Chinese Imports, Offshoring, Technology, and European Workers: Three Essays in *Empirical Economics*

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Chapter 1

Introduction

Rapidly growing trade in goods and services as well as advances in technologies have created new opportunities for product markets, capital investments, and economic growth. However, they have also created threats, as the opening up to the market economy of low-income countries and technological growth raised the concerns about the future of works in advanced economies. In spite of a large number of theoretical and empirical studies in analysing the impacts of these factors on labour market outcomes, relatively little attention has been devoted to the role played by labour market institutions in this context. In this dissertation, I therefore investigate the impacts of imports from China (Chapter 2), offshoring (Chapter 3), and technological change (Chapter 4) on European workers and assess whether the effects depend on the country-specific institutional framework.

China's accession to the World Trade Organization (WTO) in 2001 was one of the significant episodes in the economies of developed countries during the last two decades. On the one hand, it has been shown that Chinese import competition induced technological upgrading in European firms from both aspects of innovation and adoption of new technologies, thus contributing to higher productivity, growth, and welfare (Bloom, Draca and Van Reenen, 2016). On the other hand, the literature on the labour market effects of Chinese import competition in specific industrialised countries reported the employment and earnings loss for workers that were most affected by Chinese imports.[1] Although, as showed in the study of Dauth, Findeisen and Suedekum (2014) for Germany, in the aggregate, losses could be more than offset by gains from export exposure. Hence, the overall employment effect may be quite country-specific, given the large variations across these countries regarding the labour market institutions.

In Chapter 2, **The China Shock, Employment Protection, and European Jobs**, which is joint work with Ronald Bachmann and Joel Stiebale, we examine the effects of Chinese import competition on transitions into and out of employment, and analyse the role of Employment protection legislation (EPL) in this context. Using comparable worker-level data for 14 European countries, we find that the increased exposure to Chinese imports was associated with higher worker flows from employment to unemployment, and with a reduced probability that unemployed workers become employed. In addition, our results suggest that while a high level of EPL shields incumbent workers against the risk of job loss due to Chinese competition, it prevents (re-)entry of individuals into employment. We also show that these effects strongly differ by worker groups and the tasks performed on the job. Therefore, despite higher benefits for insiders, stricter employment regulations may lead relatively unproductive jobs to be safeguarded, that is "creative destruction" may be prevented, at least in the short run. This in turn could imply lower productivity growth in the longer run – thus reducing the positive productivity effects found by Bloom *et al.* (2016) – and eventually lower employment in the affected sectors.

Apart from import competition in the form of final products, offshoring has also raised concerns that jobs previously held in industrialized countries will be relocated to other — particularly low-wage— countries, generating widespread and lasting job losses and inequalities. A broad literature has incorporated many of

[1]See, for example, Autor, Dorn and Hanson (2013); Autor, Dorn, Hanson and Song (2014); Pierce and Schott (2016); Bloom *et al.* (2016).

these concerns and has analysed how offshoring affects wage, employment, and displacement.[2] Economic theory regarding the role of labour market institutions in determining the impact of offshoring on unemployment predicts a non-monotonic relationship between the cost of offshoring and unemployment in the presence of collective bargaining (Ranjan, 2013). More precisely, in this model, the possibility of offshoring induces unions, foreseeing the threat of jobs moving abroad, to set lower wages and firms to hire *more* workers, as long as the offshoring cost is relatively high. Once the offshoring cost becomes sufficiently small, however, unemployment increases as it becomes profitable to substitute offshored input for domestic workers.

In Chapter 3, **Offshoring, Collective Bargaining, and European Jobs**, which is joint work with Daniel Baumgarten and Joel Stiebale, we examine the effects of offshoring on employment transitions in 20 European countries. We contribute to the existing literature in two aspects. First, by providing comparable evidence for a large number of European countries, we try to grasp a broader picture of how offshoring hits workers' jobs. Second, we analyse empirically how the offshoring effects vary with cross-country differences in collective bargaining coverage rates. Our results indicate that offshoring increases the risk that employed workers become unemployed but this effect is dampened in countries with high collective bargaining coverage. In these countries, offshoring is, however, negatively associated with transitions from unemployment to employment.

A third area on which most of the recent public debate has concentrated is the transformation of works due to advances in technologies. As with the uncertainties about the future of works in the context of globalisation, one question that arises here is whether national institutional settings play any role?

In Chapter 4, **Do labour market institutions matter? The joint impacts of technology and labour market institutions on employment structure in Europe**, I investigate the joint impacts of technology and two labour market institutions —namely, employment protection legislation and collective bargaining coverage— on the share of employment in high-, medium-, and low-wage occupations. Various sources in the literature report that technological advancements have shifted labour demands away from workers in routine jobs in the middle of the wage distribution, while increased demands for labours in non-routine cognitive and non-routine manual activities, which are usually performed by workers in the top and bottom of the wage distribution, respectively. Although the pattern of job polarisation has been observed in many developed countries, the data shows us large cross-country differences in the magnitude and extent of this phenomenon. Therefore, I try to contribute to the literature on the drivers of change in the extent of routinization among advanced countries by providing empirical evidence on the role of labour market institutions. In addition, I analyse heterogeneous effects across different worker groups, particularly with respect to gender, age, and education. By combining the industry-level data on the intensity of Information and Communication Technologies (ICT) with individual-level microdata for nine European countries, my results indicate that, first of all, consistent with the routinization hypothesis, technological change is associated with a lower share of employment in

[2] See, for instance, Hummels, Munch and Xiang (2018) for a review of the literature on the labour market effects of offshoring.

middle-wage occupations and a higher share of employment in high-wage occupations. In addition, the results suggest that while employment protection mandates seem to play a role in mitigating the extent of technology-based routinization, the contribution of collective bargaining seem to be negligible. Finally, I show some important differences between socio-demographic groups, e.g., with respect to gender, age, and skill, in the impacts of technology and labour market institutions.

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Chapter 2

The China Shock, Employment Protection, and European Jobs

Co-authored with Ronald Bachmann and Joel Stiebale

2.1 Introduction

Free trade has come under increasing scrutiny from both politicians and economists in recent years, focused particularly on the potentially adverse effects for workers in highly industrialized countries. One of the major milestones toward free trade was China's accession to the World Trade Organization (WTO) in 2001, which was accompanied by important reductions in tariffs and quotas. As a result, China's share of world manufacturing exports increased from almost 2% to 18.8% between 1991 and 2013 (Autor, Dorn and Hanson, 2016), and the share of Chinese exports to countries from the European Union relative to world manufacturing exports rose from approximately 2% in 1998 to more than 7% in 2007.[1] A number of empirical studies on individual countries have analyzed the labor-market responses and distributional consequences of exposure to Chinese trade (see next section), yet the role of labor-market institutions in shaping the labor-market effects of China's exports on industrialized countries has hardly been investigated.

In this article, we therefore analyze the effects of the large increase in Chinese exports in the early 2000s on European workers. In our analysis, we focus on the manufacturing sector as it accounts for the large majority of the increase in Chinese exports. Taking a cross-country perspective allows us to account for the effects of one of the most important labor-market institutions, employment protection legislation (EPL). We aim at answering the following research questions. First, what were the overall effects of imports from China on European workers' flows into unemployment and unemployment exit rates, and what role did the prevailing institutional framework in European labor markets, particularly EPL, play in this context? Second, which types of workers were most affected, and which types of workers benefited most from higher EPL?

To answer our research questions, we exploit comparable microdata across 14 European countries from Eurostat's European Union Labour Force Survey (EU-LFS), which contains information on employment status, occupation, and socioeconomic characteristics at the worker level. We combine these worker-level data with trade flows at the industry level from the UN Comtrade database in order to capture exposure to Chinese imports. This approach allows us to investigate the effects of Chinese imports on workers' transitions probabilities between employment and unemployment.

To account for possible endogeneity of Chinese imports, we apply an instrumental variable (IV) strategy that passes a number of robustness tests.

Our contribution to the literature is threefold. First, we provide comparable evidence on the labor-market effects of China's WTO accession for a large number of European countries, whereas the previous literature has largely focused on individual countries.[2] The focus on a large set of industrialized countries is of great importance to assess the potential costs and benefits of international trade exposure for the workers from a set of countries making up the majority of the European Union. Second, we analyze job losses and job findings (measured by worker transitions between employment and unemployment), also for various demographic groups, which

[1] Authors' calculations from Comtrade data for all EU countries except Malta.

[2] Bloom, Draca and Van Reenen (2016) is a notable exception; however, they focus on adjustments at the firm level rather than the impact on individual workers.

allows us to investigate important aspects of worker welfare. Third, we examine how the effects of imports from a low-wage country vary with cross-country differences in labor-market institutions of importing countries.

This approach allows us to shed light on the importance of EPL by analyzing how a common economic shock within industries can lead to diverse labor-market adjustments across countries, a question that is highly relevant from an economic policy point of view.

2.2 Literature

A number of studies have investigated the labor-market effects of imports from China to specific industrialized countries. For the United States, these studies generally reported larger declines in manufacturing employment and earnings of workers that were most affected by Chinese imports, with the analysis taking place at the regional level (Autor, Dorn and Hanson, 2013), the plant level (Pierce and Schott, 2016), and – most closely related to our study – the worker level (Autor, Dorn, Hanson and Song, 2014). In a related vein, Bernard, Jensen and Schott (2006) showed that increased exposure to import competition from China leads to lower probability of plant survival and to a sharp decrease in plant employment and output growth in the United States. Chan (2017) found that the effects of Chinese imports differ across US states with distinct labor-market characteristics such as union density and minimum wages.

Looking at firm-level adjustments in 12 European countries over the period 1996 to 2007, Bloom *et al.* (2016) found that higher levels of Chinese import competition caused a decrease in employment and in the share of unskilled workers at the industry level. In addition, they found that Chinese imports led to an almost 15% increase in patenting, increased adoption of information technology, and higher productivity of European firms. For Germany, Dauth, Findeisen and Suedekum (2014) found that rising imports from China and Eastern Europe had a mild adverse effect on employment at the regional level, while, in the aggregate, losses were more than offset by gains from export exposure.

Worker flows, especially job losses and hirings, have been extensively analyzed in the literature. Job loss (or the fear of job loss) has been shown to have important negative consequences for long-term earnings (see, e.g., Jacobson, LaLonde and Sullivan, 1993 for a seminal article), job satisfaction (Origo and Pagani, 2009), mental health (Reichert and Tauchmann, 2017), and overall worker well-being (Böckerman, Ilmakunnas and Johansson, 2011). Low hiring rates imply long unemployment duration, which can have major effects on human capital depreciation (Schmieder, von Wachter and Bender, 2016) and negative signaling effects (Kroft, Lange and Notowidigdo, 2013), both leading to negative duration dependence and low life satisfaction (Ochsen and Welsch, 2011). At an aggregate level, Elsby, Hobijn and Şahin (2013) showed for Organisation for Economic Co-operation and Development (OECD) countries that unemployment inflows and outflows jointly determine the dynamics of the unemployment rate. They also argued that the relative importance of the two flows for the unemployment rate depends on the institutional context of the countries analyzed.

In addition, a large literature examines the role of EPL for labor markets. In a study on seven industrialized countries, Kahn (2007) found important differences between sociodemographic groups in the impact of EPL on joblessness and temporary employment. As for the role of EPL for worker flows, higher EPL can be expected to reduce worker outflows from employment since higher costs for employers to dismiss workers make firing less attractive for a given level of productivity. Because employers are forward-looking, higher EPL also decreases vacancy creation and therefore inflows to employment. Hence, EPL lowers labor turnover but has ambiguous effects on unemployment (Mortensen and Pissarides, 1999).

Empirical evidence is in line with this theory: Higher EPL is associated with lower aggregate labor-market flows, and there is no clear association between EPL and the unemployment rate (Martin and Scarpetta, 2012). Bassanini and Garnero (2013) investigated the impact of dismissal regulations on worker flows using cross-country and time-series variation for OECD countries. Their findings point out that job protection regulations tend to reduce the rate of within-industry job-to-job transitions. However, they find no significant effect on industry switching or transitions to non-employment. Similarly, Haltiwanger, Scarpetta and Schweiger (2014) found that more restrictive labor-market regulations are associated with smaller firm-level job flows and employment adjustments, in particular in those industries and firm-size classes in which technological and market-driven factors require labor adjustments more regularly. The welfare effects of lower labor-market flows (caused by higher EPL) are not clear-cut, however, as discussed above.

Our article is also related to a large literature on the effects of international competition induced by trade liberalization more generally (e.g., Pavcnik, 2002; Trefler, 2004; Amiti and Konings, 2007; De Loecker, Goldberg, Khandelwal and Pavcnik, 2016). There is also a large literature on how the impact of trade exposure varies with occupation, education, gender, and other characteristics within a single country (e.g., Traiberman, 2019; Utar, 2018; Dauth, Findeisen and Suedekum, 2018, , to name a few recent contributions.), and on the labor-market effects of offshoring (e.g., Grossman and Rossi-Hansberg, 2008; Antras, Fort and Tintelnot, 2017) and foreign direct investment (Bachmann, Baumgarten and Stiebale, 2014). By contrast, our article focuses on the effects of international competition from China rather than offshoring from high- to low-wage countries or foreign direct investment.

Contributions in the international trade literature have argued that increased exposure to foreign competition induces domestic firms to downsize and leads to a reallocation of resources across firms (Melitz, 2003; Pavcnik, 2002). The reduction in domestic production might be partly offset, however, by firms reallocating workers to other activities. For instance, Bloom, Romer, Terry and Van Reenen (2013) developed a theory to show that Chinese competition can decrease the returns to old production activities and reduces the opportunity cost of new activities such as innovation if production factors are “trapped” inside firms because of market frictions (see also the overview of related literature in Shu and Steinwender (2019)). It is plausible that workers are more likely to be “trapped” inside firms in countries where EPL and thus firing costs are high. EPL will thus affect the speed at which firms can adjust their production process through hiring and firing and the level of reallocation of resources across firms (Aghion, Burgess, Redding and Zilibotti, 2008).

Although workers' risk of becoming unemployed might be higher when EPL is low, unemployed workers might benefit from reallocation induced by import competition, in particular when firing costs are low. During our sample period, China mainly had a comparative advantage in the production of products with low skill and technology intensity. We find it plausible that relatively unskilled workers and those performing routine tasks are most likely to be negatively affected by this reallocation process.

2.3 Data and Descriptive Evidence

In our empirical analysis, we use microdata on individual workers, in particular for their labor-market status, transitions between labor-market states, and sociodemographic characteristics, as well as data on Chinese imports at the country-sector level and on EPL at the national level. Microdata at the individual level come from the EU-LFS database, which includes all EU member states as well as Norway, Iceland, and Switzerland. For reasons of data availability with respect to both EU-LFS and the other data sources described below, our final sample of analysis consists of 14 European countries: Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Italy, Slovak Republic, Spain, Sweden, and the United Kingdom.

The EU-LFS is based on national household surveys conducted by the national statistical agencies of the participating countries. The resulting data are of high quality and are fully representative for the resident population (Eurostat, 2018). Furthermore, the underlying surveys apply harmonized concepts and definitions, for example, for the economic sector (Nomenclature of Economic Activities [NACE]) and the occupation (International Standard Classification of Occupations [ISCO]) of individual workers, which enables us to perform a cross-country comparison.

The EU-LFS data consist of repeated cross-sections of workers. As the data include information on a person's current and previous labor-market status, we can identify a worker's transitions between labor-market states. The data also enable us to compute the stock of employed, unemployed, and non-participating individuals, along with transition rates between every labor-market state by year and country. In the data, an individual's current labor-market status is defined according to the International Labour Organization (ILO) standard.[3] By contrast, the labor-market status in the previous year is based on self-perception of the interviewed person. Although these two definitions might not overlap perfectly, using both to identify labor-market flows from one year to the next is preferable to alternative approaches, which would not allow for consistent measurement across countries (see Bachmann and Felder, 2020 for details).[4] The EU-LFS data have been used in a related context by a number of other studies, for example, Angrist and Kugler (2003).

Employment protection legislation (EPL) refers to the rules governing the hiring

[3]By this standard, a person is defined as employed if he or she performed some work for wage/salary or for profit or family gain, or—if temporarily not at work—had a formal attachment to his or her job or was with an enterprise; and as unemployed if he or she was without work, currently available for work, and seeking work (ILO, 1988).

