-run decline of employment in the relevant sectors of about 5% due to an increase of the number of robots by 24% between 2005 and 2014. In developed countries, this decline of employment amounts to 0.43%, while in emerging economies it reaches almost 11%. However, we find that robotisation especially in manufacturing has substantial positive spillover effects on employment outside the sector in emerging economies, unlike in developed countries. Third, robots in developed countries reduce off-shoring and have an impact on employment in emerging economies of -8% over 2005 – 2014.

All in all, these results demonstrate that if there are concerns about automation, and robots in particular, these should first and foremost address to emerging economies. This is in line with the warnings by the World Bank regarding the share of occupations subject to automation in middle- and low-income countries (see World Bank, 2016).

1.2 Background, data and descriptive statistics

There is no empirical consensus on the consequences of automation on employment. Mainly, this is related to the fact that there are several channels through which automation operates in the production process. Specifically, Acemoglu and Restrepo (2018) illustrate four mechanisms that might counterbalance the displacement effect of automation: a productivity effect, a capital accumulation effect, the deepening of automation (operating through an increase in productivity) and the creation of new tasks. Instead, the authors point to some risks related to the phase of automation (excessive automation) or to the capability of the labour market to adapt to the new required skills.[1]

The current literature has tackled the impact of robots on employment using two approaches. The first used a panel setting with data at the country-industry level and has found weak or no economic effects (see Graetz and Michaels, 2015; De Backer et al., 2018). The second looks at the role of robots for local labour markets and has found a detrimental effect in the US and the EU (see Acemoglu and Restrepo, 2017; Chiacchio et al., 2018)[2].

We obtain data on robots from the International Federation of Robotics (IFR) and they refer to machines that are "automatically controlled, reprogrammable, multipurpose manipulator, programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications" (International Organisation for Standardization, ISO). Our data for robots is available for 43 countries in seven broad sectors and 13 sub-sectors within manufacturing. To get data on employment, value added and capital input, we merge it with industry-level information available from the Socio Economic Accounts (SEA) of the World Input-Output Database (WIOD) and use market exchange rates provided by WIOD to convert nominal values into US dollars. After the merge we remain with 41 countries and 15 sectors. The time dimension is reduced to 2005-2014 because of data availability. In the IFR database, information for Mexico and Canada is lumped together under "North America" before 2011. Therefore we impute them using the yearly growth rate of robots in Canada and Mexico after 2010.

By looking at the stock, table 1.1 shows that in 2014 robots were primarily installed in

[1]As regards this last point, see Warning and Weber (2018) on the consequences of digitalization on the hiring process. The authors find no impact of company-internal digitization on hirings and separations, while vacancies and abandoned searches increase.

[2]Except Dauth et al. (2017) that have found no effects for Germany.

Japan, in the US, in the largest economies of the EU, but also in some emerging economies, such as China, India and Brazil. The last column reports the average growth of value added between 2000 and 2014, but the evidence is mixed: within each of the two country groups, robots were installed in fast- as in slow-growth countries.

Given that robots perform their tasks at constant quality and almost an unlimited number of times, industries characterized by a large share of workers that carry out repetitive tasks, may find it profitable to substitute workers for robots. For this reason, we look at the change of robots between 2014 and 2005 together with the labour intensity in 2005, at the industry level. Table 1.2 reveals that, at the global level, robots spread as much in labour-intensive sectors as in capital-intensive sectors. This is particularly visible in emerging countries where automotive is more capital intensive, while in developed economies robots increased mainly in sectors such as automotive, basic metals and electronics that display a more intense use of labour.

In figure 1.1 we plot the time series of the stock of robots across countries to give a flavour of the evolution over time in both groups. We plot Japan and China in a separate graph due to their extreme values within their groups. Among developed economies, after Japan, Korea (Republic) emerges as one of the first investors of robots alongside the United States and Germany, while Italy reveals a declining trend. As regards emerging economies, India, Brazil and Mexico show the highest level of stock, followed by a mixture of Asian and European countries and Russia. China stands out as the country that has bought more robots than any other country in the world since 2013 and is expected to expand even more, given the planned target of 100,000 robots per year by 2030.

In addition, we present some descriptives at industry level. We follow the same classification as in Acemoglu and Restrepo (2017) and use those industries resulting from merging the robot database with the socio-economic accounts of the World Input-Output database. The striking fact of Figure 1.2 is that the distribution of robots across industries is almost identical in developed and emerging countries. In both sub-regions the installation of industrial robots regards essentially the manufacturing sector and is concentrated in the automotive industry.

Table 1.1: Descriptive statistics by country, overall sample, 2014.

Country	Robots	Employees ('000s)	Average Δ ln(VA) 2014-2005	Country	Robots	Employees ('000s)	Average Δ ln(VA) 2014-2005
Japan	295829	53310	0.00	Turkey	6286	20049	0.07
United States	219434	145951	0.04	Switzerland	5764	4161	0.07
China	189358	858367	0.15	Indonesia	5201	74641	0.11
Korea, Republic of	176833	17547	0.07	Denmark	5119	2575	0.05
Germany	175768	38307	0.05	Hungary	4302	3834	0.08
Italy	59823	18127	0.04	Finland	4178	2196	0.05
Taiwan	43484	8308	0.03	Slovakia	3891	1896	0.11
France	32233	24545	0.05	Portugal	2870	3794	0.05
Spain	27983	15495	0.06	Russian Federation	2694	60265	0.14
United Kingdom	16935	26412	0.05	Slovenia	1819	745	0.06
India	11760	314882	0.11	Romania	1361	6171	0.12
Sweden	10742	4518	0.06	Norway	1008	2588	0.08
Brazil	9557	93704	0.09	Ireland	667	1593	0.07
Czech Republic	9543	4326	0.09	Greece	392	2625	0.04
Mexico	9277	25686	0.05	Bulgaria	197	2685	0.10
Netherlands	8470	7228	0.05	Croatia	121	1304	0.07
Canada	8180	16794	0.06	Estonia	83	561	0.11
Belgium	7995	3795	0.06	Lithuania	57	1157	0.10
Australia	7927	10669	0.09	Latvia	19	791	0.10
Austria	7237	3697	0.06	Malta	12	172	0.07
Poland	6401	12311	0.08				

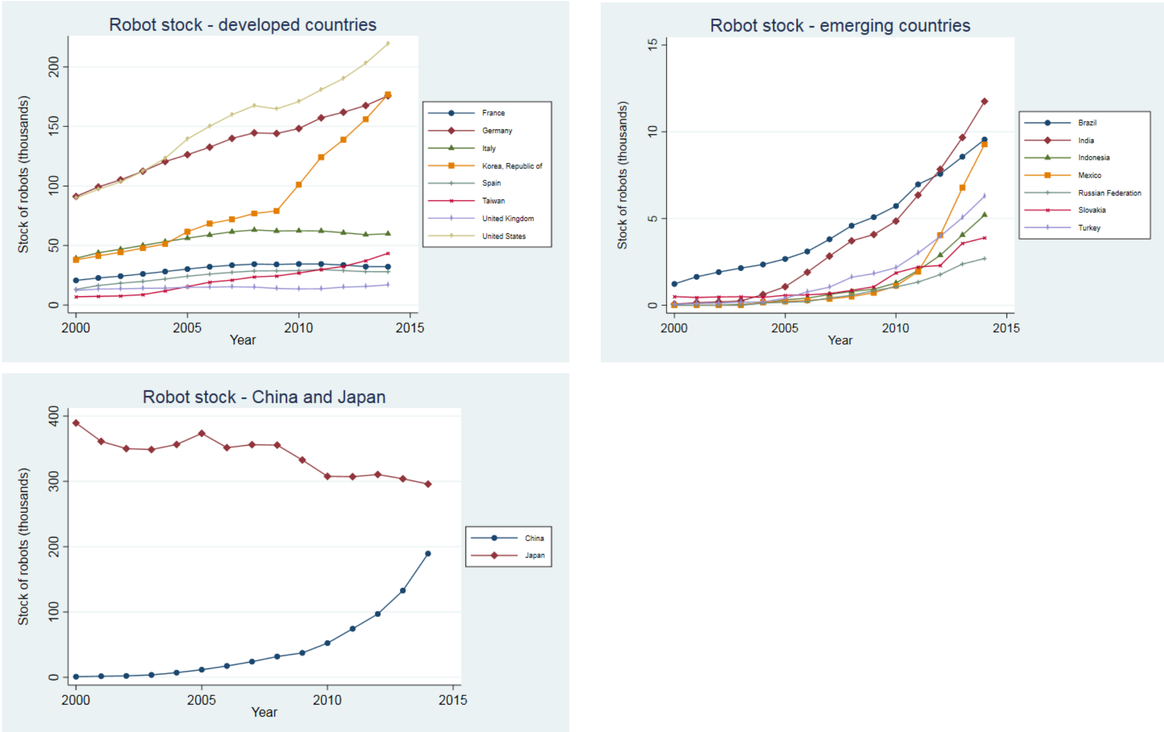
Source: IFR and SEA (WIOD)

Table 1.2: Descriptive statistics by sector, overall sample.

Sector	World		Developed economies		Emerging economies	
	Δ Robot stock 2014-2005	Labour intensity (2005)	Δ Robot stock 2014-2005	Labour intensity (2005)	Δ Robot stock 2014-2005	Labour intensity (2005)
Education/research&development	2	6.4	-21	6.5	64	6.2
Textiles	3	2.4	-2	2.4	17	2.3
Basic metals	1172	1.8	1257	2	940	1.2
Wood and Paper	-23	1.8	-39	2	22	0.9
Automotive	6019	1.6	5106	2.1	8509	0.1
Construction	28	1.6	29	1.8	25	0.9
Rubber, plastic and mineral products	733	1.4	201	1.6	2183	0.8
Industrial machinery	249	1.4	-64	1.2	1102	1.8
Electronics	3035	1.3	2995	1.4	3143	1.1
Food and beverages	749	1.1	878	1.3	397	0.6
Agriculture	13	0.9	14	0.6	9	1.6
Chimicals and fuel	306	0.8	383	0.8	96	0.8
Mining and quarrying	4	0.5	4	0.4	1	0.9
Utilities	1	0.4	-1	0.4	8	0.6

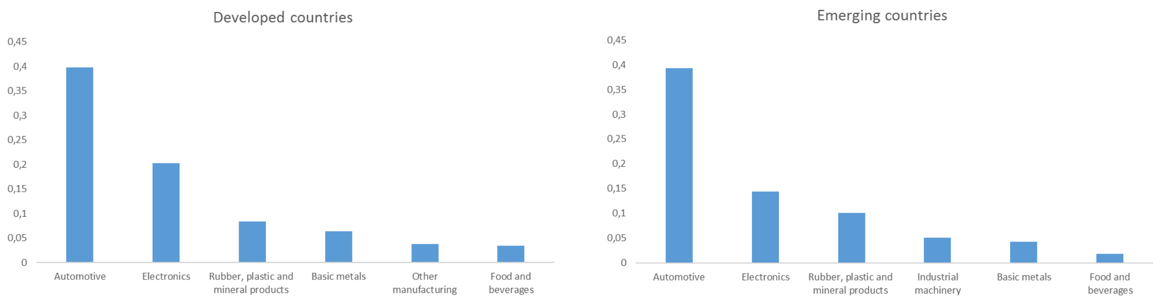
Source: IFR and SEA (WIOD) .

Figure 1.1: Evolution of the stock of robots (in ’000s)



Note: Selected countries.
Source: IFR.

Figure 1.2: Share of robot by industry, developed and emerging countries (2014)



Source: IFR.

1.3 Theoretical and empirical approach

We run our analysis assuming a standard Cobb-Douglas production function for output Y in sector i, country j and year t, $Y_{ijt} = L^{\alpha}_{ijt}K^{\beta}_{ijt}$. We log-linearize the production function and derive the labour demand as follows,

$$ln(L_{ijt}) = ln(\alpha) + ln(Y_{ijt}) - ln(W_{ijt}), \quad (1.1)$$

where W_{ijt} denotes the wage in sector i, country j, year t. We work with equation 1.1 and add as covariate the log of robot stock lnR_{ijt}. As we show in Section 2, robots increased more in labour-intensive sectors. Therefore we also include a dummy equal to one if the ratio employees/capital compensation in sector i, country j is larger than the country mean in year t, and zero otherwise. Following the approach of De Backer et al. (2018), we use this variable also in an interaction with robots. To avoid contemporaneous endogeneity, we measure the labour intensity at the beginning of the sample period, namely, 2005.

Moreover we have to deal with two other sources of potential endogeneity. First, in developed and emerging markets both employment and robot stock may be affected by transitory fluctuations of other factors such as foreign investments, financial frictions or trade tariffs, which would bias the estimated effect of robots upwards. To tackle this problem, we follow Karabarbounis and Neiman (2013) and use cross-country variation in trends in the stock of employment and robots. This eliminates the influence of temporary contemporaneous shocks.

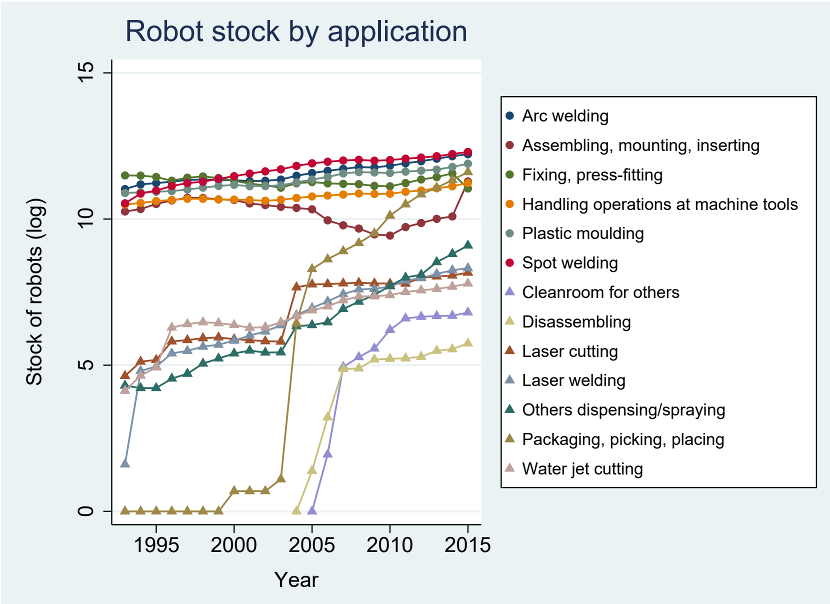
Second, reverse causality might be an issue. For instance, the abundance of workers may decrease the incentive to install robots. To deal with this issue, we start from the consideration that our estimation would be unbiased, if robot investments were exclusively the result of the intrinsic properties of this type of automation, such as its technological level and the tasks it can do. The IFR dataset provides the number of robots in each task (named "application") at country level. Robots are classified in 35 applications, clustered in 6 macro-classes: handling operations and machine tending, welding and soldering, dispensing, processing, assembling and disassembling, cleaning. A general trend that we detect from the data is that robot usage starts in few applications and over the years it spreads across all the other application. This reflects one facet of technological improvement of automation, namely, the practical ability of carrying out more and more tasks. It is also called "automation at the extensive margin" (see Acemoglu and Restrepo, 2018) and it is key for displacement of workers. Of course, the widening of robot usage across applications is not unbound from the structure of employment. For instance, the scarcity of cleaners and the abundance of assemblers could lead to more use of cleaning robots. However, cleaning robots would be exogenous to aggregate employment.

In Figure 1.3 we plot the evolution of applications worldwide. We compare applications where robot usage is among the highest (top 25th percentile) in 1993 with applications that experienced the largest (top 25th percentile) increase of robots between the beginning of the series and 2015. No application is in both groups: this already indicates that the increase of the stock of robots goes hand-in-hand with a robotization across applications. The figure helps us visualize our reasoning about the instrument we are going to introduce, namely, if technical change is the practical ability of automate several different applications, the increase of technical change correlates positively with a lower dispersion of robots across applications. Indeed the dispersion in 1993 for the selected application is much lower than in 2015, just as for all applications, which can however not be shown within one figure.

In practical terms, we generate the share of robots in each application and we compute the index of technical progress TP_tas the inverse of the standard deviation of the shares in year t. The logic behind is that the higher is the capability of robots of doing different tasks and the more even is their distribution among the applications, the lower will be the standard deviation, hence the higher will be the TP index.

In order to motivate our instrument, we use a stylized analytical framework to explain the usage of robots depending on their technological frontier. To this purpose, we simplify the range of robots to type 1 and type 2, with each type corresponding to a cer-

Figure 1.3: Robot stock (log of) by application. In circle applications with top robot usage in 1993, in triangle application with top robot growth between 1993 and 2015.



Source: IFR.

tain task. A given output of robots $Y_{R,t}$ shall be produced according to the following CES function

$$Y_{R,t} = \left[(\tau_{1,t} R_{1,t})^{\frac{\epsilon-1}{\epsilon}} + (\tau_{2,t} R_{2,t})^{\frac{\epsilon-1}{\epsilon}} \right]^{\frac{\epsilon}{\epsilon-1}} \tag{1.2}$$

where $R_{i,t}$ is the stock of robot i and $\tau_{i,t}$ its technological frontier in time t. The parameter ϵ describes the elasticity of substitution between the two types of robot, or tasks. We show later that our results do not depend on the degree of complementarity or substitutability of the tasks. We assume the product market of robots being competitive, therefore the price of robot P_i corresponds to its marginal product. Moreover, we are not interested in the absolute usage of robots, but rather in their relative demand, thus we write (algebra in the Appendix)

$$\frac{R_{1,t}}{R_{2,t}} = \left(\frac{\tau_{1,t}}{\tau_{2,t}} \right)^{\epsilon-1} \left(\frac{P_{2,t}}{P_{1,t}} \right)^{\epsilon} \tag{1.3}$$

As usual, price shocks impact the usage of robots as predicted in a standard downward sloping demand curve. In particular, we use a stochastic specification of the technological frontier τ that allows us to generalize the advancement in technology in each type of robot. The laws of motion of technology are given by

$$\begin{aligned} \tau_{1,t} &= \tau_{1,t-1}(1+g_{1,t}) \\ \tau_{2,t} &= \tau_{2,t-1}(1+g_{2,t}) \end{aligned} \tag{1.4}$$

where $g_{i,t}$ is the technological shock of robot type i, with bivariate density function $(g_{1,t}, g_{2,t} \mid t-1) \sim F(\tau_{i,t-1}, \tau_{j,t-1})$. Here we distinguish between two technologies.

- One that advances with shocks to only one type of tasks in machines and generates automation at the intensive margin (*deepening of automation* in Acemoglu and Restrepo, 2018), with conditional expectation of $g_{1,t}/g_{2,t}$ given by the function

$$E(g_{1,t}/g_{2,t} \mid t-1) = f(\tau_{1,t-1}, \tau_{2,t-1}) \qquad \frac{df}{d\tau_{1,t-1}} > 0, \frac{df}{d\tau_{2,t-1}} > 0 \tag{1.5}$$

- The other that proceeds by spreading and affecting more and more tasks (automation at the extensive margin), where the advancement in tasks i favors the advancement in task j. In this case, the conditional expectation of the relative shock are governed by

$$E(g_{1,t}/g_{2,t} \mid t-1) = f(\tau_{1,t-1}, \tau_{2,t-1}) \qquad \frac{df}{d\tau_{1,t-1}} < 0, \frac{df}{d\tau_{2,t-1}} > 0 \tag{1.6}$$

  Conversely to the first type of technological advancement, this second type creates labour displacement.

In other words, in case of automation we condition the shock on technology i to the frontier of both technologies in time $t-1$, with the impact from an additional innovation to the frontier of i being smaller than the impact from an additional innovation to the frontier of j. This setting does not prevent infinite technological progress, but it foresees a challenge in improving further a technology relative to another one, when the first is leading in the technological frontier.

Now we explore which implications this specification has on our demand for robots. With ϵ larger than one, i.e. robots being gross substitute, the relative demand of robots is described by equation (1.3). If $\tau_{1,t}$ is leading, i.e. it is the more advanced technology, then $R_{1,t} > R_{2,t}$ (up to price differences). For the property of the distribution function, τ_1 being the leader, τ_2 will tend to catch up. This will increase the demand for R_2 relative to R_1 and, by definition, reduce the dispersion of robots across the two classes. In case ϵ is smaller than one, namely, with robots being gross complement, if $\tau_{1,t}$ is leading, then $R_{1,t} < R_{2,t}$. For the same mechanism as above, further shocks to the technological frontier of the robots will make τ_2 catch up and R_1 increase, again with the result of reducing the dispersion.

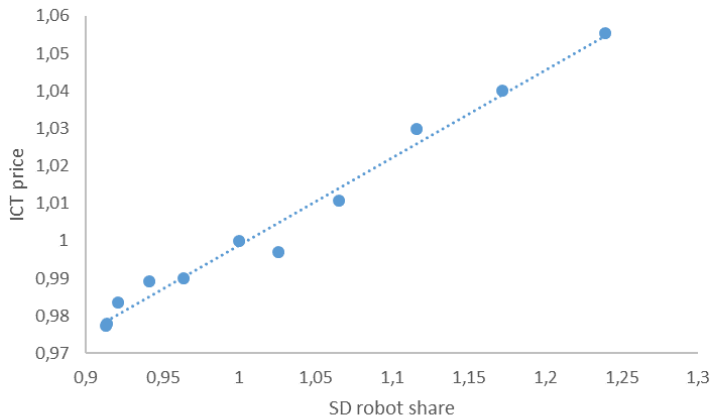
Logically, this stylized approach suggests a negative correlation of technological change and robot dispersion, which we will exploit for instrumenting purposes. As a general multivariate measure for the dispersion we can use the standard deviation of the demand for robots. We present its derivation (algebra in the Appendix) in the case of ϵ larger than one and τ_1 leading,

$$SD_{R,t} = Y_{R,t} \left(\frac{\tau_{1,t}^{\epsilon-1}}{P_{1,t}^{\epsilon}} - \frac{\tau_{2,t}^{\epsilon-1}}{P_{2,t}^{\epsilon}} \right) \frac{1}{2}. \tag{1.7}$$

In order to check the plausibility of this measure, we compare it with another technological input that has recently experienced a technological improvement, namely, Information Communication Technologies (ICTs)[3]. In particular we compare the average standard deviation of the robot shares with the average ICTs price index for a set of European countries and the US. The countries of the sample are Austria, Denmark, France, Germany, Italy, the Netherlands, Spain, United Kingdom, United States. The source of the ICT price index is EUKLEMS 2005-2015. Figure 1.4 shows the scatter plot of the two series. In order to avoid spurious correlation from both series trending downward, we compute the correlation of the residuals from regressing each variable on a constant and a linear trend. We get a value of 0.91.[4]

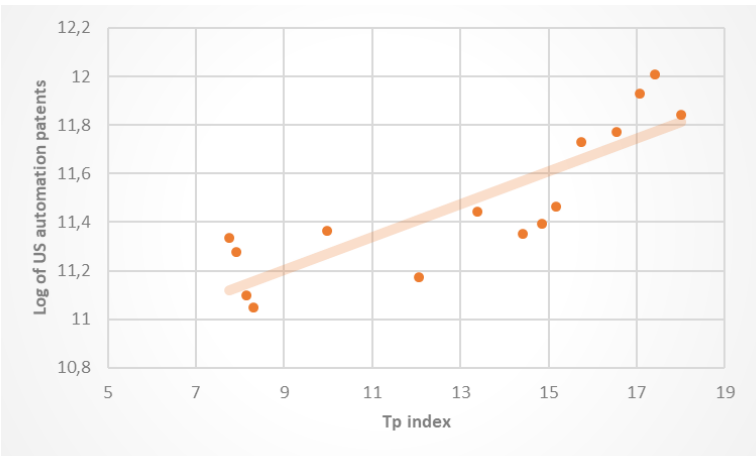
[3]See Carbonero et al. (2017) for the labour market implications of a declining ICT price.
[4]We have also computed the correlation on the first difference of each series: 0.74.

Figure 1.4: Standard deviation of robot share across applications versus ICT price index, 2005-2015 (2005=1).



Source: IFR and EUKLEMS.

Figure 1.5: TP index versus automation patents, US, 2000-2015 (2000=1).



Source: Authors' calculations.

Lastly, given our assumption that robots are one example of a broader automation wave, we compare our TP measure with the number of automation patents, available for the US. Information on patents come from Google[5]. For the definition of *automation patent* we rely on Mann and Püttmann (2018): it represents a "device that carries out a process independently". According to the authors this definition embeds, among others, robots as well as self-driving vehicles. Figure 1.5 displays the two series normalized to 1 in year 2000. The evolution of both overlap significantly and the correlation is 0.83.

[5]http://www.google.com/googlebooks/uspto-patents.html

Finally, our estimation equation includes equation 1.1, the log of robots, the dummy for labour intensity in 2005, the interaction of robots with labour intensity, country and sector fixed effects:

$$L_{ij} = \gamma_0 + \gamma_1 Y_{ij} + \gamma_2 W_{ij} + \gamma_3 R_{ij} + \gamma_4 R_{ij} \times li_{05} + \gamma_5 li_{05} + X_i + Z_j + u_{ij}, \tag{1.8}$$

where X_i is the sector fixed effect, Z_j the country fixed effect and the other variables represent the linear trend in the log of the corresponding measure. While this estimates the employment effects within the sectors where robots are installed, we consider potential spillover effects between sectors below in section 1.4.2.

1.4 Results

1.4.1 Effects on employment

Table 1.3 displays the result for the OLS approach[6]. At the global level, the variable *robot stock* has a coefficient of -0.034 and is statistically significant at the one percent level. This means that an increase of ten percent in the stock of robots decreases employment in the relevant sectors by 0.34%. To quantify the impact, if the average number of robots increases by more than 20% as it happened between 2005 and 2014, employment would fall by 1%. The impact seems to be concentrated in labour-intensive sectors, for which the estimates point to a coefficient of -0.066. Moreover, the global effect is most likely due to emerging countries, with a coefficient of -0.056. Here, given the change in robots between 2005 an 2014, we estimate a negative impact on employment of 2%, mainly driven by labour-intensive sectors.

[6]In what follows, we exclude China in the regression for emerging countries. While the point estimates of the robot effects including China would be even larger, estimation uncertainty would be strongly inflated (results available upon request).

Table 1.3: Employment regressed on robot and labour intensity. OLS approach.

Dependent variable: employment	World		Developed countries		Emerging countries	
robot stock	-0.034^{***}	-0.004	-0.002	-0.001	-0.056^{**}	0.034
	(0.013)	(0.011)	(0.005)	(0.007)	(0.024)	(0.021)
robot stock × labour intensity		-0.066^{***}		-0.002		-0.145^{***}
		(0.014)		(0.008)		(0.018)
labour intensity	-0.005	0.017^{***}	0.003	0.003	0.004	0.045^{***}
	(0.004)	(0.006)	(0.002)	(0.003)	(0.006)	(0.007)
N	477	477	360	360	103	103
R^2	0.91	0.92	0.86	0.85	0.87	0.91

Regression using the trend variables, with country and industry fixed effects. Trends are the coefficients of regressions on a linear trend. Robust standard error in parentheses. Significance levels: *, **, *** indicate significance at 0.10, 0.05 and 0.01. Controls: value added, wage. Estimates are weighted by sectoral employment in 2005.

Table 1.4: Employment regressed on robot and labour intensity. IV approach.

Dependent variable: employment	World		Developed countries		Emerging countries	
robot stock	-0.209^{***}	-0.247^{**}	-0.024^{**}	-0.051^{**}	-0.305^{***}	-0.054
	(0.056)	(0.125)	(0.009)	(0.021)	(0.048)	(0.456)
robot stock × labour intensity		0.046		0.038		-0.268
		(0.098)		(0.023)		(0.469)
labour intensity	-0.014^{***}	-0.029	0.003	-0.004	-0.038^{***}	0.050
	(0.005)	(0.033)	(0.003)	(0.006)	(0.010)	(0.159)
N	477	477	360	360	103	103
R^2	0.61	0.54	0.81	0.78	0.41	0.60

Regression using the trend variables, with country and industry fixed effects. Trends are the coefficients of regressions on a linear trend. Robust standard error in parentheses. Significance levels: *, **, *** indicate significance at 0.10, 0.05 and 0.01. Controls: value added, wage, sector fixed effects. Estimates are weighted by sectoral employment in 2005.

We conducted a first-stage regression of the robot variable on our instrument and other covariates from equation 1.8. We get a positive significant coefficient of TP index on the stock of robots. Moreover, TP index has a likelihood ratio test statistic of 38. Thus, there is a strong linkage between robots and the instrument. In Table 1.4 we show the results of the IV approach. All the coefficients are larger than those with OLS and, apart from the one of the interaction, they turn out to be even more precise. Thus, the negative employment effects of robots do not seem to be driven by endogeneity issues. The magnitude at the global level increases to -0.209 that implies a negative impact on overall employment in the relevant sectors over 2005-2014 of 5%. For developed countries we get a negative effect on employment of 0.43%, while for emerging economies our estimates point to a robots-driven reduction of employment of more than 11%.

Assessing whether these impacts are comparable to those in the previous literature, we use the aggregate impact of robots on employment found by Acemoglu and Restrepo (2017), according to which one more robot reduces aggregate employment by 5.6 workers. We compute how many robots have been installed in the US between 2000 and 2014 and reduce employment by that amount multiplied by 5.6. We get a drop of employment of 0.52% (or 0.57% for all developed countries), very close to our baseline effect of 0.43%.

1.4.2 Special effects within and outside manufacturing

Robots play a special role in manufacturing, but are also used in other sectors. This section takes a more detailed look at the employment effects of robotisation along the sectoral dimension. First, we seek to measure robots effects in manufacturing and the rest of the economy separately. Second, we will investigate spillover effects between the sectors.

According to our data, 85 percent of all robots are located in manufacturing. Besides manufacturing, our data show robot usage in utilities, construction, education and research, agriculture and mining.

For estimating separate effects in the two sectors, we interact the robots measure with an indicator dummy for employment observations stemming from manufacturing and from outside manufacturing. In particular, this allows for different coefficients in these two sectors. The results are shown in Table 1.5.[7]

The small negative employment effect in the developed countries that we determined above comes from job losses in manufacturing. Outside manufacturing, only a minor insignificant impact is estimated. In contrast, in the emerging countries, we find similar negative effects of robot usage both in and outside manufacturing. Furthermore, here, labour intensity plays an important role: The negative effects are of about three times

[7] Here, China was included in order to increase the relatively limited number of observations on the sectoral level.

the size in case of labour-intensive production (baseline effect plus interaction effect), and they are highly statistically significant.

Table 1.5: Robot stock within and outside manufacturing.

Dependent variable: employment	World		Developed countries		Emerging countries	
robot stock manufacturing	−0.142***	−0.013	−0.033***	−0.044**	−0.297**	−0.192
	(0.030)	(0.043)	(0.008)	(0.020)	(0.139)	(0.165)
robot stock non-manufacturing	−0.182***	−0.006	−0.015*	−0.035*	−0.339**	−0.180
	(0.31)	(0.050)	(0.009)	(0.20)	(0.141)	(0.191)
labour intensity	−0.003	0.069***	0.002	−0.002	−0.002	0.127*
	(0.003)	(0.014)	(0.001)	(0.004)	(0.012)	(0.066)
rob manufacturing × labour intensity		−0.201***		0.012		−0.414*
		(0.048)		(0.022)		(0.213)
rob non-manufacturing × labour intensity		−0.215***		0.029		−0.334*
		(0.040)		(0.022)		(0.171)
N	477	477	360	360	117	117
R^2	0.59	0.66	0.78	0.77	0.08	0.04

Regression using the trend variables. Trends are the coefficients of regressions on a linear trend. Standard error in parentheses. Significance levels: *, **, *** indicate significance at 0.10, 0.05 and 0.01. Controls: value added, wage. Estimates are weighted by sectoral employment in 2005.

Beyond sector-specific effects, potential spillovers between the sectors are of special interest. While job losses due to automation appear within the sectors where robots are used, effects across the sectors can mirror factors such as complementarities of robots and services or infrastructure, demand for capital goods or intersectoral labour supply shifts. For estimating the cross effects, we first calculate the average robot stock from manufacturing and non-manufacturing sectors, respectively. Then, we amend the baseline regression in Table 1.5 by manufacturing robots in the equations for non-manufacturing sectors and vice versa. This delivers the spillovers over and above the robot effects within sectors.

Table 1.6 contains the results. Formally, the variable *cross-sect robot stock* holds the cross effects in both directions, i.e. manufacturing robots in non-manufacturing equations and vice versa. In addition, *cross-sect non-manufacturing robot stock* stands for cross effects only from non-manufacturing robots on manufacturing employment.

In developed countries, we find no relevant interactions across sectors. This is in line with evidence from Acemoglu and Restrepo (2018) and Chiacchio et al. (2018). A different

Table 1.6: Spillover effect of robots across sectors.

Dependent variable: employment	**World**	**Developed countries**	**Emerging countries**
cross-sect robot stock	0.186**	−0.011	0.252***
	(0.080)	(0.014)	(0.073)
cross-sect non-manufacturing robot stock	−0.090***	0.002	−0.101**
	(0.34)	(0.018)	(0.041)
labour intensity	−0.004	0.002	−0.006
	(0.003)	(0.002)	(0.007)
N	475	358	117
R^2	0.72	0.80	0.70

Regression using the trend variables, with country and industry fixed effects. Trends are the coefficients of regressions on a linear trend. Standard error in parentheses. Significance levels: *, **, *** indicate significance at 0.10, 0.05 and 0.01. Controls: robot stock in manufacturing, robot stock in non-manufacturing, value added, wage. Estimates are weighted by sectoral employment in 2005.

result of positive spillover effects is found by Dauth et al. (2017) for Germany. However, our estimation outcome does not change when we exclude the US from the sample or consider only European developed countries. In contrast, in the emerging countries, robots in manufacturing have substantial positive spillovers on non-manufacturing employment. The reverse effects are also positive, but weaker, since the effect specific to non-manufacturing robots, which is to be added to the baseline effect, is negative. While our previous results have shown that robotisation strongly reduces employment in the emerging countries within the sectors of robot usage, the spillover results open up a certain perspective: importantly, robotisation in manufacturing is accompanied by the creation of non-manufacturing jobs. This is one crucial aspect when thinking about future paths of labour market development.