[4]As we discuss in the Appendix, and document in Table 2.A.1, dropping observations with contradictory employment status based on alternative definitions does not affect our results notably.

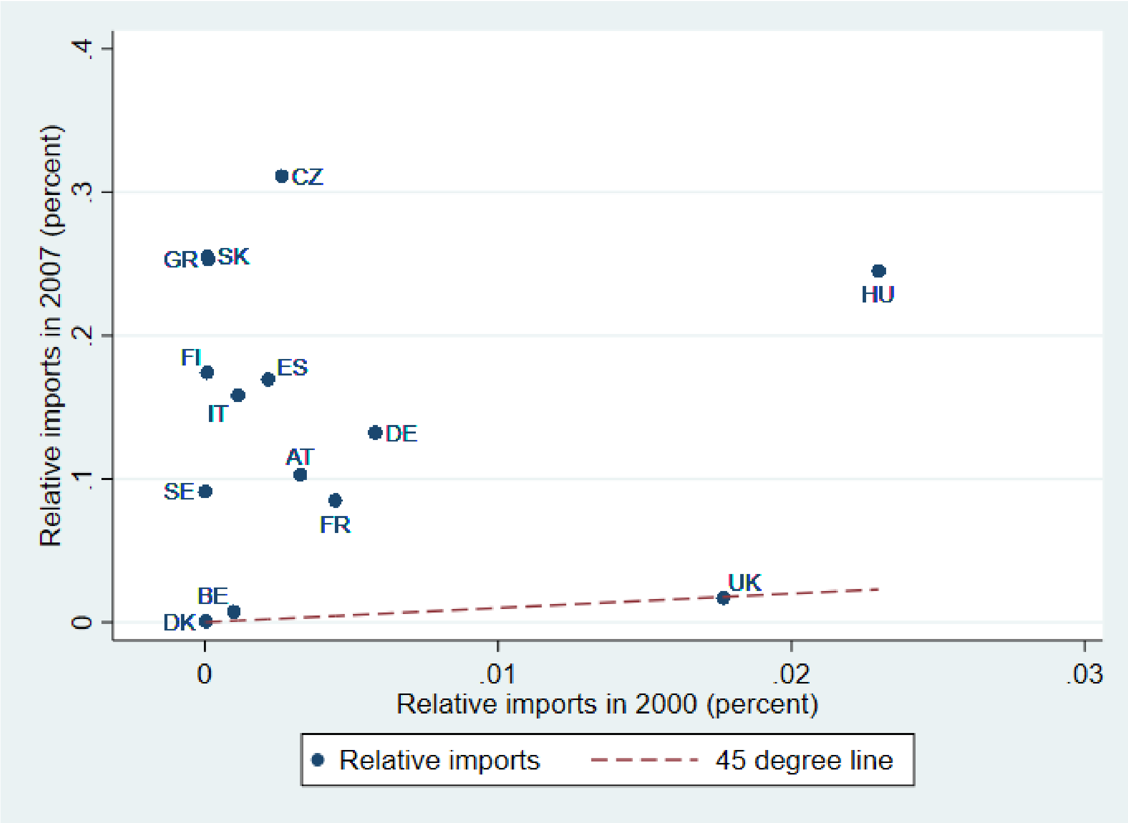
and firing of workers, which are summarized by EPL indicators constructed by the OECD (OECD, 2013). These indicators measure the requirements with respect to notification, negotiation, and authorization before an employment relationship is terminated by the employer, as well as severance pay, and the definition and costs of unfair dismissal. The more difficult and/or costly the requirements make the hiring or firing of a worker, the higher the value of the EPL indicator, which ranges from one to five. The OECD provides two main EPL indicators, one for regular workers, including provisions for collective dismissals, and one for temporary workers. As there are more regular workers than temporary workers in the countries we analyze, we select the EPL indicator that applies to regular workers for our analyses.

We provide descriptive evidence on labor-market transitions between employment and unemployment, as well as on EPL in Figures 2.A.1 and 2.A.2 in the Appendix. (Hereafter, numbering for all Appendix material is prefaced with an "A.") The transition rates generally behave very differently across the countries in our sample. While the transitions from employment to unemployment mostly display relatively strong fluctuations, the transitions from unemployment to employment are more constant over the time period analyzed. The trends in the strictness of employment protection of regular contracts for European countries in our sample are also relatively subdued. The levels of EPL for regular workers increased slightly in three countries (Belgium, France, and the United Kingdom), decreased in five countries (Austria, the Czech Republic, Finland, Slovakia, and Sweden), and remained unchanged in six countries (Denmark, Germany, Greece, Hungary, Italy, and Spain).

We obtained information on trade flows from the UN Comtrade (United Nations International Trade Statistics) database. The database contains annual bilateral imports and exports by product category for more than 170 countries. Trade values are available in various aggregations. We use data classified using 4-digit SITC (standard international trade classification) Rev. 3 codes that we match and aggregate to 3-digit industry level codes at the NACE classification using a correspondence table by the UN. A detailed description of the database can be found in Autor *et al.* (2013). The main focus of our empirical analysis is on manufacturing sectors (which account for more than 95% of trade flows in goods), although we did not drop sectors related to agriculture, mining, and fuel products (which together account for less than 5%). Data on domestic production is obtained from the OECD STructural ANalysis (STAN) database, in which production (or gross output) at current prices corresponds to the value of goods and services produced in a certain industry or occupation in country c and year t. We present descriptive statistics for our main variables of interest in Table 2.A.2.

Figure 2.1 shows the significant rise of imports originating from China as a share of domestic production for the EU countries in our sample between 2000 and 2007. This increase varies considerably across countries. For example, the share of China's imports in domestic production increased notably in the Czech Republic (from less than 0.01% of GDP in 2000 to more than 0.3% of GDP in 2007), while it remained quite low and unchanged for Denmark and the United Kingdom during this period. The share of Chinese imports in imports from all low-income countries increased from 35% to 70% during our sample period. For our sample, variation in Chinese imports across occupations, countries, and time accounts for 94% of the variance of low-income imports.

Figure 2.1: Imports from China as a Share of Domestic Production, 2000 and 2007



Sources: Comtrade, Eurostat, European Union Labour Force Survey (EU-LFS), authors' calculations.

2.4 Methodology

The aim of our empirical analysis is to identify the effects of Chinese imports on worker flows in European countries. For this purpose, we need a measure of import exposure that can be matched to individuals. One challenge in the empirical analysis is that imports are measured at the industry level but worker-level information in the EU-LFS contains sectoral information at the 1-digit level only, which is far too broad to construct a measure of import exposure. However, EU-LFS contains information about an individual's occupation at the 3-digit level. Further, we obtained information about the distribution of occupations across industries at the 3-digit level, from Eurostat's tailor-made extraction procedure.[5] We are therefore able to follow Ebenstein, Harrison, McMillan and Phillips (2014) and Baumgarten, Geishecker and Görg (2013) in assigning the industry-level variables using the distri-

[5]See https://ec.europa.eu/eurostat/documents/1978984/6037342/EULFS-Database-UserGuide.pdf; the service is available through Eurostat user support at https://ec.europa.eu/eurostat/help/support.

bution of occupations across industries. Our mapping of occupations to industries varies across countries and years to account for differences in industry composition across regions and time. It should be noted that a large number of occupations are specific to broad industries in which they are typically employed. For instance, consider workers within the group "plant and machine operators and assemblers." Examples of 3-digit occupations in our sample within that group include "metal-processing plant operators", "chemical-processing-plant operators", "textile-, fur- and leather-products machine operators", and "food and related products machine operators". We therefore believe that using occupations instead of industries to measure workers' exposure to Chinese imports is a valid strategy.

Our occupation-specific variables, that is, import exposure, as well as the industry-level control variables contained in vector W below, are constructed as:

$$Y_{oct} = \sum_{j=1}^{J} \frac{L_{ojct}}{L_{oct}} Y_{jct} \tag{2.1}$$

where Y_{oct} is a sectoral/occupation-specific variable such as import exposure for occupation o in country c at time t. Variable L is the level of employment and industries are denoted by j. The distribution of industries across occupations (L_{ojct}/L_{oct}) thus allows us to map industry-specific variables (Y_{jct}) into occupation-specific variables (Y_{oct}). We use this procedure also to define our measure of exposure to Chinese imports, IMP^{Ch}_{oct} as the value of industry/occupation o's imports from China in country c and year t relative to domestic production $(DomProd_{oct})$. As this assignment of industries to occupations is likely to introduce some measurement error, the coefficients of our ordinary least squares (OLS) and instrumental variable (IV) estimates are likely to be biased downward in absolute value.

To analyze the effects of Chinese imports on worker flows, we relate the probability of making a transition from employment to unemployment, and from unemployment to employment, to our measure of import exposure as follows:

$$Pr(U_{ioct}|E_{ioc,t-1}) = F\left(IMP_{oc,t-1}, EPL_{c,t-1}, IMP_{oc,t-1} \times EPL_{c,t-1}, X_{i,t-1}, W_{oc,t-1}, C_{c,t-1}, \alpha_c, \delta_{t-1}\right) \tag{2.2}$$

$$Pr(E_{ioct}|U_{ioc,t-1}) = F\left(IMP_{oc,t-1}, EPL_{c,t-1}, IMP_{oc,t-1} \times EPL_{c,t-1}, X_{i,t-1}, W_{oc,t-1}, C_{c,t-1}, \alpha_c, \delta_{t-1}\right) \tag{2.3}$$

Indicator variable U_{ioct} takes on value 1 if individual i working in occupation o in country c in period $t-1$ becomes unemployed in time period t; flows from unemployment to employment (E_{ioct}) are defined analogously. $IMP_{oc,t-1}$ measures the level of import exposure for an occupation — scaled by domestic production — for which the level of imports is assigned to occupations in each country using equation (2.1). EPL is a country-specific measure of employment protection. We are particularly interested in the effects of import exposure and how it varies with the level of employment protection, captured by the interaction term $IMP_{oc,t-1} \times EPL_{c,t-1}$.

In addition, we include a large number of control variables. X denotes individual characteristics, specifically, sex, marital status, age (with the categories young:

15–29 years, middle-aged: 30–54, and elderly: 55–64), and education (with the International Standard Classification of Education [ISCED] categories low: ISCED 0-2; medium: ISCED 3-4; and high: ISCED 5-6). Moreover, to account for cross-sectoral differences in production technology or competition, we control for occupation/industry-country specific control variables (W), namely, sectoral production, labor productivity, the average wage, and capital intensity; C is a vector of country-specific variables, that is, GDP per capita (in log terms) and the annual growth rate of real GDP. The variables α_c and δ_t are country and year fixed effects that control for macroeconomic changes common to all countries and permanent cross-country differences in institutions. We experiment with functional forms for $F(.)$ by estimating logit, probit, and linear probability models. As the results turn out to be very similar, we report only the results from the probit model.

Although we introduce a large set of control variables, including country, occupation, and year fixed effects, one might be concerned about possible remaining unobserved factors that lead to an increased inflow of Chinese imports, and simultaneously affect subsequent labor-market outcomes. As a result, Chinese imports might be endogenous to occupation-country-level employment outcomes. We address this issue by conducting an IV approach based on lagged import shares similar to Bloom *et al.* (2016).[6] Specifically, we use $\left(IMP_{o,1998} \times \frac{IMP_{t-1}}{IMP_{1998}}\right)$ as an instrument for $IMP_{oc,t-1}$ where IMP_{t-1} are Chinese imports to *all* European countries across industries at time period $t-1$ and $IMP_{o,1998}$ denotes import exposure of occupation o, again to all European countries, in the base period, the year 1998.

The idea behind the instrument is to capture time-series variation in Chinese supply shocks. These supply shocks are likely to have a greater impact on industries in which China has a comparative advantage (see Bloom *et al.*, 2016), which is captured by the initial conditions weight $IMP_{o,1998}$. The instrument is not country-specific to avoid some endogeneity concerns that arise when using initial conditions as instruments. This is likely to be a strong instrument as it has been shown that over the 1997 to 2005 period, more than three quarters of the aggregate growth of Chinese imports was from the expansion of existing products rather than from adding new products (Amiti and Freund, 2010). The IV specifications are implemented as a control function approach whereby residuals from a first-stage regression are inserted into second-stage probit models.

A remaining concern for the instrument described above is that the initial level of Chinese imports may be correlated with unobservable characteristics at the occupation level that determine subsequent labor-market outcomes. We believe this outcome is unlikely since the initial level of Chinese imports is likely to reflect past comparative advantage of China rather than European labor-market conditions. Nonetheless, as a robustness check, we use an alternative IV, the exposure to Chinese imports at the occupational level in the United States ($IMP^{US}_{o,t-1}$). As this measure has substantial variation within occupations over time, this specification allows us to control for occupation fixed effects.[7]

[6]In contrast to Bloom *et al.* (2016), our import exposure variable and the corresponding instrument are specified in levels rather than differences over time since we are unable to follow individuals over a long time period.

[7]While our benchmark instrument also varies across occupations and time, most of its variation stems from differences across occupations in the base year 1998.

2.5 Results

We start our analysis by estimating the conditional transition probability into and out of unemployment as described by Equations 2.2 and 2.3, using both a regular probit model and a control function approach. In a second step, we investigate the role of EPL in detail. In a third step, we examine heterogeneous effects on various worker groups. Finally, we conduct a battery of robustness tests in order to assess the validity of our results.

2.5.1 Impact of the China Shock and EPL on Labor Market Transitions

We start by giving a brief overview to what extent higher imports from China affect workers' employment security. To do so, we analyze the transition rate from employment to unemployment, and unemployed workers' job-finding probability. Table 2.1 presents the core results of our econometric analysis for our main variables of interest for the transition probability from employment to unemployment (panel A) and the transition probability in the reverse direction (panel B).[8]

The coefficients on the relative imports variable suggest that higher exposure to Chinese imports is correlated with a higher transition rate from employment to unemployment. A potential concern about these results is that our import variable might be endogenous to employment outcomes, thus raising concerns about a potential bias in the coefficients. To address this concern, we instrument our imports variable with lagged import shares multiplied with the overall growth in Chinese imports as explained in the Methodology section The first-stage results reported in the middle section of panel A indicate that our instrument is a strong predictor of relative imports (i.e., the F -test statistic is equal to 203.09). Turning to the second stage (in the top section of panel A), the results of the control function (CF) approach reported in column (2) show that the coefficient remains significant and even increases compared to the baseline specification reported in column (1).

As for the transition rate from unemployment to employment (panel B), exposure to imports from China is strongly negatively correlated with the unemployment outflow rate. This finding can be interpreted as higher exposure to Chinese imports reducing the job-finding rate of the unemployed and therefore increasing the duration of unemployment. Again, we use a control function approach to account for potential endogeneity. As in the case of the transition rate from unemployment to employment, the instrument is strong (F-statistic: 390). Sign and significance remain robust to the use of instruments and the coefficient changes only slightly.

[8] Additional control variables as explained in the Methodology section are included but not displayed. A full set of results is displayed in Table 2.A.3.