1.4.3 Further effects via off- and re-shoring

The second part of this paper seeks to answer the following question: to what extent has the internationalization of production influenced the role of robots in different countries? In particular, the significant difference in the impact of robots on employment growth between advanced and emerging countries begs the question whether the latter group suffers from automation because of their integration in global supply chains. The following analysis, therefore, aims at quantifying the effects of automation on employment conditioned on trade dynamics.

Indeed, there is a flourishing discussion dealing with potential shocks of off-shoring and re-shoring on employment caused by the spread of automation both in developed and developing economies. UNCTAD (2016) argues that the historical labour cost advantage of low-income countries might be eroded by robots if they become cheap and easily substitutable for labour. According to this scenario, the most affected industry should be manufacturing. This adverse effect might be strengthened by the growing labour quality in developing countries and the ensuing rise in labour costs. The Boston Consulting Group, for instance, reports that wages in China and Mexico increased by 500 per cent and 67 per cent between 2004 and 2014, respectively (Sirkin et al., 2014). These and other issues might have pushed some companies, like General Electric and Plantronics, to shore the production back home (see, respectively, Crooks, 2012; Cattan and Martin, 2012).

This convergence in cost competitiveness is likely to continue in the future, eroding the incentives for producers to move their activities from developed to developing countries.

The results of a study A.T. Kearney demonstrate that countries that have previously benefited from off-shoring will witness overall more job loss due to automation than onshore countries (Gott and Sethi, 2017).

Nevertheless, it is claimed that off-shoring will keep on going at the same time. China remains the country receiving most of the investment flows. Even though labour cost has increased, indeed, developing countries experience also a rise of local markets with new needs and new demands. For instance, the Chinese middle class could potentially be bigger than the entire US population by 2020 (Atsmon and Magni, 2012).

In the econometric analysis we want to answer these questions: do robots reduce off-shoring in developed countries? If yes, does this harm employment in emerging countries? Regarding the first question, we compute the off-shoring index similar to the literature by using the share of imported non-energy inputs from emerging countries in total non-energy inputs. We conduct a similar analysis as for employment in subsection 1.4.1 except for the wage variable, for which we use a wage difference of developed country *i* with the wage of emerging countries weighted for the relative amount of imports with country *i*. Regarding the second question, for each sector of each emerging country we generate a variable that measures the stock of robots in the relative sector in developed countries, weighted by the flow of exports towards each sector in each developed country. This helps us assess the impact "abroad" of robots in developed countries taking into account the trade activity (in this way we control for those countries that installed many robots but have a low activity of import-export with emerging countries, and therefore are less pivotal for an employment effect there). We call this measure *trade-weighted robots* and we use it to explain employment in emerging countries (controlling for the domestic stock of robots). As for the first exercise, we use a wage difference of each emerging country with the set of developed countries, weighted by the trade activity.

Table 1.7 displays the results for the first analysis. The OLS approach delivers weakly significant positive results for the effect of robots on offshoring, while we do not get any further evidence from the interaction. With the IV approach, we get a negative coefficient of -0.073 significant at the 5% level. The coefficient is slightly larger than the one found by De Backer et al. (2018), the difference likely arises from the off-shoring index computed, in our paper, using only emerging countries [8]. As regards the interaction term, there seems to be no significant difference between labour- and capital-intensive sectors. Considering the increase of robots in developed countries between 2005 and 2014 leads to an impact on off-shoring of almost -1.3%. Such a negative effect is in line with previous evidence and with the hypothesis that the use of robots may induce certain industries to reduce the amount of inputs produced abroad. The next step, then, is to check whether the lower share of imports caused by the spread of robots in developed countries has had any consequence on the level of employment in emerging economies. For this, we use the trade-weighted robots measure.

[8] When we run the IV regression in Table 1.7 using off-shoring with imports from all the countries we get a coefficient of robots stock of -0.061, very close to their result.

Table 1.8 displays the results for the second analysis. The OLS estimation provides weak evidence of an effect of robots in developed countries on employment in emerging countries, with more insights from the interaction with labour intensity. Indeed, robots in developed countries seem to have a negative impact on employment in capital intensive sectors of emerging countries, while in labour intensive sectors the impact is slightly positive. Using an IV approach for tackling the problems of endogeneity, we get a larger negative effect. The coefficient for our trade-weighted robots is -0.459, significant at 1% level. A change of trade-weighted robots in line with the change between 2005 and 2014, namely, 12% is connected to a fall of employment of 5.5%.

Table 1.7 and 1.8 established negative effects of robotization in developed countries on off-shoring in developed and on employment in emerging countries. We connect the two in a plausibility check, as re-shoring is likely to operate as a channel for the employment losses. We would expect that the drop in exports of the emerging countries resulting from Table 5 and the drop in the wage bill of the emerging countries resulting from Table 6 are of similar magnitude. The first effect may be a bit larger because, due to a labour share of about 50%, part of the drop in exports would affect profits and not the wage bill. Since the off-shoring index is defined as the share of imported non-energy inputs in total non-energy inputs, we apply the IV effect of -0.073 percent from Table 5 to the value of non-energy inputs in developed countries imported from emerging countries, averaged over 2005-2014. This delivers 6.4 bn USD. Regarding the employment effect, we apply the IV estimate of -0.459 percent from Table 6 to the wage bill from the emerging economies averaged over 2005-2014. This delivers 4.8 bn USD. In view of the a-priori expectations explained above, we conclude that both estimates stand in a sensible relation.

1.5 Conclusion

In this paper we present new evidence on the role of robots for employment and trade. In particular, we document that the use of robots is increasing rapidly in both developed and emerging countries. Given the globalisation of the supply chain, we also look at

Table 1.7: The impact of robots on off-shoring in developed countries.

Dependent variable: off-shoring in developed countries	**OLS**		**IV**	
robot stock	0.040**	0.022	−0.073**	−0.119*
	(0.019)	(0.020)	(0.032)	(0.064)
robot stock × labour intensity		0.036		0.066
		(0.028)		(0.073)
labour intensity	−0.010	−0.017**	−0.005	−0.017
	(0.007)	(0.008)	(0.007)	(0.012)
N	360	360	360	360
R^2	0.34	0.35	0.08	0.04

Regression using the trend variables, with country and industry fixed effects. Trends are the coefficients of regressions on a linear trend. Robust standard error in parentheses. Significance levels: *, **, *** indicate significance at 0.10, 0.05 and 0.01. Controls: value added, wage difference. Estimates are weighted by sectoral employment in 2005.

whether robots influence the trend in off-shoring in developed countries and, through that, employment in emerging countries. In other words, we explore whether the rise in robotization leads to re-shoring, i.e. the fact that firms in developed countries may find it more profitable to bring production back home after having it previously off-shored to low-cost, emerging economies.

We find that robots lead to a drop in global employment in the relevant sectors of 5% between 2005 and 2014. The impact is rather low in developed countries, -0.43%, but much more pronounced in emerging countries with about -11%. However, we find that robotisation especially in manufacturing has substantial positive spillover effects on employment outside the sector in emerging economies, unlike in developed countries. These estimates come out using an instrumental variable approach where we use an index of technological progress of robots, defined as their ability to perform different tasks, to isolate the demand for automation. We confirm the result of De Backer et al. (2018) with a more robust approach and show that robots reduce the trend in off-shoring. In this regard, we find that robotization in developed countries negatively affects employment in emerging countries, providing the first evidence of cross-country effects via robot-

Table 1.8: The impact of robots in developed countries on employment in emerging countries.

Dependent variable: employment in emerging countries	**OLS**		**IV**	
trade-weighted robot stock	−0.015	−0.125**	−0.459***	−0.319
	(0.045)	(0.060)	(0.155)	(0.235)
trade-weighted robot stock × labour intensity		0.132*		−0.198
		(0.070)		(0.413)
labour intensity	−0.004	0.033***	−0.004	0.014
	(0.004)	(0.008)	(0.009)	(0.040)
N	103	103	103	103
R^2	0.91	0.94	0.61	0.61

Regression using the trend variables, with country and industry fixed effects. Trends are the coefficients of regressions on a linear trend. Robust standard error in parentheses. Significance levels: *, **, *** indicate significance at 0.10, 0.05 and 0.01. Controls: value added, wage difference, domestic robots, domestic robots interacted with labour intensity. Estimates are weighted by sectoral employment in 2005.

driven re-shoring. In sum, detrimental effect of robots on employment concentrate in emerging economies, taking place both within countries and through the global supply chain.

Evidently, this questions the conventional strategy of developing countries to grow by attracting low-pay manufacturing employment. Therefore, macroeconomic business models of emerging economies have to be rethought for the future. Exploiting positive spillover potential on jobs outside manufacturing depicts a promising path for labour market development. (Weber SOURCE FOLLOWS).

Looking at robotization provides a good proxy regarding the impact of automation for mechanical tasks, which represents, however, only a subset of tasks currently carried out by human workers. Collection of data on artificial intelligence would allow to widen the analysis to a broader range of automation (see the discussion the impact of artificial intelligence on labour markets in Ernst et al., 2018). This also concerns the impact of flexible and individualised production techniques on global value chains (compare Dachs et al., 2019; De Backer and Flaig, 2017; Strange and Zucchella, 2017).

1.6 Aknowledge

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2 Inspecting the Relation of Search Costs and Search Duration

Abstract. Fixed search costs, i.e., costs that do not vary with search duration, can amplify the cyclical volatility of the labor market. To assess the size of fixed costs, we analyze the relation between search costs and search duration using German establishment data. An instrumental variable estimation shows no relation between search duration and search costs. We conclude that search costs are mainly fixed costs. Furthermore, we show that a search and matching model, calibrated for Germany with fixed costs close to 75 percent, can generate labor market volatility that is consistent with the data.
This study has seen the collaboration of my coauthor, Hermann Gartner.

2.1 Introduction

The cyclical variation of vacancies, unemployment and labor market tightness is empirically much larger than explained by the standard search and matching model (Shimer, 2005). A way to solve this puzzle is suggested by Pissarides (2009). He extends the standard model by distinguishing two types of search costs: those that depend on the duration of the vacancy and those that are fixed, i.e., independent from the duration of the vacancy. Pissarides shows that a high share of fixed costs over the total search costs generates the elasticity of tightness with respect to productivity, as observed in the data. However, up to now, there is no empirical evidence on the plausibility of this theoretical extension.

Our contribution is twofold. First, we empirically assess the link between search duration and search costs, and additionally, we provide evidence on the variation of search costs across firm and vacancy characteristics. Second, we provide as a numerical illustration a search and matching model for Germany with the observed structure of search cost to compare the volatility generated by the model with the volatility of the German labor market.

The related literature highlights the importance of fixed costs in the matching process. Fujita and Ramey (2007) discuss vacancy creation costs that are sunk costs. They ague that these costs affect the propagation of shocks to the vacancies by giving firms an incentive to smooth the creation of vacancies. Shao and Silos (2013) show that fixed costs raise the volatility of the value of a vacancy. Via this channel, fixed costs also influence the dynamic of the labor share. An extensive discussion of the Pissarides (2009) model is given by Silva and Toledo (2013). They highlight the difference between sunk and nonsunk (i.e., training) fixed costs. In most papers, the search costs are calibrated indirectly by matching other values such as the job-finding rate.

Search costs represent a wide range of expenditures, such as vacancy posting, screening and negotiation activity with candidates, headhunters or human resources staff. Despite the important implications for search models, there is scant research on the size and structure of search costs. Exceptions are, for example, Dolfin (2006) and Barron et al. (1997) or, for Germany, Mühlemann and Pfeifer (2016), but they all have no information on search duration and therefore do not distinguish between fixed and variable costs.

2.2 Theoretical background

Let us first clarify the argument of Pissarides (2009) to solve the unemployment volatility puzzle. It can be pinned down analytically as follows. The job creation condition in the canonical model is

$$\frac{p-w}{r+s} = \frac{c}{q(\theta)}, \tag{2.1}$$

where p is labor productivity, w is the wage, r is the risk-free interest rate, s is the separation rate, c is the standard search cost per period and $q(\theta)$ is the vacancy filling rate.

According to the matching function, the vacancy filling rate depends on labor market tightness θ, the ratio between vacancy and unemployment. Note that $1/q(\theta)$ is the search duration and $c/q(\theta)$ is the total search cost. It follows that the total search costs move one to one with the duration of a vacancy. We will empirically test this.

The elasticity of tightness with respect to p can be expressed as

$$\epsilon_\theta = \frac{1}{\eta}\frac{p - \epsilon_w w}{p - w}, \tag{2.2}$$

where ϵ_w is the elasticity of the wage with respect to productivity shocks. η is the elasticity of new matches with respect to unemployment.

Under the standard calibration with flexible wages, $\eta = 0.5$ in the Cobb-Douglas constant return matching function, $p = 1$ and equilibrium values of $w = 0.983$ and $\epsilon_w = 0.985$, ϵ_θ takes a value of 3.7, while the observed elasticity in the U.S. is approximately 7.56. This is the core of the unemployment volatility puzzle. Note that in Germany, where our data come from, the puzzle also exists. The volatility of tightness relative to productivity in Germany is, in fact, twice as large as that in the U.S.[1]

When adding fixed costs H, the job-creation condition changes as follows:[2]

$$\frac{p - w}{r + s} = \frac{c}{q(\theta)} + H. \tag{2.3}$$

The elasticity of θ with respect to p computed from (3) is

$$\epsilon_\theta = \frac{1}{\eta}\frac{p - \epsilon_w w}{p - w - (r + s)H}. \tag{2.4}$$

The higher the fixed search costs H, the lower ϵ_θ is, which is the reaction of tightness to a productivity shock. The intuition is as follows. A positive productivity shock leads to more vacancies created by the firms. This increases labor market tightness as well as

[1] For a detailed discussion about the volatility of the German labor market, see Gartner et al. (2012).

[2] According to Pissarides, fixed search costs H enter the model without modifying the Nash-bargaining equation because this is a cost not taken into account at the moment of the bargain, but it enters the value of a new vacancy.

vacancy duration. A higher duration also raises the search costs and thereby dampens the incentive to create vacancies. However, the higher the share of fixed search costs, the smaller this dampening effect is, and the higher the elasticity of θ is. Pissarides shows in a calibration exercise that if the share of H in total search costs is approximately 93%, we end up with an elasticity consistent with the data for the U.S.

Note that the costs and the duration in the theoretical model are expected (i.e., ex ante) values. Later in the empirical model, we use realized (i.e., ex post) values. Under rational expectations, there are only unsystematic differences between ex ante and ex post values. They will be captured by the error term in our regression. Moreover, the model assumes the homogeneity of firms and workers. In the data, firms and workers are heterogenous. We deal with this by using control variables and by running robustness checks for subgroups. Additionally, we apply an IV estimation using instruments that are exogenous for the firm.

2.3 Data and descriptive evidence

We use the German Job Vacancy Survey, conducted by the Institute for Employment Research (IAB), a random sample of establishments with at least one employee, stratified by 23 economic sectors and 7 firm size classes (see Moczall et al., 2015). The yearly survey started in 1989 and includes information on the number of vacancies, worker flows, and various firm characteristics. It also contains a number of questions concerning the very last case of a successfully recruited worker, such as gender and age of the hired worker, the qualification required for the job, the duration of search, and the recruiting channels used by the employer.

In the 2014 and 2015 waves, we included two further questions referring to the last case of recruiting: "What is the total number of hours spent on this recruitment?" and "If you add up all other costs, including advertising, headhunters, travel expenses, etc., which further costs (without labor costs) emerged for this recruiting?" The first question refers to what we call the *search hours*, and the second refers to the *monetary search* *costs*. To account for both the monetary search costs and the costs of the recruiting staff of the establishment, we multiply the hours spent on recruiting by the average hourly cost of labor at size, sector, yearly level,[3] and we add it to the monetary search costs. This measure is the *compounded search cost*.[4] We compute the vacancy duration as the time span between the date when the search started and the date when the applicant is selected. The dataset for our analysis contains 9,048 observations.

We provide the descriptive evidence across establishments and vacancy characteristics and search channels in Table 2.1. The average compounded search costs are 1,576 Euros, similar to the result of Mühlemann and Pfeifer (2016).

Our data also reveal a substantial heterogeneity in search costs and search duration. First, the monetary cost and the working time for searching is higher in larger establishments and if qualificatory requirements are high. Second, additional skill requirements, such as experience and leadership, are associated with longer duration and higher costs. Third, searching for workers on part-time or temporary contracts requires lower search costs. Finally, the channels used to find the workers reveal some unexpected results:[5] according to the survey, employers spend more when they use a private employment agency, when they advertise the job internally, or when they use the internet.

More intuitive are the consequences of hiring a trainee or a new staff through social contacts. In these cases the search costs are lower. It is worthwhile to note that the Federal Employment Agency (BA, *Bundesagentur für Arbeit*) is a relatively cheap search channel for employers, but it is also related to a long vacancy duration. Further descriptive results across sectors can be found in Table B1 in the Appendix. The data reveal that those sectors affected by high compounded search costs also need a longer search time (in days) to find the right staff.

[3]The data come from the German Federal Statistical Office.

[4]Note that we have no information on multiple recruitments at the same time. We believe, however, that the possible bias caused by parallel hirings is small. Most of the establishments are small and have only a few cases of recruitments. Forty-five percent of the establishments that report the last case of hiring had only one hiring within a year, and 67 percent had no more than 2 hirings. Therefore, multiple recruitments at the same time are rare. Furthermore, an internal evaluation by a pretest showed that if there were multiple hirings, in 54 percent of cases, it was for different types of positions.

[5]Note that the use of multiple channels is possible.

Table 2.1: Descriptive statistics according to plant and vacancy characteristics

Characteristics		Monetary search costs (Euros)		Search hours		Search duration (days)		Comp. search costs (Euros)	
Plant size (# employees)	<20	395	(1480)	17	(26)	72	(79)	906	(1792)
	20-49	582	(1829)	19	(24)	62	(67)	1192	(2261)
	50-199	788	(2678)	20	(34)	66	(85)	1478	(3297)
	200-499	2568	(8162)	18	(17)	68	(68)	3241	(8541)
	>500	1374	(3524)	22	(31)	63	(58)	2371	(4120)
Qualification	Unskilled, max. 1 year of training	159	(514)	18	(32)	49	(56)	685	(1345)
	Vocational qualification	489	(1354)	17	(23)	67	(79)	1004	(1691)
	Master craftsman, technician	1384	(3310)	22	(30)	76	(87)	2201	(3962)
	Bachelor's degree	2005	(8150)	23	(26)	67	(64)	2943	(8238)
	Master's degree or similar, PhD	2806	(6640)	28	(40)	79	(73)	3997	(7366)
Additional skills	Long experience	1655	(4867)	22	(31)	78	(76)	2467	(5454)
	Leadership skills	3476	(7669)	30	(45)	87	(82)	4594	(8386)
Type of contract	Part-time	306	(967)	16	(23)	62	(87)	765	(1191)
	Temporary contract	472	(1607)	18	(28)	61	(67)	1041	(2025)
Search channels	Newspaper	1202	(4124)	21	(27)	75	(77)	1834	(4334)
	BA	910	(4110)	22	(29)	74	(78)	1601	(4442)
	Own web site	1291	(4508)	21	(30)	75	(80)	2060	(4922)
	Internet	1318	(4500)	24	(31)	82	(88)	2156	(4823)
	Unsolicited application	910	(4813)	19	(26)	72	(89)	1520	(5060)
	Private job placement	4315	(8217)	30	(33)	93	(107)	5371	(9028)
	Internal job advertisements	1653	(6093)	22	(37)	69	(65)	2522	(6564)
	Social contact	547	(2363)	17	(25)	71	(89)	1097	(2699)
	Trainee	825	(2187)	17	(19)	84	(116)	1413	(2608)
Overall mean		920	(3652)	19	(28)	67	(75)	1576	(4051)

Mean and standard deviation (in parentheses), weighted values. 9,048 observations. Source: German Job Vacancy Survey 2014 and 2015. The survey weights are based on strata for 23 economic sectors and 7 firm size classes.

2.4 The empirical relation of search costs and search duration

Turning to the econometric analysis, our aim is to check whether and to what extent the compounded search costs (henceforth simply search costs) are related to the search duration, conditional on vacancy and establishment observables. Search costs and search duration enter the estimation model in logs because of a higher explanatory power than in a level specification. Thus, the coefficient can be interpreted as elasticity of search costs with respect to search duration. At first, we present results from an OLS approach to document the comovements in the data. Because of potential endogeneity, we interpret these results as correlations not as causations. Later, we use an instrumental variable approach that allows for a causal interpretation.

The results of the OLS models are presented in Table B6. We add subsets of covariates progressively from Model 1 to Model 3 to provide information on the specific contribution of the characteristics. The results confirm the descriptive evidence, with more consistent results for the search channels - the inclusion of search costs improves strongly the explained variation of the dependent variable. The coefficient is positive and significant in all specifications. Model 1, regressing only on firm size and sectors, shows an elasticity of search costs to search duration of 37%. In Model 2, we account also for qualification, further skill requirements, and type of contract, and the elasticity shrinks to 32%. Looking at Model 3, where we account for all controls, the elasticity is much smaller: a 10% increase in search duration is associated with an increase in the search costs of 2%. The result reveals a positive relation of search costs and duration, but the elasticity is much smaller than one, as asserted by the canonical search and matching model.

In regard to the control variables, the table shows that large firms face higher search costs and that required qualification and additional skills are positively correlated with search costs, while hiring a worker for a temporary or a part-time contract is correlated with lower search costs.

Concerning the search channels, when firms search via social contacts or among the trainees, they save on some search costs. The coefficient of the Federal Employment Agency (BA) is the smallest among the channels with a positive correlation. Using a newspaper or private job placement is associated with the highest search costs. Finally, hiring an underexperienced worker correlates positively with the search costs; a possible reason for this is that employers with high search costs accept underexperienced staff to finish the search sooner (this is a finding of Brenčič and Norris (2009)). This is a causal question that we leave for future research.

The OLS estimates can be criticized because there may be unobserved firm characteristics that influence search duration as well as search costs. Therefore, we adopt, here, an instrumental variable approach. As instruments we use variables that are exogenous for the firm and that are motivated by the standard search and matching model. According to the model, the expected duration of the vacancy is a function, $1/q(\theta)$, of labor market tightness. Therefore, we use the log of labor market tightness at district (*Kreise*) level to instrument the search duration.[6] The first stage regression model is basically a matching function. We estimate fixed effects for 400 districts, and thus, the result is driven by the time variation within the districts. The same control variables as in Model 3 are included.

Table 2.3 displays the first and second stage estimation. In the first stage, labor market tightness is significant and reveals an impact on search duration consistent with the matching model: a higher number of vacancies makes the hiring process more competitive for the firms and increases search duration, while a higher number of unemployed makes the hiring process quicker and reduces search duration.

In the second stage, the significance of the logarithm of search duration vanishes, implying that search duration does not correlate with the search costs. In other words, these results suggest that search costs are mainly fixed. To summarize, according to the OLS estimate, search costs move very little with search duration. The instrumental variable estimate confirms and strengthens this search cost structure. In the next session, we calibrate a search and matching model for the German labor market, and we assess

[6] Labor market tightness is defined as vacancies over unemployed.

Table 2.2: OLS regression: Search cost and search duration

Dependent variable: log of compounded search costs		**Model 1**		**Model 2**		**Model 3**	
log of search duration		0.37^{***}	(0.01)	0.32^{***}	(0.01)	0.20^{***}	(0.01)
Plant size (# employees)	<20	-0.21^{***}	(0.04)	-0.20^{***}	(0.04)	-0.09^{**}	(0.03)
	50-199	0.22^{***}	(0.04)	0.19^{***}	(0.04)	0.06	(0.03)
	200-449	0.53^{***}	(0.06)	0.43^{***}	(0.06)	0.15^{**}	(0.05)
	>500	0.82^{***}	(0.06)	0.61^{***}	(0.06)	0.37^{***}	(0.06)
Qualification	Unskilled, max. 1 year of training			-0.39^{***}	(0.05)	-0.32^{***}	(0.04)
	Master craftsman, technician			0.35^{***}	(0.07)	0.23^{***}	(0.06)
	Bachelor's degree			0.53^{***}	(0.06)	0.44^{***}	(0.05)
	Master's degree or similar, PhD			0.65^{***}	(0.04)	0.60^{***}	(0.04)
Additional skills	Long experience			0.22^{***}	(0.03)	0.15^{***}	(0.03)
	Leadership skills			0.29^{***}	(0.06)	0.25^{***}	(0.05)
Type of contract	Part-time			-0.17^{***}	(0.04)	-0.11^{**}	(0.04)
	Temporary contract			-0.15^{***}	(0.03)	-0.09^{**}	(0.03)
Search channels	Newspaper					0.79^{***}	(0.03)
	BA					0.16^{***}	(0.03)
	Own website					0.27^{***}	(0.03))
	Internet					0.41^{***}	(0.03)
	Unsolicited application					-0.01	(0.03)
	Private job placement					0.76^{***}	(0.06)
	Internal job advertisements					0.31^{***}	(0.03)
	Social contact					-0.20^{***}	(0.03)
	Trainee					-0.13^{*}	(0.06)
Mismatch	Underqualification					-0.05	(0.06)
	Underexperience					0.16^{**}	(0.05)
Sectors		Yes		Yes		Yes	
	R^2	0.18		0.24		0.39	

Robust standard errors in parentheses. 9,048 observations. Reference group: Plant size 20-49, Vocational qualification. Significance levels: *, **, *** indicate significance at 0.05, 0.01 and 0.001. Industry coefficients are in Table B2 in the Appendix.

the role of the structure of search cost for the unemployment volatility puzzle.

We run several additional regressions as robustness checks. We estimate separate regressions for three qualification levels of the new hires and separate regressions for industry and service sectors. Furthermore, we estimate a model with a fixed effect on a 3-digit occupation level. The results of these regressions are stable for the OLS and IV regressions. The result is also stable when we use as instrument unemployment and vacancies, separately, instead of tightness. The results are available in the Appendix.

Table 2.3: IV Regression: Search cost and search duration

	First-stage FE	Second-stage FE
Dependent variable	log of search duration	log of compounded search costs
log of tightness	0.55***	
	(0.00)	
log of search duration		−0.35
		(0.15)
R^2	0.10	0.26

Robust standard errors in parentheses. 9,048 observations, F statistics in the 1 stage 27.42. Significance levels: *, **, *** indicate significance at 0.05, 0.01 and 0.001. Controls: plant size, qualification, required additional skills, type of contract, search channels, and sectors.

2.5 The role of search costs

As discussed in Section 2.1, Pissarides (2009) shows that the existence of fixed search costs increases the response of tightness to a labor productivity shock. In the absence of data on the search cost structure, he proposes a tentative calibration of how the elasticity of tightness, ϵ_θ, changes with different shares of fixed over total search costs. To relate our empirical finding on search costs in Germany to the unemployment volatility puzzle, we have to calculate the impact of fixed search costs in a model calibrated for the German labor market.

Following Pissarides (2009), we assume a Cobb-Douglas matching function $m = m_0 u^\eta v^{1-\eta}$, and we use the job creation condition (equation 3) and the wage equation

$$w = (1-\beta)z + \beta(p + c\theta + f(\theta)H) \tag{2.5}$$

to solve the model for the two endogenous variables θ and w.

The output is normalized to one. To calibrate the model with monthly data, we adopt the key structural parameters from long-run values established in the literature (see Table 2.5). We set $\eta = 0.75$, estimated in Kohlbrecher et al. (2016), for Germany. We obtain the job-finding probability, separation rate and labor market tightness from Gartner et al. (2009).

In most other applications, the search costs are chosen to match the tightness or the job-finding rate. As we have information on the search costs, we go another way: the total search cost presented in Section 3.2 is 1.576 Euro. The average monthly value added per worker in 2014 and 2015 is 5.155,72 Euro.[7] Thus, the search cost as a share of workers' monthly output is 31%. We compute the model for several combinations of c and H, keeping the total search costs constant at 0.31. Finally, the nonlabor income z is then chosen to match the tightness θ.

Table 2.4: Parameter values

Parameter	Value	Description	Source/Target
r	0.004	Interest rate	Pissarides (2009)
s	0.013	Exogenous separation rate	Gartner et al. (2009)
z	0.86	UB and value of leisure time	Tightness
m_0	0.2	Matching efficiency	Job-finding probability
η	0.75	Unemployment elasticity	Kohlbrecher et al. (2016)
β	0.75	Share of labor	$\beta = \eta$ (efficiency)
		Mean values	
θ	0.39	Mean tightness	Gartner et al. (2009)
$m_0\theta^{1-\eta}$	0.13	Job-finding probability	Gartner et al. (2009)

[7]Source: German Federal Statistical Office. The values for 2015 are deflated to 2014 price levels.

Table 2.5: Model results at different combinations of search costs.

H	c	H_s	$\frac{c}{q(\theta)} + H$	ϵ_θ
0	0.104	0	0.31	7.16
0.02	0.097	0.07	0.31	7.58
0.08	0.078	0.25	0.31	8.93
0.14	0.056	0.46	0.31	11.24
0.23	0.027	0.74	0.31	17.06

Table 2.5 displays the results. The first line assumes no fixed search costs, as in the canonical search model. It turns out that the elasticity of tightness with respect to labor productivity ϵ_θ equals 7.16. To compare it with the data, we compute the elasticity using the summary statistics from Gartner et al. (2009). The elasticity in the data is much larger and amounts to 17.09. This gap reflects the existence of the unemployment volatility puzzle in Germany as well.

In the subsequent lines, we show the implications of an increasing share of the fixed component H for the elasticity of the labor market tightness. As we have shown in the empirical section, the data suggest that the share of fixed costs is large. When the fixed costs reach about three-quarters of the overall search costs, precisely 74%, the model generates the amplification of the labor market tightness that we see in the data. This result gives support, at least for Germany, to the solution of the Shimer puzzle proposed by Pissarides (2009).

We have applied a basic search and matching model to relate the results to Pissarides (2009). One might argue that the assumption of an exogenous separation rate is plausible for the U.S. but not for Germany, where the volatility of the separation rate is higher (see Gartner et al., 2012). The separation rate can also be modeled as an endogenous variable. This would establish an additional channel for amplifying the volatility. A discussion of this can be found in Fujita and Ramey (2012).

2.6 Conclusion

In this paper, we compute the size of search costs and analyze the relation of search costs with search duration. Using new information from the German Job Vacancy Survey, we measure the cost of advertising the job, paying headhunters, and inviting and screening candidates as well as the cost of the staff within the establishment that deals with the hiring process. According to an OLS analysis, the elasticity between search costs and search duration is 0.20. This is much smaller than one, as assumed in the canonical search and matching model. If an IV regression is applied, with labor market tightness at the district level as the instrument, we find no significant relation between search duration and search costs. This suggests that search costs are mainly fixed costs, as proposed by Pissarides (2009).

We calibrate the Pissarides (2009) model for Germany. The model can generate the elasticity of labor market tightness with respect to productivity of 17.09 when the search costs are composed in large part by fixed costs, as is consistent with our empirical finding.

The German Job Vacancy Survey allows for a deeper analysis of the heterogeneity of search costs and can thus help foster a better understanding of matching in the labor market. Future research should analyze in greater detail the relation of search costs with different matching technologies related with different search channels. The relation of search costs with recruiting intensity (Davis et al., 2013) is also an issue for future work.

2.7 Aknowledge

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3 The Fall of the Labour Income Share: the Role of Technological Change and Search Frictions

Abstract Documenting an average drop of the labour share of 8 percentage points for eight European countries and the US between 1980 and 2007, we analyse the role of technological progress and labour market frictions. According to our results, while capital-labour substitution in general was not crucial, Information Communication Technology (ICT) is a promising channel to explain the decline in the labour share, given an estimated elasticity of substitution of 1.18. Considering labour market imperfections slightly dampens the estimated substitution effect at aggregate level. Additionally, by modelling the substitution between ICT and labour with a set of key labour market variables, we find it to be linked to both the share of routine occupations (positively) and the share of high-skill workers (negatively) with a similar strength.
This study has seen the collaboration of my coauthors, Enzo Weber and Christian J. Offermanns.

3.1 Introduction

The labour income share (LS) is discussed in empirical studies on income distribution and in several macroeconomic calibrations. LS constancy is one of the so-called Kaldor's facts, and a value of 2/3 is usually adopted. However, recent studies reveal that the LS has declined for most of the OECD countries since the 1980s [OECD (2012), Raurich et al. (2012), Arpaia et al. (2009)]. This decline might be only temporary; however, it appeared at the same time that the adoption of new technologies gave rise to job polarization and occupational displacement, phenomena that are considered, at least in the public debate, to be irreversible. We contribute to the literature by theoretically and empirically analysing the substitution between Information Communication Technologies (ICT henceforth) and labour, together with labour market imperfections and institutional and structural labour market variables.

We first compute the labour share based on labour income data from the EU KLEMS database for eight European countries and the US. The aggregate LS dropped from 71 percent to 63 percent between 1980 to 2007[1]. There is substantial heterogeneity in the speed and the timing of the decline, but - except for Denmark - all the countries display a persistent drop in LS after 1990. Secondly, we look at the evolution of the price index for a specific type of capital input, namely, ICT. According to a wide range of studies, indeed, the decline in the price for computers and digital equipment is the source of important new trends in the production process, such as automation and occupational displacement. EU KLEMS provides the gross fixed capital formation price index for ICT and non-ICT and we show that the decline of the capital investment price is connected mainly to the downward evolution of the ICT equipment price. Building on that, we set up a theoretical framework to rationalize the relationship between ICT price, hiring costs and the labour share. The model provides two harmful mechanisms for the labour share, a labour-ICT substitution effect and a hiring cost effect, which we quantify by estimating the elasticity of substitution between ICT capital and labour.