Table 2.1: Probability of becoming (un)employed in response to changes in relative imports from China

Panel A: Prob (**E**→**U** Transition)

	Probit (1)	CF (2)	Probit (3)	CF (4)	Probit (5)	CF (6)
EPL	-0.205***	-0.205***	-0.200***	-0.188***		
	(0.068)	(0.068)	(0.068)	(0.068)		
IMP	2.787***	4.099**	9.227**	33.64***	3.236***	5.244***
	(0.810)	(2.055)	(4.617)	(6.574)	(0.851)	(1.892)
EPL × IMP			-2.517	-11.03***		
			(1.829)	(2.540)		
EPL⩾Mean=1					-0.042*	-0.041
					(0.025)	(0.025)
EPL⩾Mean=1 × IMP					-1.068	-1.846
					(1.460)	(2.102)
Observations	3,331,966	3,331,966	3,331,966	3,331,966	3,331,966	3,331,966
First-stage results, dependent variable: IMP						
$IMP_{o,98} \times \frac{IMP_{t-1}}{IMP_{98}}$		7.04e-13***		8.01e-13***		
		(5.09e-14)		(1.28e-13)		
$IMP_{o,98} \times \frac{IMP_{t-1}}{IMP_{98}} \times EPL$				-3.58e-14		
				(3.34e-14)		
R-Squared		0.577		0.578		
F-test of excluded instruments		203.09		163.08		
First-stage results, dependent variable: IMP ×EPL						
$IMP_{o,98} \times \frac{IMP_{t-1}}{IMP_{98}}$				1.96e-13		
				(2.08e-13)		
$IMP_{o,98} \times \frac{IMP_{t-1}}{IMP_{98}} \times EPL$				6.27e-13***		
				(7.56e-14)		
R-Squared				0.603		
F-test of excluded instruments				118.51		
Kleibergen-Paap Wald rk F-Statistic				47.13		

Table 2.1: Probability of becoming (un)employed in response to changes in relative imports from China, continued

Panel B: Prob (**U**→**E** Transition)

	Probit (1)	CF (2)	Probit (3)	CF (4)	Probit (5)	CF (6)
EPL	-0.145	-0.146	-0.133	-0.143		
	(0.133)	(0.133)	(0.134)	(0.133)		
IMP	-6.604***	-7.508***	7.234	-4.740	-3.868***	-3.579
	(1.267)	(2.625)	(6.772)	(9.474)	(1.492)	(3.091)
EPL× IMP			-5.440**	-1.062		
			(2.689)	(3.619)		
EPL⩾Mean=1					-0.070	-0.070
					(0.045)	(0.046)
EPL⩾Mean=1 × IMP					-6.490***	-6.432***
					(1.912)	(2.690)
Observations	297,930	297,930	297,930	297,930	297,930	297,930
First-stage results, dependent variable: IMP						
$IMP_{o,98} \times \frac{IMP_{t-1}}{IMP_{98}}$		7.72e-13***		1.27e-12***		
		(3.91e-14)		(1.53e-13)		
$IMP_{o,98} \times \frac{IMP_{t-1}}{IMP_{98}} \times EPL$				-1.87e-13***		
				(4.39e-14)		
R-Squared		0.643		0.647		
F-test of excluded instruments		390.49		441.21		
First-stage results, dependent variable: IMP ×EPL						
$IMP_{o,98} \times \frac{IMP_{t-1}}{IMP_{98}}$				1.00e-12***		
				(2.27e-13)		
$IMP_{o,98} \times \frac{IMP_{t-1}}{IMP_{98}} \times EPL$				3.89e-13***		
				(6.57e-14)		
R-Squared				0.666		
F-test of excluded instruments				259.62		
Kleibergen-Paap Wald rk F-Statistic				72.81		

Notes:Standard errors (SE) in parentheses. SEs are clustered at the occupation-year level. IMP represents Chinese imports as a fraction of domestic production (i.e., $\frac{IMP_{t-1}}{DomProd_{t-1}}$). The regressions also include full sets of country and year dummies. Control variables: age, gender, marital status, education, gross domestic product (GDP) growth, per capita GDP; sectoral: labor productivity, domestic production, capital intensity, wages (in 1998). Authors' calculations for the time period 1998–2007. CF, control function; EPL, employment protection legislation; E, employed; U, unemployed. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The sample-average marginal effects of the variable "relative imports," corresponding to coefficients in column (1) of panels A and B, imply that a 1 percentage point (pp) increase in relative imports from China is associated with an increase in the probability of making a transition from employment to unemployment by 0.19 pp and a decrease in the probability of making a transition from unemployment to employment by 2.4 pp. These findings are similar to the average marginal effects that we estimate from the IV-probit models in column (2), namely 0.28 pp for the propensity to become unemployed in panel A, and 2.9 pp for the probability of becoming employed in panel B. The size of these marginal effects is equivalent to 6 to 10% of the mean transition probabilities per year.[9] The results indicate that Chinese competition has quantitatively important effects, particularly for the job prospects of employed and unemployed workers.

Turning to our research question on the role EPL plays for the labor-market adjustment to the China shock, we start by looking at the coefficient on EPL only. For the transition rate from employment to unemployment (panel A in Table 2.1), the negative and significant coefficient suggests that stricter dismissal regulations (associated with higher EPL) go together with a lower transition probability from employment to unemployment. This finding is in line with theoretical predictions as higher adjustment costs can be expected to lead to lower worker flows. For transitions from unemployment to employment, we find no significant correlation with the level of EPL.

To investigate whether EPL has an influence on the labor-market effects of Chinese imports, we examine the interaction between employment protection regulations and imports from China on the transition rates between employment and unemployment. For the transition rate from employment to unemployment, the results of the probit model do not show a significant coefficient for the interaction of EPL and Chinese imports (column (3) in panel A of Table 2.1). The interaction term becomes statistically significant, however, in the control function approach. The instruments are again strong, with an F-statistic for the interaction of approximately 118 in the first stage and a value of the Kleinbergen-Paap Wald F-statistic of approximately 47. The negative coefficient on the interaction term suggests that Chinese imports affect the transition rate from employment to unemployment to a varying extent in countries with levels of EPL that differ.[10]

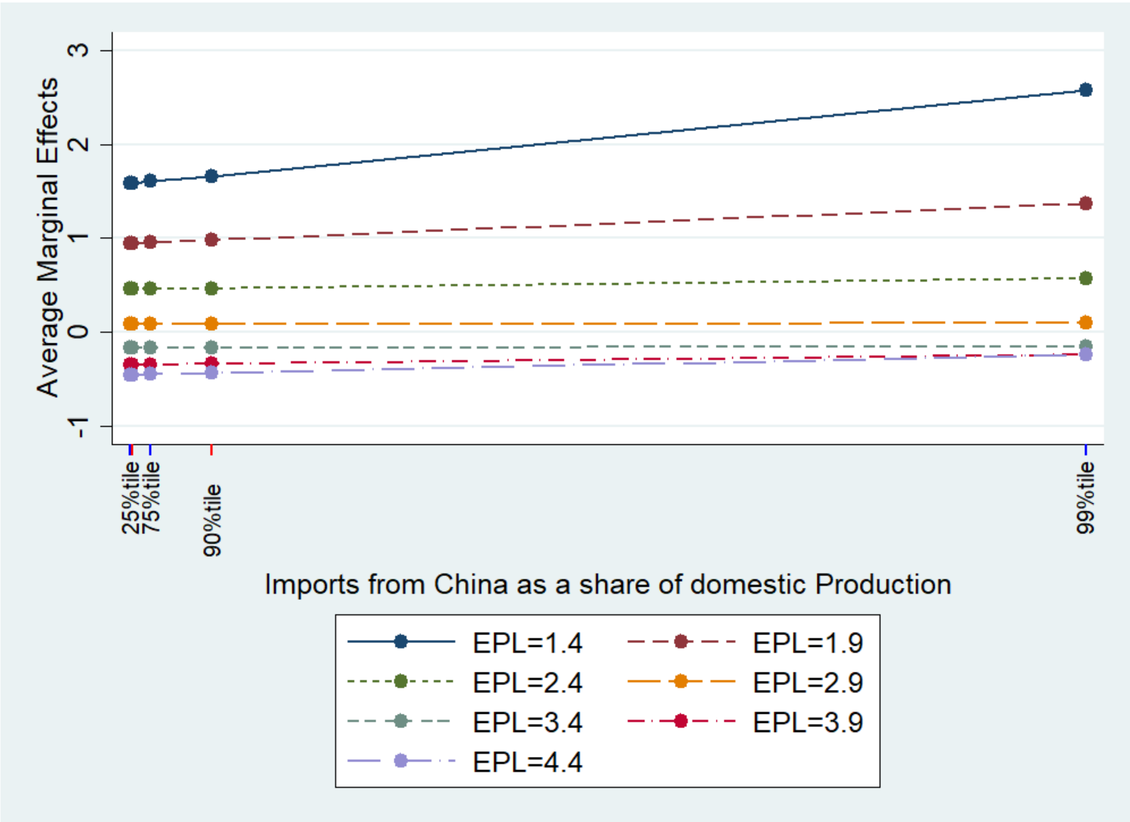
To quantify the importance of the level of EPL for the size of the import effects in more detail, Figures 2.2 and 2.3 show average marginal effects of a 1 pp increase in relative imports for a range of values of EPL and initial values of imports. As can be seen in Figure 2.2, for small values of EPL below the mean (which equals 2.45), an increase in relative imports raises the probability of transiting from employment to unemployment substantially. For instance, for a level of EPL equal to 1.9, a 1 pp increase in import exposure increases the probability of transition to unemployment by about 1 pp for initial values of import exposure between the 25th and the 90th

[9] As documented in Table 2.A.2, yearly transition probabilities are equal to 3% for transitions from employment to unemployment and 27% for transitions from unemployment to employment.

[10] Note that in non-linear models such as the probit model, a negative coefficient for the interaction term does not necessarily imply a lower marginal effect (see, for instance, Greene, 2010). As we discuss below, however, marginal effects of Chinese imports on transitions to unemployment are indeed lower when EPL is high.

percentile. The effect is even twice as large when the value of EPL equals 1.4 and the initial level of Chinese competition is high. By contrast, for levels of EPL above the mean, the effect on the probability of making a transition is close to zero. Therefore, EPL seems to shield workers from the risk of becoming unemployed as a result of Chinese competition.

Figure 2.2: Average Marginal Effects of Relative Import on Probability of Transition to Unemployment



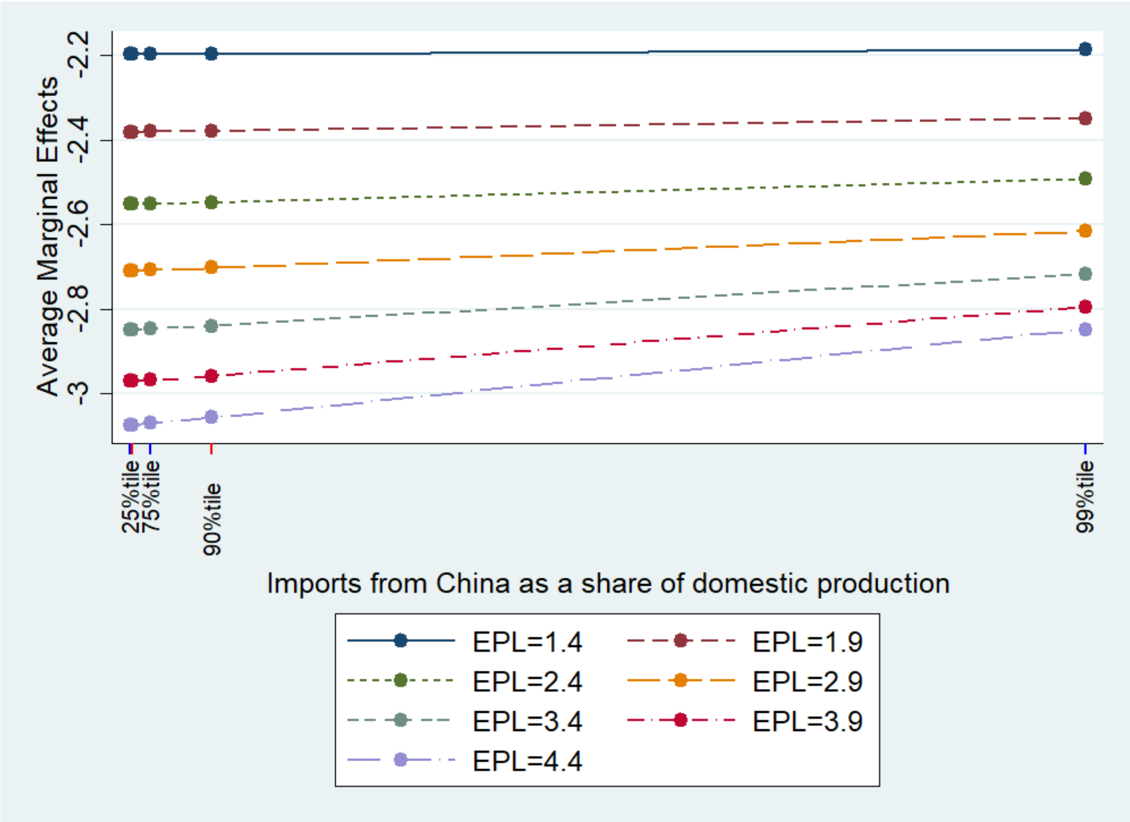
Source: European Union Labour Force Survey (EU-LFS), authors' calculations.
Note: Marginal effects are in percentage points. Average levels of imports and employment protection legislation (EPL) are 0.0009 and 2.45, respectively.

To illustrate the importance of EPL, consider the effects of a marginal increase in import exposure for initial values of Chinese imports between the first and the third quartile of the distribution across workers in our sample.[11] For instance, an increase in Chinese import exposure by 1 pp has almost no effect on average transition probabilities in countries with the highest levels of EPL in our sample, such as Greece and the Czech Republic. By contrast, a 1 pp increase in Chinese import exposure would lead to an increase in transitions to unemployment by approximately 1 pp in a country with an EPL index slightly below the mean (e.g., Belgium) and by more than 1.5 pp in a country such as the United Kingdom, which has the lowest value of EPL in our sample.

[11] As Figure 2.2 illustrates, marginal effects vary with initial values of Chinese imports but are relatively constant between the first and the third quartiles.

To analyze whether the above results are driven by the way EPL enters the regression, we construct a dummy variable that equals 1 if the value of EPL is above 2.46 (the mean of EPL in our sample), and equal to 0 otherwise.Using this variable instead of the original EPL variable yields qualitatively similar results, that is, the coefficients are still negative, but mostly insignificant.

Figure 2.3: Average Marginal Effects of Relative Import on Probability of Transition to Employment



Source: European Union Labour Force Survey (EU-LFS), authors' calculations.
Note: Marginal effects are in percentage points. Average levels of imports and employment protection legislation (EPL) are 0.001 and 2.51, respectively.

As for the transition rate from unemployment to employment, the interaction term between EPL and Chinese imports in the probit regression displays a significantly negative coefficient (column (3) in panel B of Table 2.1). Figure 2.3 shows the marginal effects of the variable "relative imports" for varying values of EPL, for the case of the conditional probability of an unemployed worker becoming employed. At lower levels of EPL, the effect of higher Chinese imports on the transition rate to employment is smaller than at higher values of EPL if the initial level of import penetration is not too high. For instance, for an EPL value of 1.4, an increase in Chinese import exposure by 1 pp is associated with a decrease in the probability of a transition out of unemployment by about 2.2 pp. When the level of EPL increases to 4.4, the estimated effect increases to more than 3 pp for low initial values of Chinese imports. One plausible interpretation for this result is that unemployed workers' employment prospects are particularly adversely affected when labor-market rigidities prevent restructuring and reallocation processes after a trade shock.

This finding implies that in countries with higher levels of EPL, imports from China are more negatively correlated with the transition rate from unemployment to employment than in countries with lower levels of EPL. While the interaction is not statistically significant in the control function approach, separate coefficients for countries below and above the mean value of EPL in columns (5) and (6) of Table 2.1, panel B, clearly indicate that the negative effects of Chinese competition are more pronounced when EPL is high. Therefore, EPL seems to aggravate the negative impact of Chinese competition on the job prospects of unemployed workers.

Taken together, these results imply that countries with low employment protection adjusted to the China shock both through the firing and the hiring margin, whereas countries with high employment protection mainly adjusted through the hiring margin. The level of EPL therefore plays an important role for the reallocation of employment as a response to Chinese imports. This finding has important policy implications, which we discuss in the conclusion.

Table 2.A.4 shows results of country-specific regressions for a few selected countries for which we observe a sufficient number of transitions (Germany, Italy, Spain, United Kingdom). For the United Kingdom, the country with the lowest average level of EPL during our sample period, Chinese imports affect only transitions from employment to unemployment significantly. In the other countries, which have substantially higher values of EPL, transitions to unemployment are much less affected, but we observe strong and significant effects on transitions to employment. These results are consistent with previous findings from the literature that labor-market adjustment occurs mainly through unemployment inflows in countries with low EPL, whereas unemployment outflows play a more dominant role in countries with high EPL (Petrongolo and Pissarides, 2008).

2.5.2 Were Worker Groups Affected in Dissimilar Ways?

Chinese import exposure differed strongly across industries, which in turn are characterized by a dissimilar composition of their workforce. As a consequence, the China shock is likely to have generated heterogeneous effects among European workers, and these effects may also depend on the level of EPL. To analyze this heterogeneity – our second research question – we use the binary version of our EPL variable introduced in the preceding section to compare low versus high EPL regimes, and we run regressions that include the three-way interaction of EPL $\times$ Chinese imports $\times$ worker characteristics. In doing so, we focus on workers' age, education, and the tasks performed on the job.

Results based on workers' age groups indicate that older workers are most strongly affected by Chinese imports (see Table 2.A.5). The corresponding sample-average marginal effects of an increase in Chinese imports for instance show that a 1 pp increase in the Chinese imports ratio is associated with an increase in the probability to become unemployed of 0.67 pp for older workers when EPL is low

(Table 2.A.6).[12] EPL seems to play some role in this context. As indicated in Table 2.A.6, the marginal effects are smaller for all age groups when EPL is high, but the effects are quite imprecisely estimated. Coefficients and marginal effects for transitions from unemployment to employment are depicted in panel B of Table 2.2 (see also panel B of Table 2.A.5 for more complete results) and panel B of Table 2.A.6. The results indicate that mostly unemployed workers between age 30 and 54 are less likely to be hired when Chinese imports increase. This negative effect is somewhat amplified when EPL is high, although the results are quite imprecisely estimated.

Table 2.2: Probability of becoming (un)employed by age group

	Panel A: Prob (**E**→**U** Transition)		**Panel B:** Prob (**U**→**E** Transition)	
	Probit	CF	Probit	CF
EPL⩾Mean=1 × IMP	-2.024	-0.845	-5.613**	-4.311
	(2.395)	(4.248)	(2.355)	(4.649)
EPL⩾Mean=1 × Age 30-54 × IMP	0.872	-1.149	-1.13	-3.17
	(2.667)	(4.329)	(3.385)	(5.396)
EPL⩾Mean=1× Age 55-64 × IMP	4.990	-3.946	-1.885	-0.148
	(3.989)	(5.662)	(9.317)	(10.88)
Observations	3,331,966	3,331,966	297,930	297,930

Notes: Standard errors (SE) in parentheses. SEs are clustered at the occupation-year level. IMP represents Chinese imports as a fraction of domestic production (i.e., $\frac{IMP_{t-1}}{DomProd_{t-1}}$). The regressions also include full sets of country and year dummies. Baseline category: Age 15-29. Control variables: Gender, marital status, education, gross domestic product (GDP) growth, per capita GDP; sectoral labor productivity, domestic production, capital intensity, wages (in 1998). Authors' calculations for the time period 1998-2007. CF, control function; EPL, employment protection legislation; E, employed; U, unemployed. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

To analyze the role of workers' skills, we classify individuals into three skill groups: low-skilled (individuals with primary or lower secondary education), medium-skilled (individuals with upper and postsecondary education and/or a completed apprenticeship), and high-skilled (individuals with tertiary education). We confirm results from the literature that the lower the skill level, the higher is the likelihood to make a transition from employment to unemployment (see Table 2.A.7, panel A). The difference between high-skilled workers and workers with lower skill increases with import competition when EPL is low as indicated by the positive interaction terms Chinese imports × low-skilled and Chinese imports × medium-skilled (see Table 2.A.7). The corresponding sample-average marginal effects suggest that a 1 pp increase in Chinese imports is associated with a 0.7 pp increase in the probability of unemployment for low-skilled workers when EPL is low; for medium-skilled workers, this coefficient is smaller, and for high-skilled workers even negative (see Table 2.A.8). Results from the control function approach, however, suggest that low- and medium-skilled workers benefit more from high EPL when imports increase, as indicated by the negative triple interaction terms. For instance, when EPL is high, the average marginal effect of a 1 pp increase in Chinese imports for low-skilled workers decreases and becomes statistically insignificant. This outcome could be attributable to EPL playing a more important role for industries and occupations

[12] We focus on worker flows from employment to unemployment here. Taking into account flows to inactivity would probably yield an even larger effect, as older workers are likely to retire in response to the China shock, which implies increased flows into inactivity.

with a high share of low-skilled workers.

Looking at the transitions from unemployment to employment, we again confirm results from the literature that low- and medium-skilled workers are less likely to make such a transition (Table 2.A.7, panel B). Low-skilled workers are affected more strongly than other skill groups by Chinese imports in their transitions from unemployment to employment, indicated by the negative interaction term between *low-skilled* and IMP. This difference is less pronounced when employment protection is high (see Table 2.3). The corresponding marginal effects (Table 2.A.8, panel) suggest that the probability that unemployed workers re-enter the labor force decreases with Chinese imports for low-skilled workers but (weakly significantly) increases for high-skilled workers when EPL is low. A potential explanation is that firms facing import competition differentiate their production from Chinese competitors toward activities that require higher skills.[13] The heterogeneity in responses across skill groups of unemployed individuals is, however, reduced when EPL is high.

Table 2.3: Probability of becoming (un)employed by skill group

	Panel A: Prob (**E**→**U** Transition)		**Panel B:** Prob (**U**→**E** Transition)	
	Probit	CF	Probit	CF
EPL⩾Mean=1 × IMP	6.698	63.14***	-27.16***	-24.38
	(9.031)	(18.63)	(9.644)	(15.54)
EPL⩾Mean=1× Low-skilled × IMP	-9.091	-70.16***	24.46**	27.74*
	(9.328)	(20.21)	(9.722)	(16.67)
EPL⩾Mean=1 × Medium-skilled× IMP	-7.219	-63.53***	20.04*	15.52
	(9.084)	(19.05)	(10.67)	(16.27)
Observations	3,331,966	3,331,966	297,930	297,930

Notes: Standard errors (SE) in parentheses. SEs are clustered at the occupation-year level. IMP represents Chinese imports as a fraction of domestic production (i.e., $\frac{IMP_{t-1}}{DomProd_{t-1}}$). The regressions also include full sets of country and year dummies. Baseline category: ISCED 5-6. Control variables: age, gender, marital status, gross domestic product (GDP) growth, per capita GDP; sectoral: labor productivity, domestic production, capital intensity, wages (in 1998). Authors' calculations for the time period 1998–2007. CF, control function; EPL, employment protection legislation; ISCED, International Standard Classification of Education; E, employed; U, unemployed. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Finally, we analyze whether the effects of Chinese imports depend on the job tasks performed by workers. This may be the case as jobs with high routine intensity are likely to be more vulnerable to imports from a low-wage country. To obtain information on the task content of occupations, we follow the strategy of Hardy, Keister and Lewandowski (2018) and use the Occupational Information Network (O*NET) database and merge it with our EU-LFS data through the occupation code.[14] To compute our measure of task routineness of an occupation, we follow an approach similar to Goos, Manning and Salomons (2014) and Hardy *et al.* (2018): We first standardize the values of task items in the first year and create the DOT task measures of Autor, Levy and Murnane (2003): routine cognitive, routine manual, non-routine cognitive analytic, and non-routine cognitive interpersonal. After that, we standardize these task content measures again and define the routine task intensity (RTI) index as $RTI = log(\frac{RC+RM}{2}) - log(\frac{NRCA+NRCI}{2})$.

Consistent with the literature (Cortes, 2016; Goos *et al.*, 2014), we find that high levels of routine intensity are associated with a higher probability of making a

[13]This finding is consistent with that of Bloom *et al.* (2016) that Chinese import competition is associated with higher innovation in European firms.

[14]Data and codes are prepared following Institute for Structural Research, 2018.

transition from employment to unemployment (Table 2.A.9, panel A). This effect is even enhanced through Chinese imports, though statistically significant only in the probit model and not in the control function approach. EPL plays a protective role in this context: With high EPL, workers in jobs with higher RTI are less likely to become unemployed than are workers in jobs with low RTI (see Table 2.4).

Table 2.4: Probability of becoming (un)employed by task content

	Panel A: Prob (**E**→**U** Transition)		**Panel B:** Prob (**U**→**E** Transition)	
	Probit	CF	Probit	CF
EPL⩾Mean=1×IMP	67.48***	175.0***	-76.68*	-410.6***
	(13.42)	(33.54)	(40.55)	(137.1)
EPL⩾Mean=1 × MediumRTI × IMP	-102.3***	-275.1***	62.14	405.8***
	(19.49)	(44.84)	(42.20)	(139.6)
EPL⩾Mean=1 × HighRTI × IMP	-70.37***	-180.9***	71.11*	404.6***
	(13.52)	(33.58)	(40.63)	(137.1)
Observations	3,270,842	3,270,842	295,004	295,004

Notes: Standard errors (SE) in parentheses. SEs are clustered at the occupation-year level. IMP represents Chinese imports as a fraction of domestic production (i.e., $\frac{IMP_{t-1}}{DomProd_{t-1}}$). The regressions also include full sets of country and year dummies. Baseline category: low RTI. Control variables: age, gender, marital status, education, gross domestic product (GDP) growth, per capita GDP; sectoral: labor productivity, domestic production, capital intensity, wages (in 1998). Authors' calculations for the time period 1998–2007. CF, control function; EPL, employment protection legislation; RTI, routine task intensity; E, employed; U, unemployed. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Turning to the results for the transition rate from unemployment to employment, we find that higher RTI is associated with a higher probability of making such a transition (Table 2.A.9, panel B). This finding is in line with the previous literature, which found a higher churning rate (i.e., higher transition probabilities both from employment to unemployment and from unemployment to employment) for workers who perform jobs with higher RTI (Bachmann, Cim and Green, 2019). This effect seems to be reversed through higher imports from China when EPL is low, indicating that workers in occupations with high RTI are most likely to be negatively affected by Chinese imports (see Table 2.4). This outcome is likely attributable to Chinese imports replacing products that are made using routine production technologies. Moreover, the estimation results suggest that when EPL is low, workers previously employed in jobs with low RTI are more likely to re-enter employment when Chinese competition rises.[15] The three-way interaction terms suggest, however, that when EPL is high and Chinese imports rise, the likelihood of exiting unemployment to employment is higher for individuals who were previously in jobs with medium or high RTI, again indicating higher churning for these worker groups.

Finally, we are interested in how the China shock affected structural change, and whether this effect was slowed by EPL.[16] To answer this question, we analyze whether exposure to Chinese imports is associated with higher transitions from unemployment to service sectors. For this purpose, we estimate multinomial probit models in which we relate the probability of making a transition from unemployment

[15]The corresponding average marginal effects are displayed in Table 2.A.10. Note that the effect for high-RTI individuals is rather large as a 1 pp increase in the Chinese imports ratio is associated with an increase in re-employment probability of approximately 6.6 pp, that is, more than 20% of the unconditional transition probability displayed in Table 2.A.2. However, this effect is also rather imprecisely estimated.

[16]We thank an anonymous referee for suggesting this extension of our analysis.

to a job in manufacturing, services, and other sectors, respectively. We document these results in Table 2.5. We find that exposure to Chinese imports increases the probability of taking up a job in a service sector or remaining in non-manufacturing industries (such as mining and agriculture) and that this effect is dampened by a higher level of employment protection. This finding indicates that high levels of EPL might slow structural change in response to rising import competition from low-wage countries.

Table 2.5: Probability of Becoming Employed in Different Sectors Conditional on Being Unemployed in the Preceding Year

Prob (**U**→**E** flows to different sectors)

Sector		MProbit	MProbit
Manufaturing	EPL	-0.491**	-0.547**
		(0.224)	(0.221)
	IMP	0.345*	1.315
		(0.205)	(2.114)
	EPL× IMP		-0.507
			(1.139)
Services	EPL	-0.247	-0.479*
		(0.307)	(0.266)
	IMP	0.169	5.301**
		(0.154)	(2.174)
	EPL× IMP		-2.777**
			(1.163)
Other sectors	EPL	0.035	-0.118
		(0.256)	(0.238)
	IMP	0.315*	3.867**
		(0.185)	(1.761)
	EPL× IMP		-1.918**
			(0.948)
	Observations	297,858	297,858

Notes:Standard errors (SE) in parentheses. SEs are clustered at the country-year level. IMP represents imports from China as a fraction of domestic production at the country-year level. Regressions also include full sets of country and year dummies. Control variables: gender, age, marital status, education, gross domestic product (GDP) growth, per capita GDP. Omitted category includes those who remained unemployed. EPL, employment protection legislation; E, employed; U, unemployed. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

2.5.3 Robustness

To assess the sensitivity of our previous estimates, we conduct a series of robustness checks. First, in order to take into account that the effect of employment protection legislation is concentrated on regular workers with permanent contracts, we control for the share of workers with temporary contracts. Second, one might be concerned that our results are driven by European exports to China, which could be correlated with Chinese imports to European countries. We therefore include a measure of export exposure to China as an additional control variable. Third, our IV strategy would be invalid if the level of Chinese imports was correlated with unobserved industry characteristics that affect subsequent employment outcome patterns. To alleviate this concern, we include a full set of 3-digit occupation dummies to capture time-invariant differences between occupations. We furthermore use an alternative instrument, Chinese imports to the United States. Fourth, we replace the time-varying controls at the country level with country-year fixed effects. A further concern is that EPL could be correlated with other labor-market institutions such as collective bargaining. For this purpose, we include a country-year specific measure of collective bargaining coverage and an interaction with Chinese imports. As shown in detail in the Appendix, our results are robust to these sensitivity checks.

Finally, we analyze whether the effects of Chinese imports differ from those of other low-income countries. In Table 2.A.14, we show results when replacing Chinese import exposure with those from all low-income countries. Corresponding marginal effects are depicted in Figures 2.A.3 and 2.A.4. The results are very similar to the preceding analysis: Imports are associated with a higher probability of transitions from employment to unemployment and vice versa, and this effect is dampened in countries with high levels of EPL.[17]

2.6 Conclusion

In this article, we analyze the effects of a large increase in Chinese exports on European workers following the accession of China to the WTO. Using comparable microdata across 14 European countries allows us to estimate heterogeneous effects across countries with various labor-market institutions.

We answer two main research questions. First, what were the effects on European workers' job security, specifically, outflows from employment to unemployment, and unemployment exit rates to employment, and how were the consequences of this shock affected by differing levels of employment protection legislation (EPL)? Second, given the important increase in Chinese imports, which types of workers were most affected, and which types of workers benefited most from higher EPL?

Our results indicate that Chinese exports strongly affected workers' job security as well as the job-finding rates of the unemployed in the European Union. In particular, we find that the increased exposure to Chinese imports was associated with higher worker flows from employment to unemployment, and with a reduced probability that unemployed workers become employed. Second, we find that countries with high levels of EPL display a stronger reduction of worker flows from unemploy-

[17]We thank an anonymous referee for suggesting this robustness check.

ment to employment as Chinese imports increased. Thus, our results indicate that a high level of EPL prevents (re-)entry of individuals into employment. Third, our results demonstrate important differences between worker groups, especially with respect to age, skill, and job tasks.

The results of our analysis have crucial implications for welfare considerations with respect to the effects of international trade on individual workers, as well as for economic policy. Increased inflows into unemployment and reduced outflows from unemployment imply the loss of job- or industry-specific human capital, as well as higher costs of searching for a new job. Furthermore, these effects seem to be stronger for some worker groups than for others. Our results thus complement the studies that have investigated the labor-market effects of the China shock on specific national labor markets (e.g., Autor *et al.*, 2013; Dauth *et al.*, 2014).

Finally, our results strongly influence our views on EPL. In countries with high levels of EPL, the hiring margin is more important for labor-market adjustment, that is, firms hire fewer workers instead of laying off incumbent ones. This strategy has the positive effect of providing higher job security to employed workers; however, it also has a number of negative effects. First, it is likely to increase the segregation of national labor markets by exacerbating the dual structure of the labor market that characterizes a number of European countries (Dolado, 2016). Second, adjustment along the hiring margin is likely to be much slower than adjustment along the firing margin. While good for incumbent workers, this means that relatively unproductive jobs are safeguarded, that is, “creative destruction” is prevented, at least in the short run. In the longer run, this could imply lower productivity growth – thus reducing the positive productivity effects found by Bloom *et al.* (2016) – and eventually lower employment in the affected sectors. Our finding that EPL slows the reallocation of workers to the service sector may be seen as evidence supporting this hypothesis.

One open question in this context is the role of direct job-to-job transitions, which we could not investigate because our cross-country data set does not include retrospective information on the occupation or sector of an employed person. Investigating the role of direct job-to-job transitions for the adjustment to the China shock using national data sets is therefore clearly warranted.

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Appendix A

In this section, we perform a number of robustness checks in order to assess the validity of the results of the specifications presented in our article.