Karabarbounis and Neiman (2014), using EU KLEMS data, find an elasticity between aggregate (i.e., ICT and non-ICT) capital and labour of 1.17. This result is questioned by Autor et al. (2017) and Lawrence (2015) who point out that the majority of studies argue in favor of an elasticity lower than one. In this paper, we provide further insights on the substitution between production inputs. Indeed, when we estimate the elasticity

[1]See O'Mahony and Timmer (2009) for an overview of the methodology and construction of the EU KLEMS database

of substitution between aggregate capital and labour, we find that it lies between 0.7 and 1, as in several previous studies[2]. However, when we separate ICT and non-ICT capital and consider them simultaneously, the elasticity between ICT capital and labour is higher than one, namely, 1.18. Given the downward trend in the ICT price, this estimated elasticity is responsible for the decline of the labour share.

The second aim of the paper is to assess the extent to which the elasticity of substitution between ICT and labour is affected by country-specific labour market variables. The literature on the impact of technological change on labour markets reveals that, on one hand, the adoption of ICT raises the demand for high-skill workers (the skill-biased view) and, on the other hand, shrinks the employment share of routine occupations (the job polarization view). A recent contribution on this topic comes from Eden and Gaggl (2018), who find important effects of ICT on routine labour. Regarding institutions, lower employment protection legislation and firm-level wage bargaining have been assessed as potential channels of the impact of higher international competition on the labour share (OECD, 2012). In this paper, we examine these forces as well as the role of unemployment benefit replacement rate and of union density. The main finding of our analysis is that countries with a high share of routine occupations (high-skill workers) also exhibit a larger (smaller) elasticity of substitution between labour and ICT capital. As both factors are of a similar strength, our findings suggest that both individual characteristics (qualification) and job characteristics (task structure) play an equal role in shaping the labour market impact of technological change. By the same token, the results connect the implications of ICT adoption to the job polarization phenomenon, the task composition of jobs and the drop in the LS.

The paper proceeds as follows. Section 3.2 documents the decline in the labour share and in the capital price index, at the aggregate and country levels. Here, we provide evidence of the different evolutions of the price of ICT and non-ICT capital. Section 3.3 discusses the most recent contributions on the impact of technological change on the labour market. In particular, we review the job polarization theory and the role of ICT

[2]For a recent meta-regression of an ample sample of papers, see Knoblach et al. (2016).

for routine tasks, which allows us in Section 3.4 to derive a theoretical setting that links the labour share, the ICT price and the hiring costs. Section 3.5 describes the data sources and the variables we use for the empirical analysis. Finally, in Section 3.6 and Section 3.7, we assess the validity of the theoretical predictions and model the elasticity parameter with state space functions of country-specific labour market variables.

3.2 The labour share and ICT facts

The shares of the national income that go to labour and capital have been considered to be constant for many years. Kaldor (1955) writes that there has been a

> relative stability of these shares in the advanced capitalist economies over the last 100 years or so, despite the phenomenal changes in the techniques of production, in the accumulation of capital relative to labour and in real income per head. (pp. 83-84)

This fact is well described with the use of a Cobb-Douglas production function that implies a constant unitary elasticity of substitution between the production inputs and steady factor shares. However, recently, several studies have highlighted a decline in the labour share for many developed countries. OECD (2012) reveals that the labour share dropped by 5 percentage points on average between early 1990s and late 2000s, arguing that the substitution between labour and the new technologies was likely the driving force of this decline and that increasing the employer-employee matching quality might help to reverse this trend. A similar drop is found by Karabarbounis and Neiman (2014) who analyze 59 countries at industry level and claim that the decline in the price of investment goods has reduced the worldwide labour share, given a global elasticity of substitution of approximately 1.25. Detailed research for the US comes from Elsby et al. (2013), who argue that the drop in the labour share has occurred mainly in the manufacturing sector, potentially as a result of the offshoring of labour-intensive production, and that changes in the institutional setting are negligible.

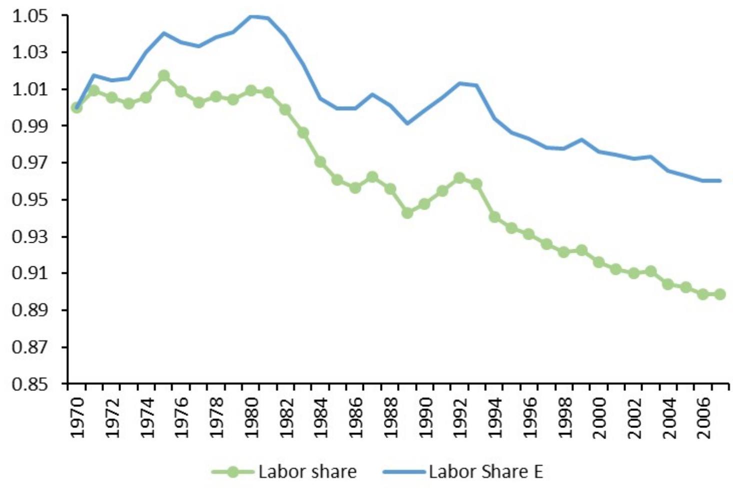

Figure 3.1: Aggregate labour share of the total labour force (blue line), aggregate labour share of employees (green marked line). Source: EU KLEMS.

Using the EU KLEMS dataset, we compute the labour share as labour compensation over value added at current basic prices between 1970 and 2007. Due to data constraint, we focus on Austria, Denmark, France, Germany, Ireland, Italy, the Netherlands, Spain and the US[3]. We derive the labour share for two subsets of the labour force, namely, employees and person engaged, the latter including the self-employed. The compensation of self-employed is imputed assuming that, at the industry level, the per-hour compensation of self-employed workers is equal to that of employees. This raises a number of issues, which are treated in detail in O'Mahony and Timmer (2009); however, for this paper, we rely only on employees. Figure 3.1 shows the aggregate labour share for the two subsets. The blue line is the labour share using employees and self-employed, while the green line uses only employees. A clear drop in both series is visible starting from 1980 and is steeper for the LS with self-employed.

Concerning the possibility that the aggregate labour share shrunk due to changes in industrial composition, it is worth mentioning that Karabarbounis and Neiman (2014), using EU KLEMS data, show that the within-industry component prevails.

The study of Karabarbounis and Neiman (2014) is the most similar to ours, as they

[3]Beginning with 1990, our EU sample represents more than 78 percent of the EU15 value added.

assess the impact of the capital price on the labour share. However, we directed our research to a specific capital asset, namely, ICT. Our motivation is twofold: first, ICT equipment, unlike non-ICT equipment, is experiencing a substantial fall in its investment price; second, ICT is the main candidate to replace labour in production (we give further details on this topic in the next section). Figure 3.2 shows the price index for total, ICT and non-ICT assets. The measure is that used in Karabarbounis and Neiman (2014), namely, gross fixed capital formation price index divided by gross value added price index. Looking at the evolution of the time series, it is clear that the decline in the

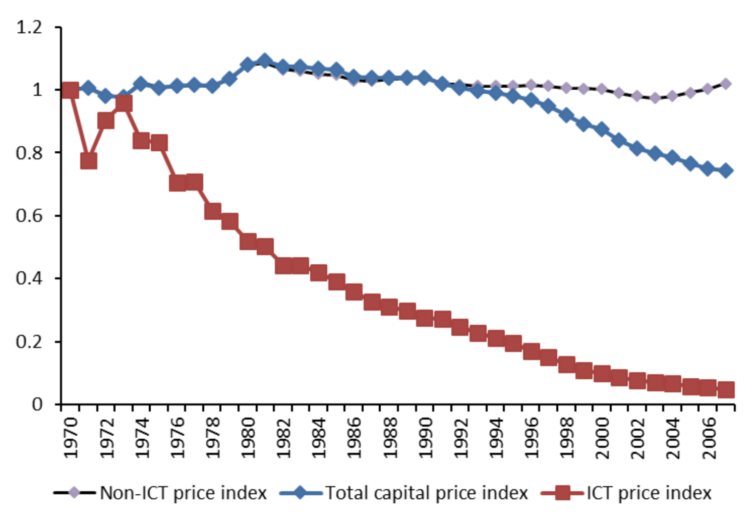

Figure 3.2: Price index per type of capital and total (average over the countries, 1970=1, source: EU KLEMS, own calculation)

total assets price index is related mainly to the ICT equipment.

Several studies on ICT equipment have been conducted since the year 2000, when new data on new technologies became available and allowed to investigate these technologies' contribution to output and productivity. The stylized facts that emerged are the following: first, ICT-producing industries experienced a high productivity growth rate between 1979 and 2001; second, similar values for labour productivity in ICT-producing sectors have been found for the US and the EU, and within Europe; finally, ICT-producing industries play a pivotal role in explaining the high labour productivity correlation among EU countries [4].

[4] See O'Mahony and Van Ark (2003)

Table 3.1: Growth rate of the ICT investment price (percent). Source: EU KLEMS.

Countries/Average	1976-1985	1986-1995	1996-2005
Austria	2.2	−3.3	−11.0
Denmark	−3.5	−9.2	−12.1
Spain	10.0	0.1	−4.7
France	9.5	−0.6	−0.9
Germany	0.5	0.0	−10.1
Ireland	8.8	−2.8	−10.9
Italy	11.1	−0.1	−8.4
Netherlands	2.5	−4.2	−9.1
US	3.4	−4.1	−8.7

Related to these facts, we observe a trend in the price of investment in ICT. We computed this trend by making use of the nominal and real gross fixed capital formation index in the EU KLEMS dataset. Table 3.1 shows the average price of ICT capital for three time spells between 1976 and 2005. In the 1976-1985 period, almost all the countries experienced a substantial increase, with the exception of Denmark. The decline in the ICT investment price began for six European countries and the US in the late 1980s and early 1990s, and it has shown a clear common path since 1996. This evolution has been documented by, among others, Bosworth and Triplett (2000) and Jorgenson (2001), who explain the drop with the gain in capacity of microprocessors and storage devices. The post-1995 acceleration shown in Table 3.1 corresponds to the marked decline in the price of semiconductors used in microprocessors to encode information in binary form.

3.3 ICT adoption and the labour market

The impressive speed of ICT adoption has raised several questions concerning its impact on labour markets. Figure 3.3 visualizes the time series for the ICT capital formation price index and the labour share of employees, which we use to estimate the elasticity of substitution between ICT and labour. Despite substantial heterogeneity, the labour share comoves in most countries with the ICT price. The following question remains: how can the two trends be related to one another?

The benchmark has long been the capital-skill complementarity framework, developed by, among others, Krusell et al. (2000) according to whom the technological change has been skill-biased and has increased the demand for high-skill workers, resulting in an increase in the skill premium. Acemoglu (2002) further develops this view by arguing that the abundance of a production input (in this case, high-skill workers) can induce a biased technological change irrespective of the elasticity of substitution, with the latter playing a main role in determining the factor reward.

However, recent literature highlights that the high substitutability of capital with labour is likely biased against middle-skill workers and particular occupational classes. Autor et al. (2003), Autor et al. (2006) and Acemoglu and Autor (2011) indeed claim that in the US labour market, a job polarization emerged around the 1990s, given a deterioration of the wage growth and employment opportunities for middle-skill workers and a substantial improvement for low- and high-skill workers.

The theoretical argument builds on the concept of tasks. Following Acemoglu and Autor (2012), "a task is a unit of work activity that produces output. A skill is a worker's stock of capabilities for performing various tasks". Accordingly, workers perform tasks in exchange for wages. Intuitively, if the assignment of skills to tasks is not one-to-one and if the set of tasks demanded in the economy is affected by technological change, we might end up with non-monotone changes of the wage and of the employability on the skill (or wage) distribution. ICT capital has been increasingly adopted for routine and "codifiable" tasks that were previously carried out by middle-skill workers, with a consequent drop in their wage growth and employment. Consequently, depending on the employment share of routine occupations[5] and on how quickly workers react to this occupational displacement, we might expect that a higher adoption of ICT lowers the labour share. Similarly, Eden and Gaggl (2018) reveal important consequences of ICT adoption on routine labour and small welfare gains from automation.

[5]We report the employment shares for abstract, routine and manual occupations in Table B1 in the appendix

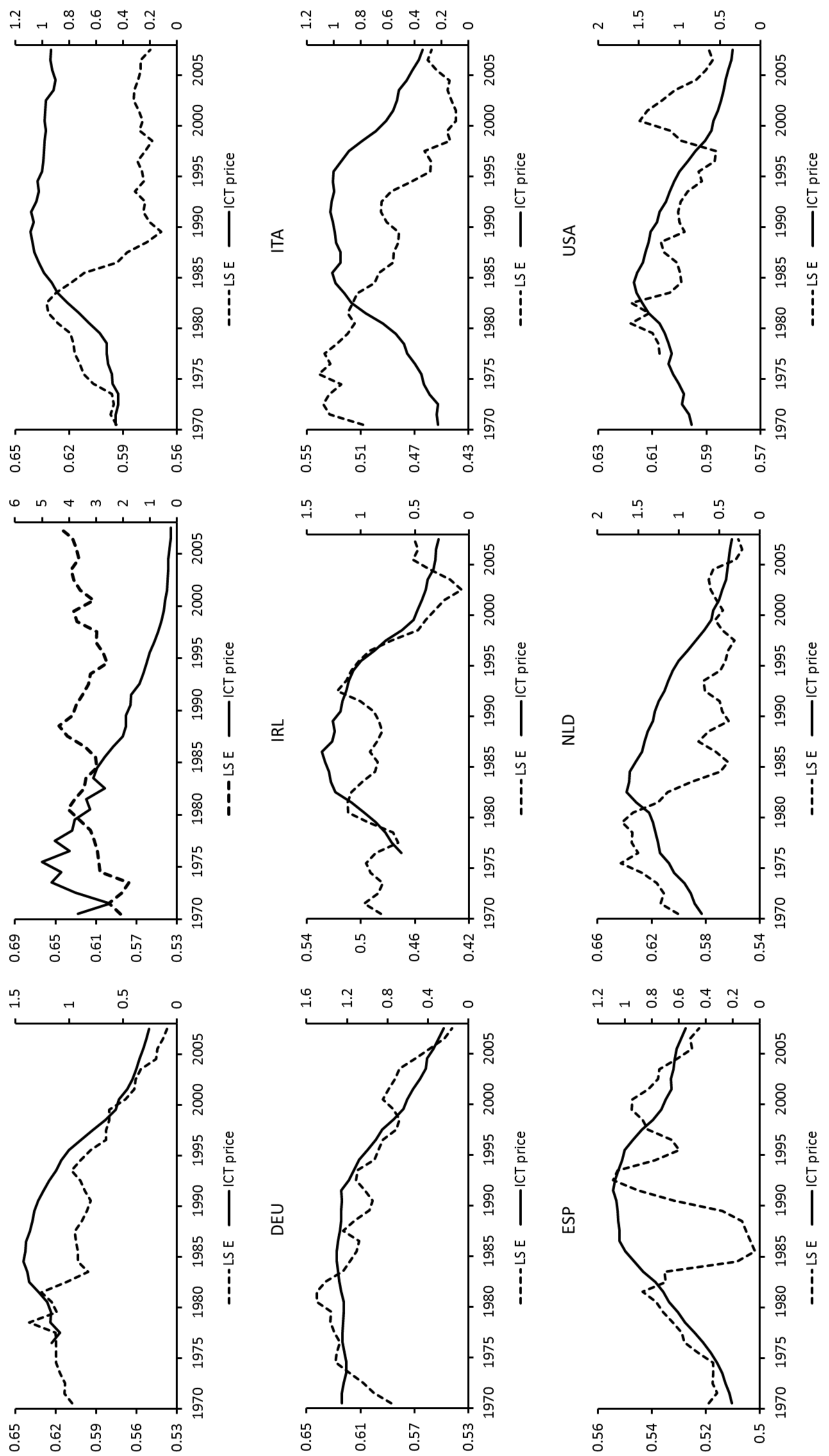

Figure 3.3: Employee labour share (continuous line, left axis), ICT index price (dotted line, right axis). Source: EU KLEMS

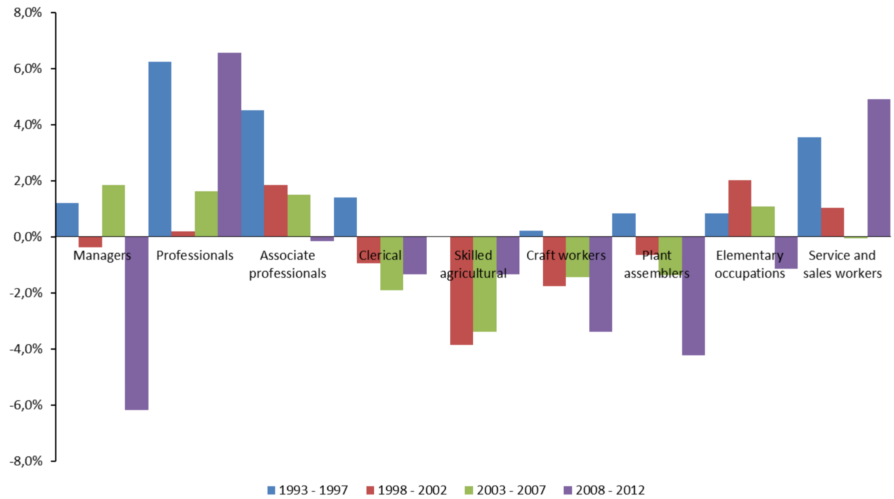

Figure 3.4: Changes in employment share per occupations. EU15 countries between 1993 and 2012 (percent, source: Eurostat)

Besides the US, there is a moderate consensus on the presence of job polarization also in Europe. Goos et al. (2014) focus on 16 Western European countries and find a pervasive job polarization between 1993 and 2010. Consoli and Roy (2015) find evidence of routine job displacement following ICT adoption in Germany, while it seems that mainly high-ranked occupations profit from this phenomenon.