First, we investigate the reliability of the labor force status variable in the EU-LFS. In order to compute labor market transitions, we need information on respondents' labor status at the time of the interview and one year prior. We derive this information from the two variables of MAINSTAT and WSTAT1Y (current and last year labor market status, respectively) of EU-LFS data. However, as the variable MAINSTAT is not available for all countries, we also use the information on the variable ILOSTAT. Unfortunately, there are some cases in which the definitions of ILOSTAT and MAINSTAT contradict each other (i.e., an individual is defined as "employed" according to ILOSTAT, but "unemployed" or "inactive" based on MAINSTAT). In our analysis, we define these observations to be employed (since we have also non-missing information on their current occupation, professional status, labor status during reference week, etc.). However, in order to examine whether our estimated coefficient are sensitive to this choice of the estimation sample, we re-run our baseline regressions using a restricted sample in which we exclude the observations for which the definitions of ILOSTAT and MAINSTAT disagree with each other. As presented in Table 2.A.1 below, our results remain unaltered and are therefore robust to this type of potential misclassification.

Second, one may be concerned that the effect of employment protection legislation is concentrated on regular workers with permanent contracts (Bassanini and Garnero (2013)). Hence, one would preferably narrow the sample by excluding those that are under temporary contracts. Unfortunately, the EU-LFS data do not provide information on the type of contract in the previous year, i.e., before a potential transition. It is therefore not possible to analyze outflow rates from jobs differentiated by contract type. Instead, as a robustness test, we include the share of workers with temporary contracts at the occupation level interacted with our relative import variable as an additional control. As the results in Columns (1) and (2) of Panels A and B in in Table 2.A.11 show, the coefficient on the interaction term between the share of temporary workers and imports is negative and significant in Panel A and only weakly significant in Panel B, but the coefficients on our main variables of interest and their significance level are qualitatively similar to those obtained in the baseline specifications.

Third, our results may be driven by European exports to China which could be correlated with Chinese imports to European countries. We therefore construct a measure of export exposure similar to our import measure at the occupation level. As this is weighted by domestic production, we include the latter as separate control variable as well. Results documented in columns (3) and (4) of Table 2.A.11 show that the coefficients on the variable exports are negative and significant, implying that higher exports to China reduce the probability of transitions into and out of unemployment. However, as the coefficients for imports show, our previous results are robust to inclusion of this additional control.

Fourth, our instrumental variable approach controls for potential endogeneity of Chinese imports to workers' labor market outcomes. However, as noted by Bloom *et al.* (2016), one could still argue that the initial level of Chinese imports might also be correlated with unobserved industry characteristics that affect subsequent employment outcome patterns, since our IV strategy does not allow us to include occupation fixed effects. In order to address this issue, we perform two types of robustness tests.

On the one hand, we re-estimate our (potentially endogenous) Probit specifications in Table 2.1 (Columns (1) and (3) of Panels A and B) and include a full set of three-digit occupation dummies to capture time-invariant differences between occupations. Estimation results are reported in Columns (1) and (2) of Panels A and B in Table 2.A.12. The results are qualitatively similar to those obtained in the baseline specification.

On the other hand, we use Chinese imports to the US, $IMP^{US}_{0,t-1}$, as an alternative instrument for our import measure. This is similar in spirit to Autor *et al.* (2013), who use import exposure in other countries with comparable characteristics. In contrast to the first alternative IV strategy, this specification allows for the inclusion of occupation fixed effects. The first-stage results, at the bottom of each panel, show that the instrument is strong and has a statistically significant relationship with import exposure. The second-stage results of this alternative instrument are qualitatively similar to the initial conditions instrument (Table 2.A.12, Columns (3) and (4) of Panels A and B). More precisely, the coefficients on the interaction terms remain negative and with similar significance levels, but they are larger in these IV specifications compared to the previous ones.

Fifth, in our main specification, we use control variables at the country-year level instead of country-year fixed effects to exploit higher variation in Chinese imports. However, as documented in Table 2.A.13, our results are robust to replacing time-varying controls at the country level with country-year fixed effects. One might be concerned that EPL picks up correlation with other labor-market institutions such as collective bargaining. For this purpose, we matched our data with information on collective bargaining coverage from the OECD which varies across countries and years. We rerun our baseline specification controlling for collective bargaining and its interaction with Chinese imports. Results documented in Table 2.A.15 show that the effects of collective bargaining in our sample are small and statistically insignificant. Most important, they do not change our conclusions on the overall effects of Chinese imports and its interaction with EPL.

Table 2.A.1: Probability of becoming (un)employed in a restricted sample

Panel A: Prob (**E**→**U** Transition)

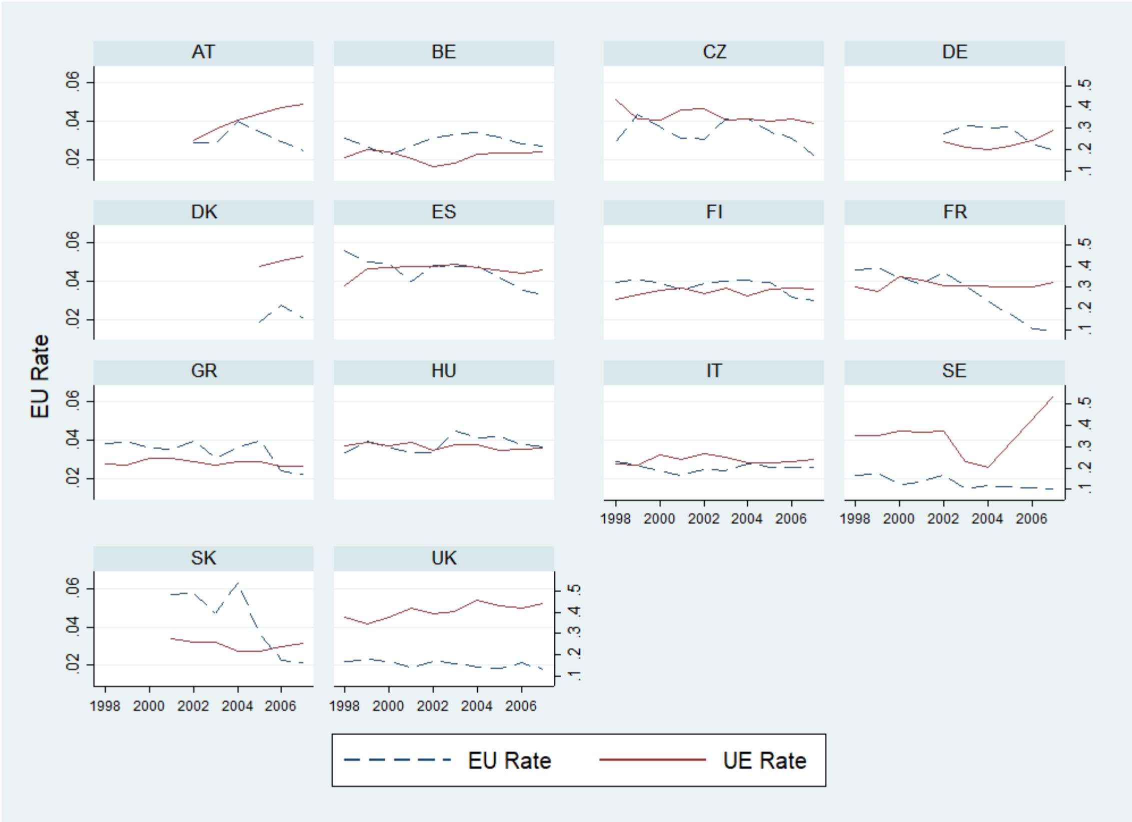
	Probit	IV-Probit	Probit	IV-Probit	EPL⩾Mean[Probit]	EPL<Mean[Probit]
EPL	-0.200***	-0.200***	-0.195***	-0.178***		
	(0.069)	(0.069)	(0.069)	(0.069)		
IMP	2.843***	4.112**	9.080**	33.50***	1.061 [1.138]	7.644***[3.671***]
	(0.807)	(1.991)	(4.611)	(9.736)	2.724[1.576]	(1.974)[0.849]
EPL × IMP			-2.439	-10.994***		
			(1.826)	(3.773)		
Observations	2,948,482	2,948,482	2,948,482	2,948,482	1,745,980	1,202,502
First-stage results, dependent variable: IMP						
$IMP_{o,98} \times \frac{IMP_{t-1}}{IMP_{98}}$		6.98e-13***		8.11e-13***		
		(4.92e-14)		(1.31e-13)		
$IMP_{o,98} \times \frac{IMP_{t-1}}{IMP_{98}} \times EPL$				-4.18e-14		
				(3.41e-14)		
R-Squared		0.589		0.590		
F-test of excluded instruments		201.29		161.99		
First-stage results, dependent variable: IMP ×EPL						
$IMP_{o,98} \times \frac{IMP_{t-1}}{IMP_{98}}$				2.31e-13		
				(2.08e-13)		
$IMP_{o,98} \times \frac{IMP_{t-1}}{IMP_{98}} \times EPL$				6.08e-13***		
				(7.15e-14)		
R-Squared				0.615		
F-test of excluded instruments				117.51		
Kleibergen-Paap Wald rk F-Statistic				46.96		

Panel B: Prob (**U**→**E** Transition)

	Probit	IV-Probit	Probit	IV-Probit	EPL⩾Mean[Probit]	EPL<Mean[Probit]
EPL	-0.172	-0.172	-0.159	-0.169		
	(0.138)	(0.138)	(0.138)	(0.138)		
IMP	-5.729***	-6.288**	8.711	-1.727	-7.378**[-8.677***]	-4.208 [-3.609**]
	(1.270)	(2.585)	(6.362)	(9.257)	(2.978)[1.857]	(2.785) [1.448]
EPL× IMP			-5.68**	-1.734		
			(2.534)	(3.791)		
Observations	273,776	273,776	273,776	273,776	164,198	109,578
First-stage results, dependent variable: IMP						
$IMP_{o,98} \times \frac{IMP_{t-1}}{IMP_{98}}$		7.77e-13***		1.29e-12***		
		(3.97e-14)		(1.55e-13)		
$IMP_{o,98} \times \frac{IMP_{t-1}}{IMP_{98}} \times EPL$				-1.89e-13***		
				(4.41e-14)		
R-Squared		0.649		0.654		
F-test of excluded instruments		384.39		441.29		
First-stage results, dependent variable: IMP ×EPL						
$IMP_{o,98} \times \frac{IMP_{t-1}}{IMP_{98}}$				1.01e-12***		
				(2.27e-13)		
$IMP_{o,98} \times \frac{IMP_{t-1}}{IMP_{98}} \times EPL$				3.86e-13***		
				(6.50e-14)		
R-Squared				0.671		
F-test of excluded instruments				258.75		
Kleibergen-Paap Wald rk F-Statistic				72.61		

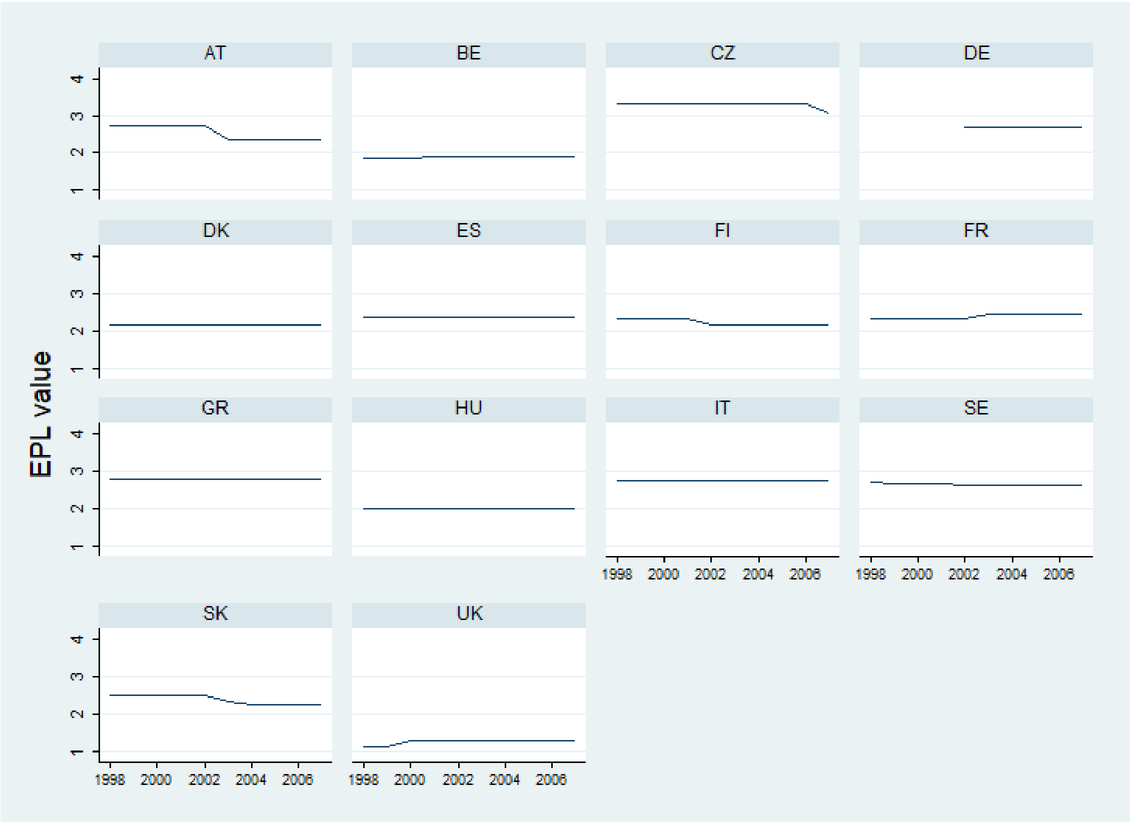
Notes:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (SE) in parentheses. SEs are clustered at the occupation-year level. IMP represents Chinese imports as a fraction of domestic production (i.e., $\frac{IMP_{t-1}}{DomProd_{t-1}}$). The regressions also include full sets of country and year dummies. Control variables: Age, marital status, education, GDP growth, per capita GDP. Sectoral labour productivity, domestic production, capital intensity, and wages (in 1998) are used as additional controls. Authors' calculations for the time period 1998-2007.

Figure 2.A.1: Transition rates from employment to unemployment (EU) and from unemployment to employment (UE), in (%) by country, 1998-2007



Notes: The left axis shows the scale for the EU rate, the right axis the scale for the UE rate. Source: EU-LFS, authors' calculation.

Figure 2.A.2: EPL index by country – individual and collective dismissals (regular contracts), 1998-2007



Source: OECD Indicators of Employment Protection, https://stats.oecd.org/.

Figure 2.A.3: Average Marginal Effects of relative import from low wage countries on probability of transition to unemployment

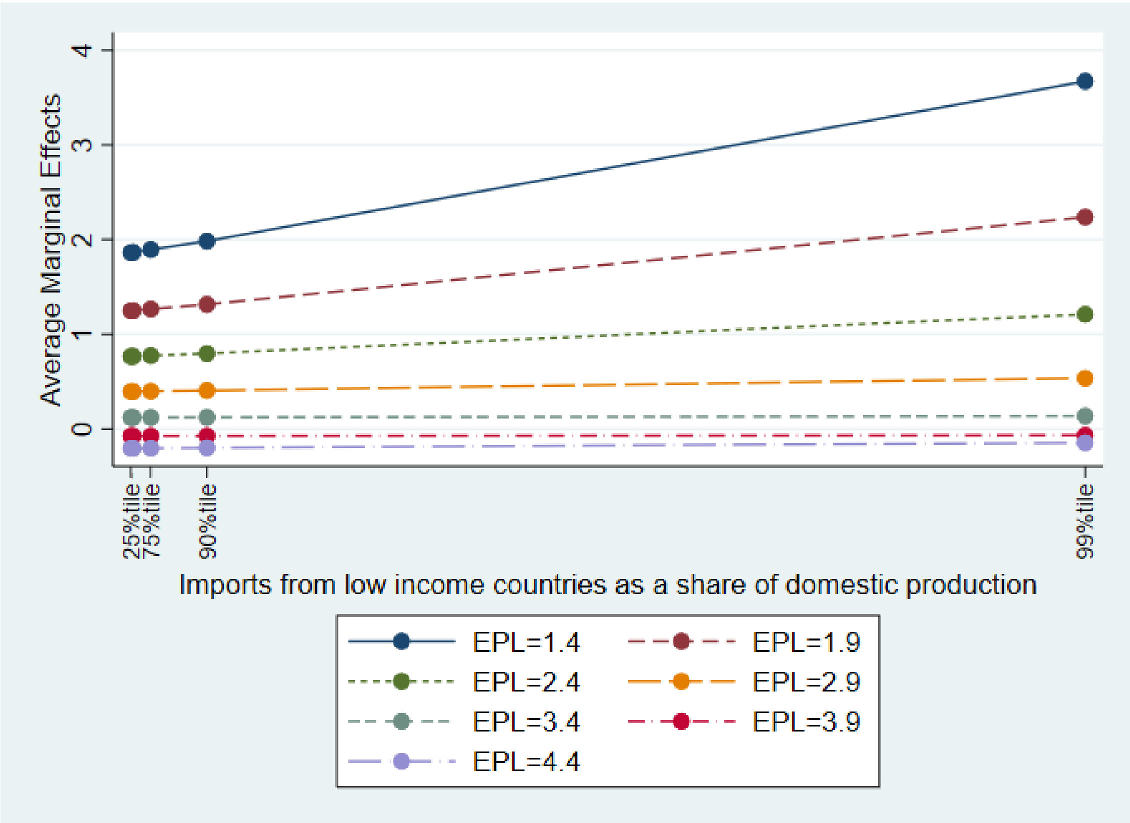


Figure 2.A.4: Average Marginal Effects of relative import from low wage countries on probability of transition to employment

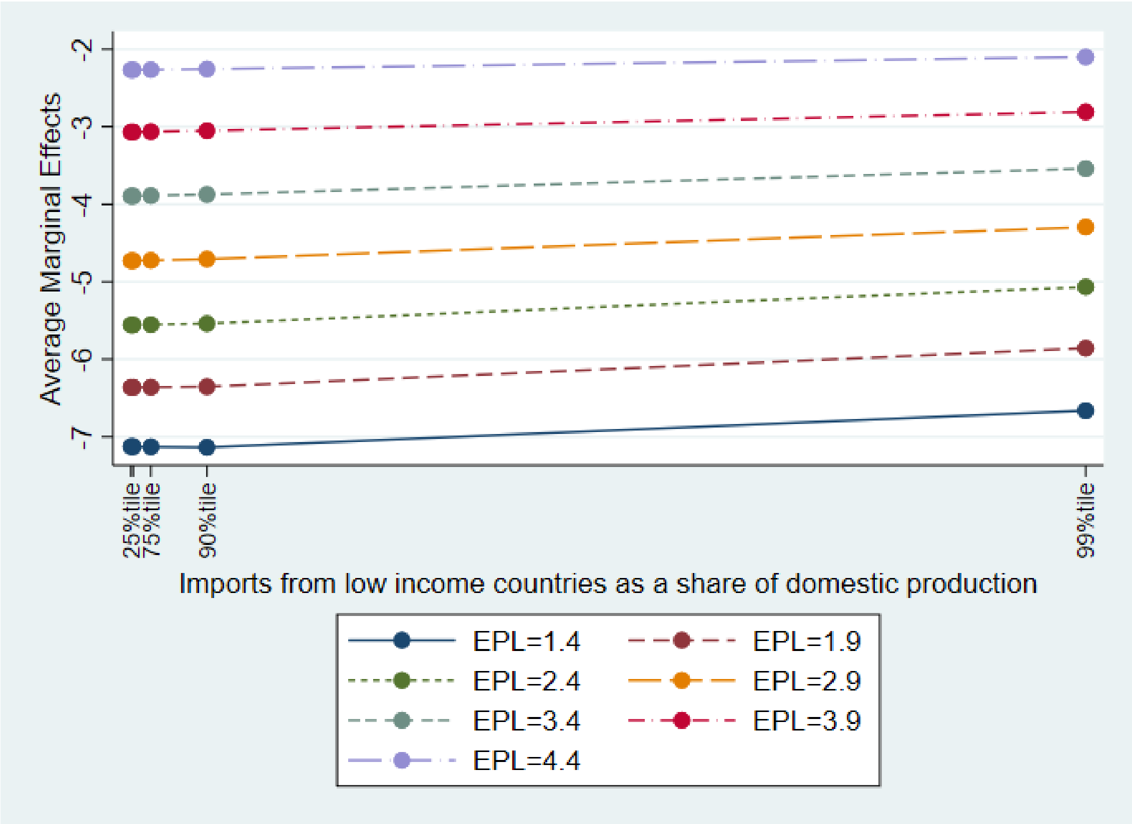


Table 2.A.2: Data description and summary statistics

Variables	**E**→**U** Sample	**U**→**E** Sample	Data source
Sex:Male	0.570	0.546	EU-LFS
	(0.495)	(0.497)	
Marital Status:Married	0.601	0.435	EU-LFS
	(0.490)	(0.496)	
Age:15-29	0.196	0.326	EU-LFS
	(0.397)	(0.469)	
Age:30-54	0.695	0.584	EU-LFS
	(0.460)	(0.493)	
Age:55-64	0.109	0.089	EU-LFS
	(0.311)	(0.285)	
Skill:Low	0.256	0.400	EU-LFS
	(0.436)	(0.490)	
Skill:Medium	0.557	0.494	EU-LFS
	(0.497)	(0.500)	
Skill:High	0.187	0.106	EU-LFS
	(0.390)	(0.308)	
Employment Protection Legislation (EPL)	2.455	2.516	OECD.Stat
	(0.511)	(0.408)	
Real GDP growth (GDP-GR)	2.776	2.843	IMF
	(2.029)	(2.180)	
log GDP per capita, current prices (US dollars)	10.14	10.06	IMF
	(0.524)	(0.544)	
log Labor Productivity$_{1998}$[a]	11.31	11.14	OECD STAN, Eurostat, EU-LFS
	(1.388)	(1.493)	
log Capital Intensity$_{1998}$[b]	9.009	8.777	OECD STAN, Eurostat, EU-LFS
	(2.039)	(2.072)	
log Sectoral Domestic Production$_{1998}$ (current prices)	24.11	24.05	OECD STAN, Eurostat, EU-LFS
	(1.438)	(1.505)	
log Wage$_{1998}$	7.990	7.830	EU-KLEMS, Eurostat, EU-LFS
	(1.787)	(1.821)	

[a] Labor productivity is computed as value added (volumes) / total number of employees.
[b] Capital intensity is defined as gross capital formation (volumes) /total employment.

Table 2.A.2: Data description and summary statistics, continued

Variables	**E→U** Sample	**U→E** Sample	Data source
Chinese imports (in absolute terms, IMP^{Ch}_{oct})	3.84e+07	4.15e+07	Comtrade, Eurostat, EU-LFS
	(1.03e+08)	(1.29e+08)	
Lag of Chinese imports (in absolute terms, $IMP^{Ch}_{oc,t-1}$)	2.95e+07	3.17e+07	Comtrade, Eurostat, EU-LFS
	(8.51e+07)	(1.07e+08)	
Domestic production ($DomProd_{oct}$)	8.53e+10	8.28e+10	OECD STAN, Eurostat, EU-LFS
	(7.33e+10)	(7.38e+10)	
Lag of domestic production ($DomProd_{oc,t-1}$)	7.79e+10	7.60e+10	OECD STAN, Eurostat, EU-LFS
	(6.69e+10)	(6.77e+10)	
Relative Chinese imports (i.e., $\frac{IMP^{Ch}_{oct}}{DomProd_{oct}}$)	0 .001	0.001	
	(0.004)	(0.005)	
Lag of relative Chinese imports (i.e., $\frac{IMP^{Ch}_{oc,t-1}}{DomProd_{oc,t-1}}$)	0 .0009	0.001	
	(0.004)	(0.004)	
$IMP_{o,98}$	5.89e+08	6.14e+08	Comtrade, Eurostat, EU-LFS
	(9.79e+08)	(1.20e+09)	
$\frac{IMP_{t-1}}{IMP_{98}}$	3.185	3.152	Comtrade, Eurostat, EU-LFS
	(1.536)	(1.503)	
$IMP_{o,98} \times \frac{IMP_{t-1}}{IMP_{98}}$	1.90e+09	1.97e+09	
	(3.76e+09)	(4.65e+09)	
Unemployment Rate	0.103	0.114	EU-LFS
	(0.032)	(0.030)	
Employment Rate	0.761	0.742	EU-LFS
	(0.075)	(0.075)	
Transition rate from employment to unemployment	0.030		EU-LFS
	(0.009)		
Transition rate from unemployment to employment		0.273	EU-LFS
		(0.072)	

DATA: Regression sample, authors' calculations for the time period 1998-2007.

Table 2.A.3: Probability of becoming (un)employed in response to changes in relative imports from China - Full set of results

Panel A: Prob (**E**→**U** Transition)

	Probit	CF	Probit	CF
EPL	-0.205***	-0.205***	-0.200***	-0.188***
	(0.0683)	(0.0683)	(0.0684)	(0.0680)
IMP	2.787***	4.099**	9.227**	33.64***
	(0.810)	(2.055)	(4.617)	(6.574)
EPL × IMP			-2.517	-11.03***
			(1.829)	(2.540)
Male	-0.0167	-0.0164	-0.0167	-0.0163
	(0.0118)	(0.0119)	(0.0118)	(0.0119)
Married=1	-0.187***	-0.188***	-0.187***	-0.188***
	(0.00526)	(0.00527)	(0.00526)	(0.00527)
Age 30-54	-0.178***	-0.178***	-0.178***	-0.178***
	(0.00622)	(0.00622)	(0.00622)	(0.00622)
Age 55-64	-0.196***	-0.196***	-0.196***	-0.196***
	(0.0134)	(0.0134)	(0.0134)	(0.0133)
ISCED 3-4	-0.180***	-0.180***	-0.180***	-0.180***
	(0.00943)	(0.00932)	(0.00942)	(0.00928)
ISCED 5-6	-0.378***	-0.378***	-0.378***	-0.377***
	(0.0159)	(0.0158)	(0.0159)	(0.0158)
GDP_GR	-0.00243	-0.00252	-0.00214	-0.00127
	(0.00466)	(0.00466)	(0.00468)	(0.00468)
log(GDP_PC)	-0.412***	-0.415***	-0.415***	-0.427***
	(0.0719)	(0.0715)	(0.0719)	(0.0712)
log(LaborPROD_{98})	-0.0590***	-0.0593***	-0.0593***	-0.0598***
	(0.0143)	(0.0144)	(0.0143)	(0.0142)
log(CAPintens_{98})	-0.0525***	-0.0517***	-0.0526***	-0.0512***
	(0.00659)	(0.00699)	(0.00658)	(0.00697)
log(PROD_{98})	0.0493***	0.0529***	0.0493***	0.0556***
	(0.0170)	(0.0179)	(0.0170)	(0.0178)
log(WAGE_{98})	-0.0192**	-0.0192**	-0.0192**	-0.0189**
	(0.00803)	(0.00807)	(0.00804)	(0.00810)
Constant	3.298***	3.238***	3.317***	3.249***
	(0.881)	(0.897)	(0.880)	(0.890)
Observations	3,331,966	3,331,966	3,331,966	3,331,966

Notes:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (SE) in parentheses. SEs are clustered at the occupation-year level. IMP represents Chinese imports as a fraction of domestic production (i.e., $\frac{IMP_{t-1}}{DomProd_{t-1}}$). The regressions also include full sets of country and year dummies. Baseline categories: age: Age 15-29; education: ISCED 0-2. Authors' calculations for the time period 1998-2007.

Table 2.A.3: Probability of becoming (un)employed in response to changes in relative imports from China - Full set of results, continued

Panel A: Prob (**U**→**E** Transition)

	Probit	CF	Probit	CF
EPL	-0.145	-0.146	-0.133	-0.143
	(0.133)	(0.133)	(0.134)	(0.133)
IMP	-6.604***	-7.508***	7.234	-4.740
	(1.267)	(2.625)	(6.772)	(9.474)
EPL × IMP			-5.440**	-1.062
			(2.689)	(3.619)
Male	0.0364**	0.0362**	0.0366**	0.0362**
	(0.0152)	(0.0151)	(0.0152)	(0.0151)
Married=1	0.0420***	0.0422***	0.0421***	0.0422***
	(0.00961)	(0.00959)	(0.00961)	(0.00959)
Age 30-54	-0.459***	-0.459***	-0.458***	-0.459***
	(0.0154)	(0.0154)	(0.0154)	(0.0154)
Age 55-64	-0.918***	-0.918***	-0.918***	-0.918***
	(0.0277)	(0.0277)	(0.0277)	(0.0277)
ISCED 3-4	0.174***	0.174***	0.174***	0.174***
	(0.0101)	(0.0100)	(0.0101)	(0.0100)
ISCED 5-6	0.338***	0.338***	0.338***	0.338***
	(0.0159)	(0.0159)	(0.0159)	(0.0159)
GDP_GR	0.0107	0.0108	0.0112	0.0108
	(0.00794)	(0.00791)	(0.00794)	(0.00788)
log(GDP_PC)	0.369***	0.371***	0.361***	0.369***
	(0.107)	(0.106)	(0.107)	(0.105)
log($LaborPROD_{98}$)	0.0588**	0.0595**	0.0584**	0.0593**
	(0.0236)	(0.0237)	(0.0237)	(0.0237)
log($CAPintens_{98}$)	0.0418***	0.0411***	0.0415***	0.0411***
	(0.00721)	(0.00754)	(0.00718)	(0.00749)
log($PROD_{98}$)	-0.00561	-0.00881	-0.00559	-0.00841
	(0.0165)	(0.0170)	(0.0165)	(0.0170)
log($WAGE_{98}$)	-0.0105*	-0.0106*	-0.0104*	-0.0106*
	(0.00566)	(0.00559)	(0.00564)	(0.00558)
Constant	-4.023***	-3.964***	-3.965***	-3.962***
	(1.203)	(1.242)	(1.204)	(1.234)
Observations	297,930	297,930	297,930	297,930

Notes:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (SE) in parentheses. SEs are clustered at the occupation-year level. IMP represents Chinese imports as a fraction of domestic production (i.e., $\frac{IMP_{t-1}}{DomProd_{t-1}}$). The regressions also include full sets of country and year dummies. Baseline categories: age: Age 15-29; education: ISCED 0-2. Authors' calculations for the time period 1998-2007.

Table 2.A.4: Regressions for separate countries

	Panel A: Prob (**E**→**U** Transition)			**Panel B:** Prob (**U**→**E** Transition)			
Country	IMP Probit	IMP AME	Observations	IMP Probit	IMP AME	Observations	EPL
DE	-0.760	-0.060	493,908	-58.55***	-20.399***	44,398	2.68
	(11.62)	(0.926)		(17.433)	(6.091)		
ES	5.074***	0.491***	216,741	-12.923***	-4.732***	35,357	2.36
	(1.576)	(0.152)		(2.165)	(0.794)		
IT	7.524**	0.434**	617,822	-10.308***	-3.924***	78,405	2.76
	(3.057)	(0.177)		(3.404)	(1.307)		
UK	69.81***	3.526***	310,544	-28.24	-9.993	10,616	1.22
	(18.39)	(0.927)		(53.829)	(19.047)		

Notes:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (SE) in parentheses. SEs are clustered at the occupation-year level. IMP represents Chinese imports as a fraction of domestic production (i.e., $\frac{IMP_{t-1}}{DomProd_{t-1}}$). The regressions also include full sets of year dummies. Control variables: Age, gender, marital status, education. Sectoral labor productivity, domestic production, capital intensity, and wages (in 1998) are used as additional controls. Authors' calculations for the time period 1998-2007.