In order to further investigate this phenomenon, we analyze the changes in occupational employment shares in Europe. We make use of a Eurostat dataset that relies on the International Standard Classification of Occupations, and we focus on 9 major classes[6]. Figure 3.4 reports the percentage change in occupational employment shares for four time periods between 1993 and 2012 in the aggregate EU15[7]. From left to right, we plot the changes for managers, professionals and associate professionals (technicians also belong to this category), which are usually referred as abstract occupations; in the middle are plotted four routine occupations, namely, clerical, skilled agricultural, craft and plant workers; on the right-hand side of the figure are elementary occupations and service and sales workers, usually associated to manual tasks. The familiar U-shaped distribution,

[6]Following the cited studies above, we neglect the armed forces.

[7]The EU15 refers to Belgium, Denmark, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, the United Kingdom, Austria, Finland and Sweden. The measure is calculated by aggregating totals from the Member States

which depicts the employment polarization in Europe, is visible in all periods.

3.4 The model

This section aims to develop a theoretical model that explains the evolution of the labour share depending on technological change and labour market imperfections. We consider for capital and labour a dynamic setting that allows us to build up a richer model compared to the one in the previous literature. In particular we include the stock of investments for capital and the stock of vacancies for labour. We, then, evaluate the steady state of the model to get back the static version and estimate it with yearly data, equivalent to what is common in the literature (see Arpaia et al., 2009; Antras, 2004).

In what follows, we make use of two assumptions. First, in contrast to that of ICT equipment, the productivity of workers is not observable before the match. Therefore, while ICT installation is frictionless, the recruitment of labour is costly in terms of money and time. Second, non-ICT capital has a constant elasticity of substitution with the remaining inputs, ICT capital and labour. We indeed consider that both ICT capital and labour are equipped with an equal stock of non-ICT capital, such as machines and plants. Employers produce output with a combination of labour force n, ICT capital k_I and non-ICT capital k_{NI} in a reduced form of production function of the type

$$y = \left\{ \beta R^{\frac{\sigma-1}{\sigma}} + (1-\beta) k_{NI}^{\frac{\sigma-1}{\sigma}} \right\}^{\frac{\sigma}{\sigma-1}},$$

$$R = \left(\alpha k_I^{\frac{\epsilon-1}{\epsilon}} + (1-\alpha) n^{\frac{\epsilon-1}{\epsilon}} \right)^{\frac{\epsilon}{\epsilon-1}},$$

where α and β are distribution parameters, ϵ is the elasticity of substitution between ICT capital and labour and σ is the elasticity between non-ICT capital and the aggregate input of ICT capital and labour. Moreover, we consider that labour markets are subject to frictions and that firms have to post vacancies and train the new employees. Thus, we assume that there is a real cost c that embeds the cost of posting the vacancy (search cost), the cost of training the new worker (adaptation cost) and the opportunity cost. According to the standard search and matching framework, the aggregate flow of workers into employment in each period is given by $vq(\theta)$, where v is the number of vacancies and $q(\theta)$ is the vacancy filling rate. Given an exogenous separation rate s, the outflow of workers from employment to unemployment is sn. This implies that the law of motion of employment follows

$$n_{t+1} = (1 - s_t)n_t + v_t q(\theta_t), \tag{3.1}$$

from which we obtain the steady state relation between employment and vacancies

$$sn = vq(\theta). \tag{3.2}$$

Capital input is hired at the real cost p, which represents the investment price. This is our key price variable, beyond which we don't distinguish between rental and investment price. What the firm installs is a machine bought for – and used uniquely in – the firm. Therefore, the two prices coincide. Karabarbounis and Neiman (2014) provide a theoretical basis for this issue and show empirically the irrelevance of using a rental price different from the investment price.

The law of motion for type j of capital is given by

$$k_{j,t+1} = k_{j,t} + i_{j,t+1} - \delta_{j,t}k_{j,t}, \tag{3.3}$$

where k_j is the stock of capital j, i_j is the flow of new capital and $\delta_{j,t}$ the depreciation rate. In steady state $k_{j,t+1} = k_{j,t}$, that implies trivially that capital formation must be equal to consumed capital

$$i_j = \delta_j k_j. \tag{3.4}$$

Real profit is maximized subject to the equilibrium condition for employment (3.2) and capital (3.4) - see the Appendix for details -

$$\pi = y - wn - cv - p_I i_I - p_{NI} i_{NI}, \tag{3.5}$$

where w is the real wage. Then, we compute the first-order conditions:

$$\partial n : y^{\frac{1}{\sigma}}\xi(1-\alpha)n^{-\frac{1}{\epsilon}} = w + \lambda_n s, \tag{3.6}$$

$$\partial v : \lambda_n = \frac{c}{q(\theta)}, \tag{3.7}$$

$$\partial k_I : y^{\frac{1}{\sigma}}\xi\alpha k_I^{-\frac{1}{\epsilon}} = -\lambda_I\delta_I, \tag{3.8}$$

$$\partial i_I : \lambda_I = -p_I, \tag{3.9}$$

$$\partial k_{NI} : y^{\frac{1}{\sigma}}(1-\beta)(k_{NI})^{\frac{1}{\sigma}} = -\lambda_{NI}\delta_{NI}, \tag{3.10}$$

$$\partial i_{NI} : \lambda_{NI} = -p_{NI}, \tag{3.11}$$

where the λ_n, λ_I and λ_{NI} are the Lagrange multipliers with respect to employment and to the two types of capital and $\xi = \beta R^{\frac{\sigma-\epsilon}{\sigma(\epsilon-1)}}$. By substituting constraint (6) into (7), we obtain the labour demand

$$n = \frac{y^{\frac{\epsilon}{\sigma}}\xi^{\epsilon}(1-\alpha)^{\epsilon}}{(w+c_v)^{\epsilon}}, \tag{3.12}$$

where c_v represents the total hiring cost per employee[8]. Equation 3.12 indicates that labour demand is a derived demand and depends negatively on the wage, as the classical framework states. Interestingly, however, it also provides the intuition on how labour is affected by search frictions and the substitution with ICT capital. In a context of high substitutability between labour and ICT capital, namely, with $\epsilon > 1$, higher vacancy costs per employee or higher wages have a stronger negative impact on the amount of labour demanded because it is more convenient to run the same production with capital.

Constraints (8) and (9) give the demand for ICT capital

$$k_I = \frac{y^{\frac{\epsilon}{\sigma}}\xi^{\epsilon}\alpha^{\epsilon}}{P_I^{\epsilon}}, \tag{3.13}$$

[8]We multiply and divide the term $cs/q(\theta)$, which results from the substitution of equation 7 into 6, by n/v and we get $c\frac{sn}{q(\theta)v}\frac{v}{n}$. In steady state, the flows of workers into and out of unemployment, sn and $q(\theta)v$ respectively, are equal, and we end up with the expression $c_v = \frac{cv}{n}$, namely the total cost of vacancies per employee.

where $P_I = p_I \delta_I$, and we use 3.13 to substitute $y^{\frac{\epsilon}{\sigma}} \xi^{\epsilon}$ into n, which gives

$$n = \left(\frac{1-\alpha}{\alpha} \right)^{\epsilon} \frac{P_I^{\epsilon} k_I}{(w + c_v)^{\epsilon}}. \tag{3.14}$$

In this setting, both price and depreciation of capital determine the stock of capital. A drop in investment prices due to technological improvement is mirrored in the rise of depreciation rate of the current capital stock. In this sense, P_I represents a price index adjusted for the quality of the capital stock. To compute the labour share we multiply both sides of equation 3.14 by w/y,

$$LS = \frac{w}{y} \left(\frac{1-\alpha}{\alpha} \right)^{\epsilon} \frac{P_I^{\epsilon} k_I}{(w + c_v)^{\epsilon}} \tag{3.15}$$

and finally we use constraints 10 and 11 to solve for y and substitute it into equation 3.15, obtaining the final expression for the labour income share

$$LS = Hw \left(\frac{P_I}{w + c_v} \right)^{\epsilon} \frac{k}{P_{NI}^{\sigma}}, \tag{3.16}$$

where $k = \frac{k_I}{k_{NI}}$ and $H = \left(\frac{1-\alpha}{\alpha}\right)^{\epsilon}$. The economic prediction of the model originates from the combination of the elasticity parameter ϵ, the costs and the quantities of the inputs. Given the flat evolution of the non-ICT relative price in Figure 3.2, we clarify the implications of two different ranges of values of ϵ, under a unitary elasticty σ:

- if $\epsilon = \sigma = 1$, the two functions are of the type Cobb-Douglas. Interestingly, if we assume no hiring costs, we end up with a LS affected only by the investment price ratio and the stock ratio of ICT and non-ICT. Given an elasticity between ICT and non-ICT capital equal to one, deviations of both price and stock ratios cannot provoke a decline in the labour share. This implies that, in order to predict changes of the factor shares in a Cobb-Douglas setting, one should embed some degree of imperfection in the labour market[9];

- if $\epsilon \neq 1, \sigma = 1$, labour and ICT may be employed as complements or substitutes into the production and changes in the ICT price have different impact on the labour share. To see that, we derive the change of the LS with respect to P_I:

$$\frac{\partial LS}{\partial P_I} = Hw\epsilon \frac{P_I^{\epsilon-1}}{(w+c_v)^{\epsilon}} \frac{k}{P_{NI}}. \tag{3.17}$$

If ϵ is lower than one, a decline in the ICT price increases the labour share, because the price change is higher than the stock change. Conversely, if the elasticity is higher than one, the labour share declines because the ICT stock increases more than the downfall of the ICT price. While an elasticity equal to one would imply no role for the ICT price, the model predicts a negative effect of hiring costs on the labour share, irrespective of any parameter.

3.5 Data

Our analysis uses country-level data from EU KLEMS on compensation and number of employees, stock, depreciation, investment and price index of ICT as well as of non-ICT capital. Most of the observations are available between 1970 and 2007, while for Germany we have two series, one from 1970 to 1991 and the other from 1991 to 2007, which we merged using the overlap in 1991 in level. We focus on the labour share of employees, which we compute that as compensation of employees over value added.

Concerning the total vacancy cost, we set

$$cv = c_m m + c_u u, \tag{3.18}$$

where m is the number of matches, u is the number of unsuccessful vacancies and c_m, c_u are the relative costs. For the matches, we consider the number of workers flowing

[9]It would be equivalent to assume frictions in the capital markets, that we exclude here.

into employment from inactivity, unemployment and job-to-job transitions per year[10]. Information on this total flow into employment is available in the Eurostat database only for the period from 2010 to 2012. Therefore, we use the ILO annual flow rates from unemployment to employment and the OECD unemployment level data to construct a time series of worker flows beginning in 1984. However, this series does not comprise flows into employment from inactivity and job-to-job transition. As a consequence, we calculate an average country-specific scale factor α between the Eurostat and the ILO/OECD series using the time span in which they overlap (2010-2012). Assuming that α is constant over time, it can be applied to the ILO/OECD series to estimate the total worker flow into employment for the period before 2010[11].

According to the Data Warehouse of the German Federal Employment Agency, unsuccessful vacancies amount to 46 percent of the matches[12].

Regarding the cost of the matches c_m, we consider the search costs, the adaptation costs (initial training and lower productivity) and the opportunity costs. In this regard, we can take advantage of the results of Carbonero and Gartner (2017) and Mühlemann and Pfeifer (2016) who make use of unique survey results in order to measure the full cost of the hiring process. Our best move is to assume the shares of these costs in the wage as constant. As a plausibility check, we tested that the share of search costs changed by less than one percent between 2007 and 2014 in Germany[13]. Therefore vacancy and adaption costs for one vacancy are calibrated as 14 percent of the annual compensation per employee (5% are the search costs and 10% are the adaptation costs). We can assess the reliability of these numbers for the whole sample, by looking at the standard calibrations in the search and matching models. Search costs are generally calibrated as 30% of monthly output (see Cahuc and Le Barbanchon, 2010; Pissarides, 2009). Wages are about half of the output, then search costs correspond to 60% of monthly wages, or 5% of yearly

[10] We calibrate the job-to-job transitions as 40 percent of all the separations from employment, in line with Fallick and Fleischman (2004), Nagypál (2005) and Hobijn and Sahin (2007).

[11] The correlation between the unemployment levels from ILO, OECD and the Eurostat dataset is larger than 0.99.

[12] The series dates back only to December 2000; therefore we focus on a range between 2000 and 2003.

[13] We compared the search costs in Mühlemann and Pfeifer (2016) and those in Carbonero and Gartner (2017).

wages, that is the value we extracted.

We define the opportunity cost as the foregone profit that arises when the filled vacancy becomes productive later than expected by the employer. Using the wave 2014 of the German Job Vacancy Survey (JVS) of the Institute for Employment Research (IAB), we find that the timespan between the date the employer expects to fill the vacancy and the beginning of the employment relationship is 22 days on average. Therefore, we compute the opportunity cost as annual labour productivity minus the annual wage, weighted by the duration of the opportunity cost.

Concerning the cost of an unsuccessful vacancy c_u, we consider the vacancy costs and the opportunity costs only. We do not have information on the cost spent on an unsuccessful vacancy, but we can infer it from the duration of the vacancy. From the JVS we know that an unsuccessful vacancy lasts on average 140 days (in contrast to the 59 days of a successful vacancy). We combine this information with the result of Carbonero and Gartner (2017) on the correlation between search cost and search duration for Germany and we find that an unsuccessful vacancy costs 18 percent more than a vacancy that results in a match. Thus, we calibrate the vacancy cost as 6 percent of the annual compensation per employee. Finally, the opportunity cost amounts to the whole annual foregone profit.

We run a robustness check to allow for the possibility that an unsuccessful vacancy is followed by a new vacancy. According to the JVS in 2014, 79 percent of the unfilled vacancies become new vacancies. For these cases, we assume that the employer manage to fill the position in the second round; thus, the opportunity costs refer only to the period between the expected filling date in the first round and the starting date of the employment relationship in the second round. For the remaining 21 percent of the unfilled vacancies, we count as the opportunity cost the period between the expected filling and the rest of the year. Overall, the estimates from this calibration do not bring to different conclusions.

3.6 Estimation

The impact of the ICT investment price on the labour share is closely related to the elasticity of substitution between labour and ICT capital, as we have seen in Section 3.4. In order to estimate this elasticity, we take the log of equation 3.16 and we provide two specifications, one without and one with hiring costs

$$lnLS_{it} = a_i + \epsilon ln\frac{P_{I,it}}{w_{it}} - \sigma lnP_{NI,it} + lnw_{it}k_{it}, \tag{3.19}$$

$$lnLS_{it} = a_i + \epsilon ln\frac{P_{I,it}}{w_{it} + c_{v,it}} - \sigma lnP_{NI,it} + lnw_{it}k_{it}. \tag{3.20}$$

We use these empirical equations to check the theoretical predictions. As implied by the theoretical model, in both equations the coefficient of the last term is one; thus, the results will concern only the elasticity parameters ϵ and σ. In addition to these parameters, we provide an estimate of the elasticity between aggregate capital and labour using a reduced CES function with only two inputs.

Table 3.2 reports the estimate with country fixed effects and cross-section weights. Columns 1 and 2 refer to the elasticity between aggregate capital and labour. Under the assumption of perfect labour markets, the elasticity is 0.97, while by accounting for hiring costs, we obtain a value of 0.7. This range of values places our paper in line with a large bulk of the literature, including both of worldwide analyses and US analyses.

We then proceed to estimate our core model, which is represented by equations 3.19 and 3.20 displayed in columns 3 and 4. The elasticity of substitution between ICT and labour is 1.18 and significantly different from 1, which means that a decline of the ICT price of one percent generates an increase of the ICT stock over labour of 1.18 percent. Thus, the ICT price is a plausible channel to explain the evolution of the labour share, and the CES function is a good candidate to model it. Instead, the estimated elasticity of non-ICT capital with the rest of the inputs is not statistically different from one[14], namely the compounded production function seems to be of the form Cobb-Douglas.

[14] This result is robust to the inversion of the inputs into the CES function.

Table 3.2: Estimation of the labour share function with country FE. Dependent variable: logarithm of the labour share. Robust standard errors in parentheses.

Specification	1	2	3	4
ϵ			1.18***	1.13***
			(0.02)	(0.02)
σ			1.20	0.96
			(0.17)	(0.21)
$Aggregate$	0.97	0.70***		
	(0.04)	(0.05)		
Hiring costs		Yes		Yes
N	196	196	196	196
R^2	0.97	0.94	0.96	0.95

Column 1 and 2 refer to the elasticity of substitution between aggregate capital (ICT and non-ICT) and labour. *, **, *** indicate coefficients are different from one at the 0.10, 0.05, 0.01 significance level.

In what follows we address three main issues related to our results and to the trend of the labour share. First, which portion of the labour share decline is explained by the fall in ICT price? To answer this point, we compute the labour share using equation (19) and compare it with the actual labour share. Focusing on the time span 1986-2007, i.e. when the fall in ICT price is visible for most of the countries, equation (19) generates a falling labour share, which is not the case with an elasticity $\varepsilon = 1$. Indeed, we find that an elasticity between ICT and labour of 1.18 explains one third of the overall decline of the labour share. This is a bit less than the portion found by Karabarbounis and Neiman (2014). If we consider the period since 1992, from whereon the aggregate labour share continuously declined, with the same elasticity, equation (19) explains 60% of the fall in the labour share.

Second, the adoption of a certain type of technology is one of the determinants of the labour share. The sample we use includes the major European countries, where institutions and regulations in general play a key role in the labour market. Therefore we assess the robustness of equation (19) by taking into account potential omitted variable biases. Relevant institutions for the labour share development concern market power in the goods and in the labour market. We approximate these magnitudes by indices of the profit share and collective bargaining coverage. The estimated elasticity turns out to be 1.14 - still enough to explain a substantial drop of the labour share due to the ICT price[15].

Third, in this paper we use a standard measure for the labour share. Some authors have pointed out that the trend in the labour share may hide sectoral specific trends (Elsby et al., 2013) or a mis-allocation of the national income between capital and labour in the computation of the factor shares (Aum et al., 2018). Concerning the first critique, Karabarbounis and Neiman (2014) provided evidence that the decline is essentially within sectors. To answer the second critique, we took the extreme case of the point raised by Aum et al. (2018) and attribute the entire value of Intellectual Property Products (IPPs) to labour[16]. Our IPPs-corrected labour share, just as in Aum et al. (2018), still falls significantly over the time period considered in this paper, which is arguably the relevant period regarding the use of ICT capital. Looking at the regression, the elasticity of substitution with the IPPs-corrected labour share is 1.21, statistically different from one at 1% level, even larger than our 1.18.

We now turn to the model that accounts for the hiring costs. With this exercise, we can assess the plausibility of the substitution effect, depending on whether the elasticity parameter moves closer to or further from one. More precisely, an elasticity larger than 1.18 would imply that hiring costs exacerbate the substitution between labour and ICT. Conversely, an elasticity closer to (or even lower than) one means that computers and labour turn out to be less substitutable once search costs are considered. This cost, however, reduces the demand for labour and the labour share.

The results of the estimation of equation 3.20 are displayed in the last column. We estimate the elasticity by calibrating the term cv as explained in Section 3.5. In this case, we end up with an elasticity of substitution between ICT and labour of 1.13, lower than the elasticity without hiring costs but still significantly larger than one. This finding

[15] Karabarbounis and Neiman (2014) include the markup in their theoretical analysis of the labour share. Empirically they come to the same conclusion.

[16] This case represents the upper bound, because the lower the share of IPPs in labour income, the closer we get to our reference estimates in Table 3.2.

implies that a decline in the labour share is still explained by the drop in the ICT price, but at a lower intensity.

We note that introducing frictions via hiring costs in the model limits the substantial effect of ICT on the labour share. In the following, we explore the economic significance of this result. In details: Which part of the labour share development is not explained anymore by ICT, and what is instead explained by hiring costs? To visualize the loss in explanatory power of ICT, we compute the difference between the labour share resulting from equation 3.16 with the elasticities excluding (1.18) and including (1.13) hiring costs. We do the same for the hiring cost measure and compute the difference between the labour share with constant (average across time) hiring costs and with annual hiring costs as in the regression.

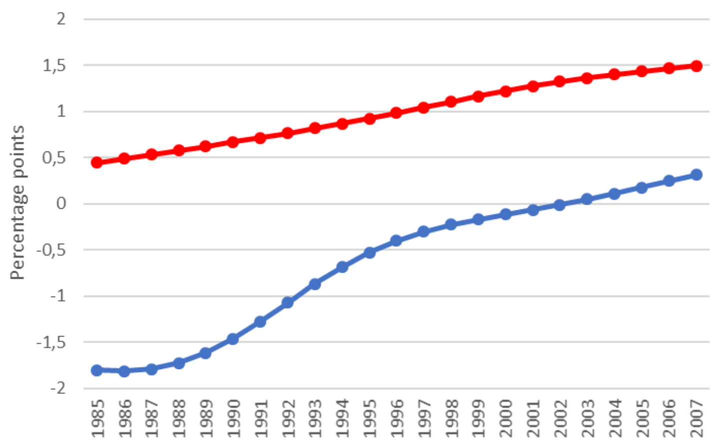

Figure 3.5: Gain in the explanatory power of hiring costs (blue line, HP trend) for the labour share vs the loss of ICT price (red line). Source: own calculation)

Figure 3.5 displays these two series, namely, the loss of and the gain in the explanatory power of the ICT price and hiring costs, respectively. While transitory fluctuations at the beginning differ, the similar trending behavior suggests that the portion of reduction of the labour share that is not provoked by the substitution effect is fairly well explained by the hiring cost effect. On average, between 1992 and 2007, ICT price loses 1.2 percentage points of reduction in labour share, corresponding to one third of its explanatory power, taken over by hiring costs.

3.7 A time-varying analysis of the elasticity of substitution

The second part of the empirical analysis seeks to verify the extent to which the impact of ICT on the LS varies with structural and institutional characteristics. Thus, we try to explain the elasticity of substitution between labour and ICT capital. As it was shown above, in times of strong ICT price decline, this elasticity is crucial for the labour share development.

Among the institutional factors, we consider the role of a set of core labour market regulations: firing restrictions, the wage bargaining level, union density and the unemployment benefit replacement rate. By limiting the reallocation of workers or by discouraging reentry into employment, these institutions might indeed affect the substitution between labour and capital and induce to a more capital-intensive production. Wage bargaining has unclear effects on the labour share, given that it influences mainly the wage dispersion, as shown in Dahl et al. (2013).

Concerning the labour force decomposition, we investigate whether the elasticity of substitution between labour and ICT comoves with the share of high-skill workers and with the share of workers in routine tasks. Thus, we can directly test the capital-skill and the job polarization hypotheses.

For this purpose, we adopt a panel-varying coefficient approach that allows for persistence and stochastic shocks. We use employment per occupation from EUROSTAT to compute the employment share of routine occupations of the European countries in our sample, while for the US we adopt employment from ILO. The share of high-skill workers is computed using the employment per skill group from EU KLEMS. Finally, concerning labour market institutions, we use the employment protection legislation, the unemployment benefit replacement rate from the OECD and the wage coordination and the union density from the ICTWSS[17].

[17] Database on Institutional Characteristics of Trade Unions, Wage Setting, State Intervention and Social Pacts from 1960 to 2014

3.7.1 The PVC Model

Binder and Offermanns (2007) have suggested a model for functional coefficient dependence in an error-correction cross-country panel data framework. In particular, their approach is parsimonious as it employs the homogeneity argumentation within the pooled mean group (PMG) model of Pesaran et al. (1999): due to the different nature of mainly idiosyncratic short-run fluctuations versus the more structurally founded long-run equilibrium relationship, it appears straightforward to generalize the homogeneous long-run parameters to homogeneous functions of conditioning variables.

Although this approach entails a large degree of flexibility by employing orthogonal polynomials in the conditioning variable, it may not be suited to all models of state-dependent effects. In particular, the strict homogeneity assumption on the functional form across countries might not always be appropriate beyond the PMG framework. Here, we wish to generalize the functional coefficient dependence idea of Binder and Offermanns (2007) in three aspects: first, we allow for a country-specific fixed effect in the otherwise homogeneous functional form. Second, we introduce stochastic variation in the final effect through a state-space specification. This will enable the model to generate variation also across time, even if the candidate conditioning variable does not prove to have a significant impact on the final effect. Third, our modification to the state-space framework will allow us to account for more than one conditioning variable, which was practically not feasible in the Binder and Offermanns (2007) approach, at least for desirable degrees of flexibility.

These aspects appear to be desirable features for a model of the elasticity of substitution between labour and ICT capital. The approach outlined above enables us to generalize the fixed-effect panel regression model with interaction terms to a model where the elasticity is specified as a latent variable which is determined by a panel state-space representation. This framework has two main advantages. First, it solves the problem of the unit of measurement coming from a simple interaction between the covarying variables and the regressor of the elasticity: while the interaction approach is sensitive to linear transformations of the interaction variable, the state space approach is not. Second, it should be less subject to criticism concerning the right choice of the conditioning variable: if a candidate variable has no impact on the elasticity, the estimation is able to "reject" its influence in favor of an idiosyncratic stochastic time-varying elasticity. In case of the interaction approach, the estimation would have to reject it in favor of a constant homogeneous elasticity.

In the current section, the econometric framework for estimating the panel-varying coefficient (PVC) model is presented in a generic notation. Our model is given as follows:

$$y_{it} = c_i + \theta_{it}(s_{it})' x^*_{it} + \gamma' \omega_{it} + u_{it}, \qquad u_{it} \sim N(0, \sigma^2) \tag{3.21}$$

where c_i is the (mean) fixed effect, $\theta_{it}(s_{it})$ represents the vector of PVCs of the corresponding set of k^* regressors x^*_{it} conditional on the vector s_{it}, and γ denotes the m-dimensional vector of coefficients of the set of regressors w_{it}. The r-dimensional vector s_{it} represents a set of exogenous indicators (the conditioning variables) that are supposed to drive the final effect of x^*_{it} on y_{it}, the vector θ_{it}.

In order to implement the model, we slightly change its notation and specify the following state space model:

$$y_{it} = z'_{it} x_{it} + \gamma' \omega_{it} + u_{it}, \qquad u_{it} \sim N(0, \sigma^2) \tag{3.22}$$

$$z_{it} = \delta_i + A z_{i,t-1} + B s_{it} + v_{it}, \qquad v_{it} \sim N(0, Q) \tag{3.23}$$

where the vector $x_{it} = (1,\ x^{*\prime}_{it})'$ has dimension $k = k^* + 1$ and comprises the regressors x^*_{it} as well the constant, A is a $k \times k$ diagonal coefficient matrix, and $B = (0,\ \beta_2,\ \dots,\beta_k)'$ has dimension $k \times r$. The first element of the k-dimensional latent variable vector z_{it} is determined to capture the time-invariant fixed effect, and the remaining $k - 1$ elements $z_{2,it}$ to $z_{k,it}$ represent the PVCs $\theta_{j,it}(s_{it})$, $j = 1, \dots, k^*$, of x^*_{it}. In particular, the restrictions to the parameter vector δ_i and to the parameter matrices A and B (as well as to the variance matrix Q) imply the following state equations:

$$z_{1,it} = 0 + 1 \cdot z_{1,i,t-1} + 0' \cdot s_{it} + 0 \tag{3.24}$$

$$z_{2,it} = \delta_{2,i} + \alpha_2 z_{2,i,t-1} + \beta_2' s_{it} + v_{2,it}, \tag{3.25}$$

such that the fixed effect for country i, $z_{1,it} \equiv z_{1,i} = c_i$ is determined through its initial value $z_{1,i,0}$. The other PVCs $z_{j,it}$, $j = 2, ..., k$, are determined through a country-specific constant, the homogeneous coefficient α_j on their own lag, the homogeneous effect β_j of all conditioning variables, s_{it}, and the stochastic component $v_{j,it}$.

The model is estimated with a maximum likelihood approach using the Kalman filter. Hence, we obtain a sequence of conditional expectations for z_{it} given information from the previous period, i.e. $z_{i,t|t-1}$. For better interpretation, we compute the so-called smoothed states defined as $z_{i,t|T}$, i.e., estimates of the states given the end-of-sample information.

3.7.2 Setup

We hypothesize that the elasticity of substitution between labour and ICT capital is a function of employment protection legislation (EPL), the degree of wage coordination (COOR), the union density (DENS), the replacement rate (REPL) the share of high-skill workers (HSKILL) and the share of routine occupations (ROUT) in the economy.

We set our baseline specification (equations 3.22 and 3.23) as follows: for the dependent variable, we have

$$y_{it} = \ln LS_{it} - \ln w_{it} - \ln k_{it};$$

as regressors we have

$$x_{it} = (1, \quad \ln P_{I,it} - \ln w_{it}),$$

$$\omega_{it} = -\ln P_{NI,it};$$

and as conditioning variables, we have

$$s_{it} = (EPL_{it},\ COOR_{it},\ DENS_{it},\ REPL_{it},\ HSKILL_{it},\ ROUT_{it}).$$

Given the apparent non-stationarity of both, the dependent variable and the regressors, as well as the short time span of our sample, we estimate the model in first differences of y_{it}, x_{it}, and ω_{it}. By restricting the coefficient on the state variable's own lag α_2 to one, we allow for permanent deviations of the elasticity from any previous level. As this model choice implies a random walk-type evolution of the elasticity over time, we have to eliminate potentially distortionary drift effects from the other terms in the state equation by setting the intercept $\delta_{2,i}$ to zero and demeaning the conditioning variables. Note that these modifications do not eliminate the cross-sectional variation in the conditional means of the elasticity, as the initial value of the state variable is allowed to differ across countries and serves as an intercept. Finally, due to data constraints we leave Ireland out.

3.7.3 Results

Table 3.3 shows the estimation results for the state equation. Given the high insignificance of the coefficient, in column 2, we exclude $COOR$ from the regression. The most significant influences on the PVC of the adjusted ICT price are exhibited by the share of high-skill workers (negative) and the share of workers in routine occupations (positive). Interestingly, the impact of these variables on the elasticity of substitution is almost identical in opposite directions, revealing an even effect of educational (individual) and of task (job) characteristics. Logically, the elasticity of substitution hinges both on the task structure of the jobs present in an economy and on the qualification of the workers holding these jobs. To give a concrete example, the US typically has a comparably large share of high-skill workers (in our data 13 percentage points higher than the average for the European countries), which is usually rather complementary to new technologies. While this dampens the elasticity, the latter is increased by the relatively high routine share (16 percentage points higher than in Europe), since routine tasks are most easily replicable.

Among the institutional variables, employment protection legislation and union density reveal a weak negative correlation, in line with the view that these institutions protect the labour force from layoffs in the course of reallocation. This influence seems to have overweighed potential adverse effects that emerge if protection disincentives new hirings. The replacement rate instead displays a positive correlation with the elasticity of substitution. This result should be expected if a higher replacement rate leads to a longer unemployment duration[18]. When technological change steadily requires the reallocation of workers, longer unemployment periods lower the average employment level that can be reached. Hysteresis effects can aggravate this development. Also regarding institutions, the US-Europe comparison is ambivalent, demonstrating the benefits of a differentiated approach: while the low employment protection and union density in the US increase the country's elasticity, its low replacement rates decrease it.

In order to make a quantitative assessment of the explaining power of the model, we calculate the fitted values of the regression in Table 3.3 (right column), i.e. $\beta \vee_2 s_{it}$ from equation (25). Namely, this is the part of the elasticity that can be traced back to our explaining variables. When looking at the fitted values in 2005 (the last year where the data set is complete for all variables), we get a standard deviation of the fitted values in the different countries of 0.15. Logically, the standard deviation of the elasticities in the sample countries explained by the variables in Table 3.3 is quite substantial. For instance, reconsidering the results from Table 3.2, an elasticity of 1.00 versus 1.15 would have strong implications for the labour share development.

Two main drivers play a major role for these differences. First, countries with a high share of routine occupations also demonstrate a high elasticity of substitution between labour and ICT capital. A pattern we can observe, indeed, is that countries with a high share of routine labour display also a large elasticity of substitution. This finding is consistent with the job polarization view and with the idea that the replacement effect

[18] See Bover et al. (2002) and Layard et al. (2005) on the relationship between unemployment benefit and unemployment duration.

between labour and ICT affects mainly those occupations involved in repetitive tasks. Moreover, given the connection of the elasticity of substitution and the labour share, the results imply that the decline of the labour share might have been more marked for countries with a larger share of workers in routine occupations. Second, new technologies are complementary with skilled labour, in line with the skill-biased technological change view. As above, the insight from Table 3.3 is that countries with a high share of skilled workers might display a smoother decline or even an increase of the labour share. Overall, institutions seem to have a certain - albeit partly measured - effect, as found by Elsby et al. (2013) and OECD (2012).