Table 2.A.5: Probability of becoming (un)employed by age group

	Panel A: Prob (**E**→**U** Transition)		**Panel B:** Prob (**U**→**E** Transition)	
	Probit	CF	Probit	CF
IMP	1.418	2.543	-2.677	1.283
	(1.210)	(2.899)	(2.103)	(4.311)
EPL⩾Mean=1	-0.034	-0.035	-0.087*	-0.084*
	(0.026)	(0.026)	(0.05)	(0.049)
EPL⩾Mean=1 × IMP	-2.024	-0.845	-5.613**	-4.311
	(2.395)	(4.248)	(2.355)	(4.649)
Age 30-54	-0.171***	-0.171***	-0.463***	-0.457***
	(0.009)	(0.01)	(0.019)	(0.019)
Age 55-64	-0.232***	-0.238***	-0.996***	-0.985***
	(0.018)	(0.018)	(0.034)	(0.035)
Age 30-54 × IMP	2.534**	2.872	-2.004	-6.512*
	(1.098)	(1.981)	(2.291)	(3.648)
Age 55-64 × IMP	0.224	9.795**	1.965	-8.017
	(1.860)	(4.065)	(3.232)	(8.297)
EPL⩾Mean=1 × Age 30-54	-0.018	-0.017	0.012	0.011
	(0.012)	(0.012)	(0.019)	(0.02)
EPL⩾Mean=1 × Age 55-64	0.056***	0.062***	0.133***	0.129***
	(0.019)	(0.02)	(0.032)	(0.033)
EPL⩾Mean=1 × Age 30-54 × IMP	0.872	-1.149	-1.13	-3.17
	(2.667)	(4.329)	(3.385)	(5.396)
EPL⩾Mean=1× Age 55-64 × IMP	4.990	-3.946	-1.885	-0.148
	(3.989)	(5.662)	(9.317)	(10.88)
Observations	3,331,966	3,331,966	297,930	297,930

Notes:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (SE) in parentheses. SEs are clustered at the occupation-year level. IMP represents Chinese imports as a fraction of domestic production (i.e., $\frac{IMP_{t-1}}{DomProd_{t-1}}$). The regressions also include full sets of country and year dummies. Baseline category: Age 15-29. Control variables: Gender, marital status, education, GDP growth, per capita GDP. Sectoral labor productivity, domestic production, capital intensity, and wages (in 1998) are used as additional controls. Authors' calculations for the time period 1998-2007.

Table 2.A.6: Average marginal effects of Chinese imports on the probability of becoming (un)employed by age group and level of EPL

	Panel A: Prob (**E**→**U** Transition)		**Panel B:** Prob (**U**→**E** Transition)	
	low EPL	high EPL	low EPL	high EPL
Age 15-29	0.206	0.130	0.457	-1.096
	(0.235)	(0.313)	(1.537)	(1.731)
Age 30-54	0.327***	0.187	-1.872*	-4.454***
	(0.107)	(0.147)	(1.078)	(1.066)
Age 55-64	0.667***	0.425*	-1.896	-3.237
	(0.193)	(0.245)	(2.197)	(2.369)

Notes:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (SE), calculated by the delta method in parentheses. Table shows sample-average marginal effects of an increase in the Chinese import ratio. These are based on the coefficients in Table 2.2.

Table 2.A.7: Probability of becoming (un)employed by skill group

	Panel A: Prob (**E**→**U** Transition)		**Panel B:** Prob (**U**→**E** Transition)	
	Probit	CF	Probit	CF
IMP	-10.34	-7.192	6.496	16.77*
	(7.546)	(16.61)	(4.305)	(9.160)
EPL⩾Mean=1	-0.102***	-0.122***	-0.022	-0.019
	(0.032)	(0.033)	(0.05)	(0.05)
EPL⩾Mean=1 × IMP	6.698	63.14***	-27.16***	-24.38
	(9.031)	(18.63)	(0.05)	(0.05)
Low-skilled	0.348***	0.345***	-0.328***	-0.316***
	(0.016)	(0.018)	(0.022)	(0.022)
Medium-skilled	0.157***	0.158***	-0.129***	-0.128***
	(0.013)	(0.015)	(0.021)	(0.021)
Low-skilled × IMP	14.04*	15.47	-15.63***	-32.16***
	(7.526)	(16.68)	(5.351)	(10.63)
Medium-skilled × IMP	13.73*	11.66	-8.402*	-16.32
	(7.569)	(16.09)	(4.944)	(10.19)
EPL⩾Mean=1 × Low-skilled	0.053**	0.079***	-0.013	-0.02
	(0.023)	(0.024)	(0.029)	(0.03)
EPL⩾Mean=1× Medium-skilled	0.068***	0.091***	-0.061**	-0.058**
	(0.02)	(0.021)	(0.026)	(0.026)
EPL⩾Mean=1× Low-skilled × IMP	-9.091	-70.16***	24.46**	27.74*
	(9.328)	(20.21)	(9.722)	(16.67)
EPL⩾Mean=1 × Medium-skilled× IMP	-7.219	-63.53***	20.04*	15.52
	(9.084)	(19.05)	(10.67)	(16.27)
Observations	3,331,966	3,331,966	297,930	297,930

Notes:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (SE) in parentheses. SEs are clustered at the occupation-year level. IMP represents Chinese imports as a fraction of domestic production (i.e., $\frac{IMP_{t-1}}{DomProd_{t-1}}$). The regressions also include full sets of country and year dummies. Baseline category: ISCED 5-6. Control variables: Age, gender, marital status, GDP growth, per capita GDP. Sectoral labor productivity, domestic production, capital intensity, and wages (in 1998) are used as additional controls. Authors' calculations for the time period 1998-2007.

Table 2.A.8: Average marginal effects of Chinese imports on the probability of becoming (un)employed by education group and level of EPL

	Panel A: Prob (**E**→**U** Transition)		**Panel B:** Prob (**U**→**E** Transition)	
	low EPL	high EPL	low EPL	high EPL
Low-skilled	0.706***	0.099	-5.280***	-4.093***
	(0.249)	(0.200)	(1.328)	(0.960)
Medium-skilled	0.274**	0.234	0.159	-2.949**
	(0.111)	(0.186)	(1.212)	(1.239)
High-skilled	-0.320	2.264***	5.916*	-2.692
	(0.736)	(0.574)	(3.215)	(4.066)

Notes:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (SE), calculated by the delta method in parentheses. Table shows sample-average marginal effects of an increase in the Chinese import ratio. These are based on the coefficients in Table 2.3.

Table 2.A.9: Probability of becoming (un)employed by task content

	Panel A: Prob (**E**→**U** Transition)		**Panel B:** Prob (**U**→**E** Transition)	
	Probit	CF	Probit	CF
IMP	-63.48***	-12.69	31.39	197.3*
	(11.07)	(36.44)	(23.60)	(111.0)
EPL⩾Mean=1	-0.188***	-0.207***	-0.062	0.028
	(0.035)	(0.037)	(0.064)	(0.079)
EPL⩾Mean=1×IMP	67.48***	175.0***	-76.68*	-410.6***
	(13.42)	(33.54)	(40.55)	(137.1)
MediumRTI	0.096***	0.139***	0.183***	0.246***
	(0.023)	(0.026)	(0.04)	(0.059)
HighRTI	0.159***	0.173***	0.0963**	0.141**
	(0.021)	(0.025)	(0.041)	(0.059)
MediumRTI× IMP	59.30***	-40.39	-41.96*	-241.5**
	(11.01)	(36.73)	(24.01)	(110.9)
HighRTI × IMP	66.91***	19.35	-34.53	-199.1*
	(11.08)	(36.22)	(23.68)	(111.0)
EPL⩾Mean=1 × MediumRTI	0.161***	0.201***	-0.012	-0.111
	(0.03)	(0.035)	(0.052)	(0.072)
EPL⩾Mean=1 × HighRTI	0.182***	0.209***	-0.011	-0.102
	(0.027)	(0.03)	(0.053)	(0.072)
EPL⩾Mean=1 × MediumRTI × IMP	-102.3***	-275.1***	62.14	405.8***
	(19.49)	(44.84)	(42.20)	(139.6)
EPL⩾Mean=1 × HighRTI × IMP	-70.37***	-180.9***	71.11*	404.6***
	(13.52)	(33.58)	(40.63)	(137.1)
Observations	3,270,842	3,270,842	295,004	295,004

Notes:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (SE) in parentheses. SEs are clustered at the occupation-year level. IMP represents Chinese imports as a fraction of domestic production (i.e., $\frac{IMP_{t-1}}{DomProd_{t-1}}$). The regressions also include full sets of country and year dummies. Control variables: Age, gender, marital status, education, GDP growth, per capita GDP. Sectoral labor productivity, domestic production, capital intensity, and wages (in 1998) are used as additional controls. Authors' calculations for the time period 1998-2007.

Table 2.A.10: Average marginal effects of Chinese imports on the probability of becoming (un)employed by routine task intensity and level of EPL

	Panel A: Prob (**E**→**U** Transition)		**Panel B:** Prob (**U**→**E** Transition)	
	low EPL	high EPL	low EPL	high EPL
LowRTI	-0.654	7.270***	66.198*	-68.973**
	(1.861)	(0.313)	(35.896)	(27.892)
MediumRTI	-3.373***	-8.910***	-15.456***	16.977*
	(0.934)	(2.181)	(4.059)	(9.697)
HighRTI	0.485***	0.056	-0.636	-2.678***
	(0.116)	(0.180)	(1.096)	(0.933)

Notes:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (SE), calculated by the delta method in parentheses. Table shows sample-average marginal effects of an increase in the Chinese import ratio. These are based on the coefficients in Table 2.4.

Table 2.A.11: Regression including the share of workers with fixed-term contracts and exports from EU to China

Panel A: Prob (**E**→**U** Transition)

	Probit	CF	Probit	CF
EPL	-0.200***	-0.188***	-0.206***	-0.191***
	(0.068)	(0.068)	(0.071)	(0.071)
IMP	10.03*	36.07***	9.933**	30.51***
	(5.142)	(6.720)	(4.715)	(6.515)
EPL × IMP	-2.586	-11.09***	-2.556	-9.423***
	(1.882)	(2.537)	(1.828)	(2.490)
FTC × IMP	-0.057	-0.217**		
	(0.061)	(0.109)		
DomProd			-2.37e-13	-2.90e-13
			(2.21e-13)	(2.20e-13)
EXP			-21.94***	-24.95***
			(6.574)	(6.578)
Observations	3,331,966	3,331,966	3,124,860	3,124,860

Panel B: Prob (**U**→**E** Transition)

	Probit	CF	Probit	CF
EPL	-0.132	-0.142	-0.211	-0.219
	(0.134)	(0.133)	(0.137)	(0.137)
IMP	9.223	-0.016	6.532	-2.204
	(7.370)	(10.14)	(6.742)	(9.357)
EPL× IMP	-5.532**	-1.007	-5.072	-1.474
	(2.654)	(3.786)	(2.664)	(3.638)
FTC × IMP	-0.160	-0.471*		
	(0.132)	(0.278)		
DomProd			7.31e-13***	7.33e-13***
			(2.53e-13)	(2.41e-13)
EXP			-21.46*	-21.70**
			(11.64)	(10.47)
Observations	297,930	297,930	280,382	280,382

Notes:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (SE) in parentheses. SEs are clustered at the occupation-year level. IMP represents Chinese imports as a fraction of domestic production (i.e., $\frac{IMP_{t-1}}{DomProd_{t-1}}$). EXP represents Chinese imports as a fraction of domestic production (i.e., $\frac{EXP_{t-1}}{DomProd_{t-1}}$). FTC: Fixed-term contract. The regressions also include full sets of country and year dummies. Control variables: Age, gender, marital status, education, GDP growth, per capita GDP. Sectoral labor productivity, domestic production, capital intensity, and wages (in 1998) are used as additional controls. Authors' calculations for the time period 1998-2007.

Table 2.A.12: Inclusion of occupation fixed effects - alternative instrument

Panel A: Prob (**E**→**U** Transition)

	Probit	Probit	CF	CF
EPL	-0.232***	-0.225***	-0.205***	-0.187***
	(0.054)	(0.054)	(0.068)	(0.068)
IMP	2.356**	15.29***	8.080**	39.33***
	(1.042)	(4.554)	(3.194)	(7.710)
EPL × IMP		-5.559***		-11.75***
		(1.699)		(3.020)
Observations	3,941,299	3,941,299	3,328,205	3,328,205
First-stage results, dependent variable: IMP				
$IMP^{US}_{0,t-1}$			1.77e-12***	1.72e-12***
			(2.63e-13)	(4.19e-13)
$IMP^{US}_{0,t-1} \times EPL$				1.88e-14
				(1.24e-13)
R-Squared			0.468	0.468
F-test of excluded instruments			47.99	24.10
First-stage results, dependent variable: IMP ×EPL				
$IMP^{US}_{0,t-1}$				-1.01e-13
				(8.40e-13)
$IMP^{US}_{0,t-1} \times EPL$				1.80e-12***
				(4.17e-13)
R-Squared				0.487
F-test of excluded instruments				23.76
Kleibergen-Paap Wald rk F-Statistic				22.42

Panel B: Prob (**U**→**E** Transition)

	Probit	Probit	CF	CF
EPL	-0.061	-0.062	-0.143	-0.129
	(0.105)	(0.105)	(0.133)	(0.134)
IMP	-2.141*	-2.812	-5.934*	9.178
	(1.133)	(4.903)	(3.528)	(10.55)
EPL× IMP		0.293		-5.746
		(1.902)		(4.382)
Observations	373,735	373,735	297,706	297,706
First-stage results, dependent variable: IMP				
$IMP^{US}_{0,t-1}$			2.03e-12***	2.40e-12***
			(2.88e-13)	(5.53e-13)
$IMP^{US}_{0,t-1} \times EPL$				-1.41e-13
				(1.66e-13)
R-Squared			0.519	0.519
F-test of excluded instruments			49.57	24.50
First-stage results, dependent variable: IMP ×EPL				
$IMP^{US}_{0,t-1}$				7.03e-13
				(1.04e-12)
$IMP^{US}_{0,t-1} \times EPL$				1.75e-12***
				(4.86e-13)
R-Squared				0.536
F-test of excluded instruments				24.39
Kleibergen-Paap Wald rk F-Statistic				21.55

Notes:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (SE) in parentheses. SEs are clustered at the occupation-year level. IMP represents Chinese imports as a fraction of domestic production (i.e., $\frac{IMP_{t-1}}{DomProd_{t-1}}$). The regressions also include full sets of country and year dummies. Columns (1) and (2) include full sets of occupation dummies. Control variables: Age, gender, marital status, education, GDP growth, per capita GDP. Sectoral labor productivity, domestic production, capital intensity, and wages (in 1998) are used as additional controls. Authors' calculations for the time period 1998-2007.

Table 2.A.13: Probability of becoming (un)employed in response to changes in relative imports from China: controlling for country-year fixed effects

Panel A: Prob (**E**→**U** Transition)

	Probit	CF	Probit	CF
IMP	11.17**	37.96***	3.519***	6.486***
	(4.913)	(6.685)	(0.966)	(1.860)
EPL × IMP	-3.277*	-12.65***		
	(1.930)	(2.582)		
EPL⩾Mean=1 × IMP			-1.791	-3.806*
			(1.639)	(2.211)
Observations	3,211,631	3,211,631	3,211,631	3,211,631
First stage results, dependent variable: IMP				
$IMP_{0,98} \times \frac{IMP_{t-1}}{IMP_{98}}$		8.44e-13***		9.19e-13***
		(1.29e-13)		(8.76e-14)
$IMP_{0,98} \times \frac{IMP_{t-1}}{IMP_{98}} \times EPL$		-4.88e-14		
		(3.40e-14)		
$IMP_{0,98} \times \frac{IMP_{t-1}}{IMP_{98}} \times EPL \geqslant Mean = 1$				-2.89e-13***
				(6.74e-14)
F-test of excluded instruments		170.58		98.71
First stage results, dependent variable: IMP ×EPL or IMP ×EPL⩾Mean=1				
$IMP_{0,98} \times \frac{IMP_{t-1}}{IMP_{98}}$		2.41e-13		-1.69e-14***
		(2.07e-13)		(6.56e-15)
$IMP_{0,98} \times \frac{IMP_{t-1}}{IMP_{98}} \times EPL$		6.19e-13***		
		(7.56e-14)		
$IMP_{0,98} \times \frac{IMP_{t-1}}{IMP_{98}} \times EPL \geqslant Mean = 1$				6.51e-13***
				(4.44e-14)
F-test of excluded instruments		122.54		94.86
Kleibergen-Paap Wald rk F statistic		49.38		58.14

Notes:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (SE) in parentheses. SEs are clustered at the occupation-year level. IMP represents Chinese imports as a fraction of domestic production (i.e., $\frac{IMP_{t-1}}{DomProd_{t-1}}$). The regressions also include full sets of country-year dummies. Control variables: Age, marital status, education. Sectoral labor productivity, domestic production, capital intensity, and wages (in 1998) are used as additional controls. Authors' calculations for the time period 1998-2007.