Table 3.3: Effects of the conditioning variables on the elasticity of substitution between ICT and labour. Eight Countries, time period 1995 - 2005. *Impact* is computed as the coefficient times the standard deviation of the variable.

Determinants of the coefficient of $D(\ln P_{I,it}/w_{it})$		
HSKILL	−1.389	−1.378
p-value	0.173	0.077
impact	−0.096	−0.095
ROUT	1.382	1.389
p-value	0.117	0.113
impact	−0.093	0.094
EPL	−0.067	−0.067
p-value	0.289	0.216
impact	−0.054	−0.055
REPL	0.614	0.615
p-value	0.198	0.198
impact	0.085	0.086
DENS	−0.238	−0.237
p-value	0.291	0.281
impact	−0.046	−0.046
COOR	−0.001	-
p-value	0.987	-
impact	−0.001	-

3.8 Conclusion

The decline in the labour share and the relative increase in the capital share are becoming increasingly prominent topics in economic research. This is due to their implications for income distribution and the role of the labour input in the future. We provide an explanation for this trend considering the most recent facts on technological progress and the labour markets. We consider the evolution of the ICT investment price together with job polarization and search frictions. Theoretically, we predict a decline in the LS through two mechanisms: an ICT-labour substitution effect and a hiring cost effect. We test the plausibility of the two mechanisms by estimating the elasticity of substitution between ICT and labour.

Our results with aggregate capital (i.e., ICT and non-ICT) and labour reveal weak support for a substitution effect, a finding well established so far in the literature to date. Instead, when we disaggregate capital input into ICT and non-ICT assets, we find an elasticity of substitution between labour and ICT of 1.18. This implies that a decline of one percent in the relative ICT price is associated with an increase of ICT capital stock over labour of 1.18 percent, generating a decline in the labour share. If we include labour market frictions into our model, the elasticity shrinks to 1.13 and we show that part of the explanatory power of the substitution effect is lost in favour of the hiring cost effect.

In a second step, we analyze the determinants of ICT-labour elasticity. For this purpose, we model the latter as a function of country-specific institutional and structural labour market variables by applying an extension of Binder and Offermanns (2007) that allows for stochastic shocks through a state-space specification. We find that stronger institutions have differentiated impacts on the elasticity. Moreover, most importantly, we find that the employment share of routine occupations (high-skill workers) is positively (negatively) associated with the elasticity of substitution between labour and ICT. In particular, we show that job and individual characteristics likewise affect the impact of technological change on the labour market.

Our result connects in a direct way the job polarization and the skill biased technological change to the macroeconomic trend of the labour income share. By the same token, Hutter and Weber (2017) find in a study for Germany that increasing wage inequality just as skill-biased technical change reduces overall employment. In general, this connection between the structure and the level of employment provides interesting opportunities for future research.

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4 Final remarks

This thesis provides a macroeconomic overview of the impact of technology on the labour markets and offers the empirical evidence to some key facts of labour market frictions. With novel data at establishment level I shed light on the cost of a vacancy and its duration and I provide an empirical evaluation of the macroeconomic properties of the search and matching models. Furthermore, chapter 3 shows that search costs can contribute to the decline of the labour share.

With a closer look to technology, the results of chapter 1 and 3 show that worldwide employment is actually threatened by both computer, software and communication equipment and robots. On the one side, ICT has witnessed a dramatic drop in the investment costs that has proved to be responsible for a substantial degree of substitution between capital and labour. In particular, it gives an explanation to the decline in the labour income share in eight European countries and the US between 1970 and 2007. On the other side, the most recent wave of technological change, that has seen the diffusion of robots (especially in the manufacturing sector), has affected negatively employment in the relevant sectors, between 2005 and 2014. The novel result is that, while the impact in developed countries is low (in line with the flourishing literature), in developing countries the negative effect on employment is up to 11 percent. Moreover, Chapter 1 adds to the literature on off- and re-shoring and provides a sizable negative effect of the re-shoring trend due to robotization on employment in developing countries.

Despite the clear indications produced in this thesis on the impact of technology, ICT and robots are two of the many ingredients of the recent technological change. The frontier of the research, indeed, is currently trying to understand the labour market consequences of artificial intelligence and which tasks machines can actually take over from workers. The arena is split between optimists and pessimists. I believe that much of the (negative and positive) potential of AI has yet to come and I find convincing looking at the whole spectrum of changes that can occur. In this sense, investigating the tension between the disrupting effect and the transforming effect of jobs brought by digital tools (see Fossen and Sorgner, 2019; Felten et al., 2018), appears to me a promising path for future research.

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Appendix

A1 Derivation of the demand for robots.

$$
\begin{aligned}
Y_R &= \left[(\tau_1 R_1)^{\frac{\epsilon-1}{\epsilon}} + (\tau_2 R_2)^{\frac{\epsilon-1}{\epsilon}} \right]^{\frac{\epsilon}{\epsilon-1}} \\
\partial R_i &: Y_R^{\frac{1}{\epsilon}} (\tau_i R_i)^{-\frac{1}{\epsilon}} \tau_i = P_i \\
R_i^{\frac{1}{\epsilon}} &= \frac{Y_R^{\frac{1}{\epsilon}}}{P_i} \tau_i^{\frac{\epsilon-1}{\epsilon}} \\
R_i &= \frac{Y_R}{P_i^{\epsilon}} \tau_i^{\epsilon-1}
\end{aligned}
$$

A2 Derivation of the standard deviation of the robot stock.

$$
\begin{aligned}
SD_R =& sqrt \left[\frac{\left(R_1 - \frac{R_1+R_2}{2}\right)^2 + \left(R_2 - \frac{R_1+R_2}{2}\right)^2}{2} \right] \\
=& sqrt \left[\frac{\left(\frac{R_1-R_2}{2}\right)^2 + \left(\frac{R_2-R_1}{2}\right)^2}{2} \right] \\
=& sqrt \left[\frac{(R_1 - R_2)^2}{4} \right] \\
=& \frac{R_1 - R_2}{2} = Y_R \left(\frac{\tau_1^{\epsilon-1}}{P_1^{\epsilon}} - \frac{\tau_2^{\epsilon-1}}{P_2^{\epsilon}} \right) \frac{1}{2}
\end{aligned}
$$

Table B1: Descriptive statistics across industries

Sectors	Monetary search costs (Euros)		Search hours		Search duration (days)		Comp. search costs (Euros)	
Financial services, insurance	5110	(17007)	22	(23)	84	(81)	6179	(17261)
Machinery and equipment, electrical equipment and motor vehicles	2907	(7294)	19	(17)	69	(54)	3759	(7945)
Information and communication	1378	(3010)	25	(32)	70	(70)	2573	(3790)
Mining and quarrying, electricity, gas, steam and air conditioning supply	1432	(3089)	20	(19)	72	(68)	2450	(3469)
Coke and refined petroleum products, chemicals and plastic products	1271	(3198)	22	(62)	52	(51)	2184	(4686)
Professional, scientific and technical activities	1142	(2735)	20	(18)	73	(72)	1959	(3196)
Food; textile, clothes and furniture	1219	(4081)	17	(21)	56	(63)	1780	(4555)
Wood, paper and printing	977	(3313)	20	(26)	74	(96)	1701	(3585)
Public administration and defense; compulsory social security	720	(1228)	23	(23)	65	(60)	1670	(1743)
Water supply; sewerage, waste management and remediation activities	880	(1593)	22	(37)	66	(67)	1647	(2263)
Wholesale and retail trade; repair of motor vehicles and motorcycles	1043	(3252)	18	(25)	61	(61)	1640	(3856)
Real estate activities	975	(2214)	20	(18)	60	(56)	1637	(2450)
Arts, entertainment, recreation	773	(2451)	22	(23)	58	(52)	1561	(3045)
Basic metals, fabricated metal products	904	(2734)	18	(20)	75	(78)	1547	(2919)
Transportation and storage	584	(1559)	23	(38)	67	(79)	1438	(2416)
Education	547	(1331)	26	(39)	65	(59)	1415	(1908)
Other services	442	(1060)	18	(17)	66	(70)	1052	(1481)
Human health and social work activities	569	(2171)	15	(18)	70	(97)	981	(2244)
Construction	341	(895)	16	(23)	81	(87)	875	(1322)
Accommodation and food service activities	343	(1250)	18	(29)	64	(66)	765	(1511)
Administrative and support service activities	289	(817)	19	(35)	63	(85)	741	(1185)
Agriculture, forestry and fishing	189	(923)	15	(19)	67	(74)	588	(1130)
Overall mean	920	(3652)	19	(28)	67	(75)	1576	(4051)

Mean and standard deviation (in parenthesis), weighted values. 9,048 observations. Source: German Job Vacancy Survey 2014 and 2015. The survey weights are based on strata for 23 economic sectors and 7 firm size classes.

Table B2: Sector coefficients of Model 3

Dependent variable:	log of compounded search costs
Agriculture, forestry and fishing	−0.73***
	(0.10)
Food; textile, clothes and furniture	−0.36***
	(0.08)
Wood, paper and printing	−0.2*
	(0.09)
Coke and refined petroleum products, chemicals and plastic products	−0.08
	(0.08)
Basic metals, fabricated metal products	−0.31***
	(0.08)
Machinery and equipment, electrical equipment and motor vehicles	-
	-
Mining and quarrying; electricity, gas, steam and air conditioning supply	0.25
	(0.08)
Water supply; sewerage, waste management and remediation activities	−0.08***
	(0.08)
Construction	−0.35
	(0.08)
Wholesale and retail trade; repair of motor vehicles and motorcycles	−0.29***
	(0.08)
Transportation and storage	−0.33***
	(0.09)
Accommodation and food service activities	−0.7***
	(0.08)
Information and communication	0.24***
	(0.08)
Financial services, insurance	0.17**
	(0.08)
Real estate activities	0.3*
	(0.08)
Professional, scientific and technical activities	0.03***
	(0.07)
Administrative and support service activities	−0.57
	(0.07)
Public administration and defense; compulsory social security	−0.12***
	(0.07)
Education	−0.36
	(0.08)
Human health and social work activities	−0.57***
	(0.07)
Arts, entertainment, recreation	−0.23***
	(0.09)
Other services	−0.11**
	(0.08)

Robust standard errors in parentheses. Reference group: Machinery and equipment, electrical equipment and motor vehicles.
Significance levels: *, ** and *** indicate significance at 0.05, 0.01 and 0.001

Table B3: OLS and IV regressions: Search cost and search duration for academics, vocational training and no qualification

Dependent variable:	Academics		Vocational training		No qualification	
log of compounded search costs	OLS	IV	OLS	IV	OLS	IV
log of search duration	0.16***	−0.11	0.21***	−0.20	0.20	0.20
SE	(0.03)	(0.36)	(0.01)	(0.28)	(0.03)	(0.83)
R^2	0.41	0.37	0.34	0.22	0.23	0.24
N	1861	1861	6584	6584	1317	1317

Robust standard errors in parentheses. 9,048 observations. Controls are the same as in the table in the text. Significance levels: *, **, *** indicate significance at 0.05, 0.01 and 0.001.

Table B4: OLS and IV regressions: Search cost and search duration for manufacturing and services

Dependent variable:	Manufacturing		Services	
log of compounded search costs	OLS	IV	OLS	IV
log of search duration	0.22***	−0.25	0.19***	−0.30
SE	(0.02)	(0.31)	(0.02)	(0.28)
R^2	0.41	0.29	0.38	0.24
N	4244	4244	5204	5204

Robust standard errors in parentheses. 9,048 observations. Controls are the same as in the table in the text. Significance levels: *, **, *** indicate significance at 0.05, 0.01 and 0.001.

Table B5: OLS regression: Search cost and search duration, reference specification vs 3-digit occupational fixed effects

Dependent variable:	Ref. specification	Occupational fixed effects
log of compounded search costs		
log of search duration	0.20	0.20
SE	(0.01)	(0.01)
R^2	0.39	0.29
N	9048	9048

Robust standard errors in parentheses. 9,048 observations. Controls are the same as in the table in the text. Significance levels: *, **, *** indicate significance at 0.05, 0.01 and 0.001.

Table B6: IV regressions: Search cost and search duration with instruments tightness and vacancy-unemployment separately

Dependent variable:	tightness	$\ln v$, $\ln u$
log of compounded search costs		
log of search duration	−0.35	−0.35
SE	(0.25)	(0.23)
R^2	0.22	0.22
N	9048	9048

Robust standard errors in parentheses. 9,048 observations. Controls are the same as in the table in the text. Significance levels: *, **, *** indicate significance at 0.05, 0.01 and 0.001.

C1 Derivation of the labour share function.

We derive the first order conditions from:

$$\mathcal{L} = \left\{ \beta \left[\alpha k_I^{\frac{\epsilon-1}{\epsilon}} + (1-\alpha) n^{\frac{\epsilon-1}{\epsilon}} \right]^{\frac{\epsilon(\sigma-1)}{(\epsilon-1)\sigma}} + (1-\beta) k_{NI}^{\frac{\sigma-1}{\sigma}} \right\}^{\frac{\sigma}{\sigma-1}} - wn - cv$$

$$- p_I i_I - p_{NI} i_{NI} + \lambda_n [vq(\theta) - ns]$$

$$+ \lambda_I [\delta_I k_I - i_I] + \lambda_{NI} [\delta_{NI} k_{NI} - i_{NI}]$$

$$\partial n : \left(\frac{\sigma}{\sigma-1}\right) y^{\frac{1}{\sigma}} \frac{\epsilon(\sigma-1)}{(\epsilon-1)\sigma} \beta (k_I n)^{\frac{\sigma-\epsilon}{\sigma(\epsilon-1)}} (1-\alpha) \frac{\epsilon-1}{\epsilon} n^{-\frac{1}{\epsilon}} - w - \lambda_n s = 0$$

$$y^{\frac{1}{\sigma}} \beta (k_I n)^{\frac{\sigma-\epsilon}{\sigma(\epsilon-1)}} (1-\alpha) n^{-\frac{1}{\epsilon}} = w + \lambda_n s$$

$$\partial v : -c + \lambda_n q(\theta) = 0$$

$$\lambda_n = \frac{c}{q(\theta)}$$

By substituting λ_n we obtain

$$y^{\frac{1}{\sigma}} \beta (k_I n)^{\frac{\sigma-\epsilon}{\sigma(\epsilon-1)}} (1-\alpha) n^{-\frac{1}{\epsilon}} = w + \frac{cs}{q(\theta)}$$

$$n^{\frac{1}{\epsilon}} = \frac{y^{\frac{1}{\sigma}} \beta (k_I n)^{\frac{\sigma-\epsilon}{\sigma(\epsilon-1)}} (1-\alpha)}{w + \frac{cs}{q(\theta)}}$$

$$n = \frac{y^{\frac{\epsilon}{\sigma}} \beta^{\epsilon} (k_I n)^{\frac{\sigma-\epsilon}{\sigma(\epsilon-1)}\epsilon} (1-\alpha)^{\epsilon}}{(w + \frac{cs}{q(\theta)})^{\epsilon}}$$

Now, with respect to ICT capital

$$\partial k_I : y^{\frac{1}{\sigma}} \beta (k_I n)^{\frac{\sigma-\epsilon}{\sigma(\epsilon-1)}} (\alpha) k_I^{-\frac{1}{\epsilon}} = -\lambda_I \delta_I$$

$$\partial i_I : -p_I - \lambda_I = 0$$

$$\lambda_I = -p_I$$

By substituting λ_I we obtain

$$k_I = \frac{y^{\frac{\epsilon}{\sigma}} \beta^{\epsilon} (k_I n)^{\frac{\sigma-\epsilon}{\sigma(\epsilon-1)}\epsilon} \alpha^{\epsilon}}{(p_I \delta_I)^{\epsilon}}$$

We use the first order condition for capital ICT to substitute $y^{\frac{\epsilon}{\sigma}} \beta^{\epsilon} (k_I n)^{\frac{\sigma-\epsilon}{\sigma(\epsilon-1)}\epsilon}$ into n

$$n = \left(\frac{1-\alpha}{\alpha} \right)^{\epsilon} \frac{(p_I \delta_I)^{\epsilon} k_I}{\left(\frac{cs}{q(\theta)} + w \right)^{\epsilon}}$$

By using the FOC with respect to non-ICT capital and by multiplying the last expression by w/y, the labour share ends up having the following expression:

$$LS = (1-\beta)^{\sigma} \left(\frac{1-\alpha}{\alpha} \right)^{\epsilon} \frac{(p_I \delta_I)^{\epsilon}}{\left(\frac{cs}{q(\theta)} + w \right)^{\epsilon}} \frac{k_I}{k_{NI}} \frac{w}{(p_{NI} \delta_{NI})^{\sigma}}$$

Table B1: Employment share of occupations per task group, percent average between 1993 and 2000

Countries/Average	Abstract	Routine	Manual
Austria	31	46	22
Denmark	37	35	28
Spain	26	45	29
France	35	43	22
Germany	37	42	22
Ireland	32	42	26
Italy	27	47	26
Netherlands	45	31	24
EU	34	40	24