Table 2.A.13: Probability of becoming (un)employed in response to changes in relative imports from China: controlling for country-year fixed effects, continued

Panel B: Prob (**U**→**E** Transition)

	Probit	CF	Probit	CF
IMP	2.427	-19.17**	-4.435***	-5.752**
	(6.768)	(8.483)	(1.437)	(2.864)
EPL× IMP	-3.351	4.621		
	(2.721)	(3.361)		
EPL⩾Mean=1 × IMP			-3.959**	-1.851
			(1.992)	(2.545)
Observations	293,228	293,228	293,228	293,228
First stage results, dependent variable: IMP				
$IMP_{0,98} \times \frac{IMP_{t-1}}{IMP_{98}}$		1.33e-12***		1.09e-12***
		(1.51e-13)		(9.83e-14)
$IMP_{0,98} \times \frac{IMP_{t-1}}{IMP_{98}} \times EPL$		-2.04e-13***		
		(4.34e-14)		
$IMP_{0,98} \times \frac{IMP_{t-1}}{IMP_{98}} \times EPL \geqslant Mean = 1$				-4.25e-13***
				(8.88e-14)
F-test of excluded instruments		447.45		198.79
First stage results, dependent variable: IMP ×EPL or IMP ×EPL⩾Mean=1				
$IMP_{0,98} \times \frac{IMP_{t-1}}{IMP_{98}}$		1.08e-12***		-8.57e-15
		(2.22e-13)		(5.49e-15)
$IMP_{0,98} \times \frac{IMP_{t-1}}{IMP_{98}} \times EPL$		3.66e-13***		
		(6.45e-14)		
$IMP_{0,98} \times \frac{IMP_{t-1}}{IMP_{98}} \times EPL \geqslant Mean = 1$				6.79e-13***
				(3.31e-14)
F-test of excluded instruments		269.07		193.65
Kleibergen-Paap Wald rk F statistic		77.29		64.60

Notes:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (SE) in parentheses. SEs are clustered at the occupation-year level. IMP represents Chinese imports as a fraction of domestic production (i.e., $\frac{IMP_{t-1}}{DomProd_{t-1}}$). The regressions also include full sets of country-year dummies. Control variables: Age, marital status, education. Sectoral labor productivity, domestic production, capital intensity, and wages (in 1998) are used as additional controls. Authors' calculations for the time period 1998-2007.

Table 2.A.14: Probability of becoming (un)employed in response to changes in relative imports from low-income countries

Panel A: Prob (**E**→**U** Transition)

	Probit	CF	Probit	CF	Probit	CF
EPL	-0.204***	-0.204***	-0.202***	-0.186**		
	(0.068)	(0.068)	(0.068)	(0.068)		
IMP_LIC	3.057***	9.703***	4.983	34.98***	2.971***	10.13***
	(0.591)	(1.623)	(3.302)	(5.867)	(0.553)	(1.515)
EPL × IMP_LIC			-0.772	-9.483***		
			(1.353)	(2.141)		
EPL⩾Mean=1					-0.044*	-0.038
					(0.025)	(0.025)
EPL⩾Mean=1 × IMP_LIC					0.267	-0.676
					(1.016)	(1.591)
Observations	3,331,966	3,331,966	3,331,966	3,331,966	3,331,966	3,331,966
First-stage results, dependent variable: IMP_LIC						
$IMP\_LIC_{o,98} \times \frac{IMP\_LIC_{t}-1}{IMP\_LIC_{98}}$		6.41e-13***		2.31e-13		
		(9.69e-14)		(2.94e-13)		
$IMP\_LIC_{o,98} \times \frac{IMP\_LIC_{t-1}}{IMP\_LIC_{98}} \times EPL$				1.57e-13*		
				(8.17e-14)		
R-Squared		0.492		0.496		
F-test of excluded instruments		43.74		136.11		
First-stage results, dependent variable: IMP_LIC ×EPL						
$IMP\_LIC_{o,98} \times \frac{IMP\_LIC_{t-1}}{IMP\_LIC_{98}}$				-8.82e-13*		
				(5.26e-13)		
$IMP\_LIC_{o,98} \times \frac{IMP\_LIC_{t-1}}{IMP\_LIC_{98}} \times EPL$				9.93e-13***		
				(1.45e-13)		
R-Squared				0.547		
F-test of excluded instruments				104.69		
Kleibergen-Paap Wald rk F-Statistic				8.49		

Table 2.A.14: Probability of becoming (un)employed in response to changes in relative imports from low-income countries, continued

Panel B: Prob (**U**→**E** Transition)

	Probit	CF	Probit	CF	Probit	CF
EPL	-0.148	-0.164	-0.127	-0.177		
	(0.133)	(0.131)	(0.134)	(0.131)		
IMP_LIC	-6.095***	-14.77***	11.02***	-26.37**	-4.101***	-16.96***
	(0.972)	(2.279)	(5.304)	(12.84)	(1.013)	(3.632)
EPL× IMP_LIC			-6.856***	4.387		
			(2.081)	(4.308)		
EPL⩾Mean=1					-0.069	-0.095**
					(0.045)	(0.044)
EPL⩾Mean=1 × IMP_LIC					-5.470***	3.715
					(1.525)	(3.311)
Observations	297,930	297,930	297,930	297,930	297,930	297,930
First-stage results, dependent variable: IMP_LIC						
$IMP\_LIC_{o,98} \times \frac{IMP\_LIC_{t-1}}{IMP\_LIC_{98}}$		6.19e-13***		4.12e-13		
		(8.93e-14)		(2.81e-13)		
$IMP\_LIC_{o,98} \times \frac{IMP\_LIC_{t-1}}{IMP\_LIC_{98}} \times EPL$				7.94e-14		
				(8.02e-14)		
R-Squared		0.507		0.508		
F-test of excluded instruments		56.96		76.56		
First-stage results, dependent variable: IMP_LIC ×EPL						
$IMP\_LIC_{o,98} \times \frac{IMP\_LIC_{t-1}}{IMP\_LIC_{98}}$				-5.68e-13		
				(4.84e-13)		
$IMP\_LIC_{o,98} \times \frac{IMP\_LIC_{t-1}}{IMP\_LIC_{98}} \times EPL$				8.46e-13***		
				(1.43e-13)		
R-Squared				0.554		
F-test of excluded instruments				66.20		
Kleibergen-Paap Wald rk F-Statistic				10.74		

Notes:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (SE) in parentheses. SEs are clustered at the occupation-year level. IMP_LIC represents imports from low-income countries as a fraction of domestic production (i.e., $\frac{IMP\_LIC_{t-1}}{DomProd_{t-1}}$). The regressions also include full sets of country and year dummies. Control variables: Age, marital status, education, GDP growth, per capita GDP. Sectoral labour productivity, domestic production, capital intensity, and wages (in 1998) are used as additional controls. Low-income countries are defined according to the World Bank definition in 1998. They are: Afghanistan, Angola, Armenia, Azerbaijan, Bangladesh, Benin, Bhutan, Burkina Faso, Burundi, Cambodia, Cameroon, Central African Republic, Chad, China, Comoros, Republic of the Congo, Congo, Eritrea, Ethiopia, The Gambia, Ghana, Guinea, Guinea-Bissau, Haiti, Honduras, India, Indonesia, Ivory Coast, Kenya, Korea (the Democratic People's Republic of), Kyrgyzstan, Laos, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Moldova, Mongolia, Mozambique, Myanmar, Nepal,Nicaragua, Niger, Nigeria, Pakistan, Rwanda, Sao Tome and Principe, Senegal, Sierra Leone, Solomon Islands, Somalia, Sudan, Tajikistan, Togo, Turkmenistan, Tanzania (United Republic of), Uganda, Vietnam, Yemen, Zambia, and Zimbabwe. Authors' calculations for the time period 1998-2007.

Table 2.A.15: Probability of becoming (un)employed in response to changes in relative imports from China, controlling for collective bargaining coverage

Panel A: Prob (**E**→**U** Transition)

	Probit	CF	Probit	CF
EPL	-0.201***	-0.201***	-0.196***	-0.189***
	(0.069)	(0.069)	(0.069)	(0.068)
IMP	2.789***	4.141**	9.762**	33.72***
	(0.812)	(2.054)	(4.817)	(6.395)
CBC	-0.001	-0.001	-0.001	-0.0009
	(0.002)	(0.002)	(0.002)	(0.002)
EPL × IMP			-2.328	-10.23***
			(1.781)	(2.676)
CBC × IMP			-0.019	-0.039
			(0.035)	(0.070)
Observations	3,261,952	3,261,952	3,261,952	3,261,952
First-stage results, dependent variable: IMP				
$IMP_{o,98} \times \frac{IMP_{t-1}}{IMP_{98}}$		7.03e-13***		1.43e-12***
		(5.06e-14)		(2.25e-13)
$IMP_{o,98} \times \frac{IMP_{t-1}}{IMP_{98}} \times EPL$				-3.50e-14
				(3.62e-14)
$IMP_{o,98} \times \frac{IMP_{t-1}}{IMP_{98}} \times CBC$				-9.40e-15***
				(1.84e-15)
R-Squared		0.579		0.620
F-test of excluded instruments		193.03		90.89
First-stage results, dependent variable: IMP ×EPL				
$IMP_{o,98} \times \frac{IMP_{t-1}}{IMP_{98}}$				1.80e-12***
				(4.08e-13)
$IMP_{o,98} \times \frac{IMP_{t-1}}{IMP_{98}} \times EPL$				6.32e-13***
				(7.63e-14)
$IMP_{o,98} \times \frac{IMP_{t-1}}{IMP_{98}} \times CBC$				-2.40e-14***
				(4.79e-15)
R-Squared				0.643
F-test of excluded instruments				79.96
First-stage results, dependent variable: IMP ×CBC				
$IMP_{o,98} \times \frac{IMP_{t-1}}{IMP_{98}}$				3.06e-11***
				(9.15e-12)
$IMP_{o,98} \times \frac{IMP_{t-1}}{IMP_{98}} \times EPL$				1.24e-12
				(2.03e-12)
$IMP_{o,98} \times \frac{IMP_{t-1}}{IMP_{98}} \times CBC$				1.32e-13
				(9.49e-14)
R-Squared				0.588
F-test of excluded instruments				76.09
Kleibergen-Paap Wald rk F-Statistic				37.24

Table 2.A.15: Probability of becoming (un)employed in response to changes in relative imports from China, controlling for collective bargaining coverage, continued

Panel B: Prob (**U**$\rightarrow$**E** Transition)

	Probit	CF	Probit	CF
EPL	-0.106	-0.107	-0.096	-0.110
	(0.131)	(0.131)	(0.132)	(0.132)
IMP	-6.640***	-7.416***	8.430	-5.020
	(1.287)	(2.666)	(7.404)	(9.846)
CBC	-0.011***	-0.011***	-0.010***	-0.010***
	(0.003)	(0.003)	(0.003)	(0.003)
EPL$\times$ IMP			-3.695	2.112
			(2.527)	(4.038)
CBC $\times$ IMP			-0.104	-0.133
			(0.065)	(0.118)
Observations	293,829	293,829	293,829	293,829
First-stage results, dependent variable: IMP				
$IMP_{o,98} \times \frac{IMP_{t-1}}{IMP_{98}}$		7.72e-13***		1.76e-12***
		(3.89e-14)		(2.82e-13)
$IMP_{o,98} \times \frac{IMP_{t-1}}{IMP_{98}} \times EPL$				-9.41e-14**
				(4.69e-14)
$IMP_{o,98} \times \frac{IMP_{t-1}}{IMP_{98}} \times CBC$				-1.10e-14***
				(2.30e-15)
R-Squared		0.644		0.693
F-test of excluded instruments		393.37		152.70
First-stage results, dependent variable: IMP $\times$EPL				
$IMP_{o,98} \times \frac{IMP_{t-1}}{IMP_{98}}$				2.22e-12***
				(5.45e-13)
$IMP_{o,98} \times \frac{IMP_{t-1}}{IMP_{98}} \times EPL$				6.26e-13***
				(8.78e-14)
$IMP_{o,98} \times \frac{IMP_{t-1}}{IMP_{98}} \times CBC$				-2.75e-14***
				(6.03e-15)
R-Squared				0.709
F-test of excluded instruments				141.65
First-stage results, dependent variable: IMP $\times$CBC				
$IMP_{o,98} \times \frac{IMP_{t-1}}{IMP_{98}}$				4.03e-11***
				(1.27e-11)
$IMP_{o,98} \times \frac{IMP_{t-1}}{IMP_{98}} \times EPL$				-7.79e-13
				(2.80e-12)
$IMP_{o,98} \times \frac{IMP_{t-1}}{IMP_{98}} \times CBC$				1.36e-13
				(1.08e-13)
R-Squared				0.675
F-test of excluded instruments				113.49
Kleibergen-Paap Wald rk F-Statistic				54.29

Notes:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (SE) in parentheses. SEs are clustered at the occupation-year level. IMP represents Chinese imports as a fraction of domestic production (i.e., $\frac{IMP_{t-1}}{DomProd_{t-1}}$). The regressions also include full sets of country and year dummies. Control variables: Age, marital status, education, GDP growth, per capita GDP. Sectoral labor productivity, domestic production, capital intensity, and wages (in 1998) are used as additional controls. Authors' calculations for the time period 1998-2007.

Declaration of Contribution

Hereby I, Hedieh Aghelmaleki, declare that the Chapter "The China Shock, Employment Protection, and European Jobs" is co-authored by Ronald Bachmann and Joel Stiebale. All authors contributed equally to the chapter.

Signature of co-author 1 (Ronald Bachmann): R. Bachmann --

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Chapter 3

Offshoring, Collective Bargaining, and European Jobs

Co-authored with Daniel Baumgarten and Joel Stiebale

3.1 Introduction

The employment effects of offshoring are controversially debated among researchers and policy makers. On the one hand, offshoring can substitute foreign jobs for domestic ones. On the other hand, offshoring can lead to productivity improvements and therefore increase labour demand. While several studies investigate the effects of offshoring on the level of employment and employment transitions in a single country, little is known about the role of labour market institutions for the differential consequences of offshoring across countries.

In this paper, we aim to make progress on this front by analyzing the effects of offshoring for transitions into and out of unemployment within European countries. Specifically, we analyze to which extent the effects depend on the degree of collective bargaining. Europe provides for a nice test case to analyze this research question, as there is substantial variation in collective bargaining coverage across countries.

For our analysis, we use comparable micro data for 20 European countries from Eurostat's European Union Labour Force Survey (EU-LFS), which contains information on employment status, occupation and socioeconomic characteristics at the worker level. We use country-specific information about the assignment of occupations to industries, which allows us to combine our worker-level data with trade flows at the industry-level and to construct a measure of exposure to offshoring that varies across occupations, countries and time. We then relate the probability of employment to variation in the exposure to offshoring within occupations and countries. To account for possible endogeneity, we apply an instrumental variable (IV) strategy in which we exploit cross-industry variation in world export supply.

Our results indicate that, on average, offshoring increases the risk that employed workers become unemployed. There is, however, little evidence of negative employment consequences when collective bargaining is high. In countries with high collective bargaining coverage, offshoring seems to have negative consequences on unemployed workers, as it seems to be negatively associated with transitions from unemployment to employment.

This paper is related to several strands of literature. First, there is a number of empirical studies that focus on how offshoring affects employment level or job turnover of specific industrialised countries. For instance, using French firm-level data for periods 1986–87 and 1991–92, Biscourp and Kramarz (2007) find a strong negative association between narrow offshoring and employment, particularly for non-production workers. On the other hand, the main findings of Amiti and Wei (2009) show that manufacturing and services offshoring had little impact on employment changes of the US manufacturing industries over 1992–2000. Regarding the effects on job flows, Egger, Pfaffermayr and Weber (2007) use data for Austrian male workers and find that higher industry-level offshoring leads to lower probability of staying or transiting in a job in the manufacturing sector. For Germany, Geishecker (2008) estimates the effect of industry offshoring on the hazard rate of exiting employment. His results indicate that offshoring reduces job security irrespective of individual educational attainment. In addition, Munch (2010) analyses the impact of offshoring on transitions into a new job or unemployment for Danish workers and finds that offshoring increases the probability of becoming unemployed for low-skilled workers and the probability of changing jobs for high-skilled ones. Looking at US offshoring to China and India, Liu and Trefler (2019) show that in the presence of worker sorting, offshoring has larger effects on the probability of switching down, to a job with lower inter-occupational wage differential, than on the probability of switching up. [1]

Second, this paper speaks to the theoretical literature on the role of collective bargaining coverage for the impact of offshoring on employment. In particular, Ranjan (2013) sets up a search model with collective bargaining, in which wages are set by unions and firms choose employment. In his model, the possibility of offshoring induces unions, foreseeing the threat of jobs moving abroad, to set lower wages and firms to hire *more* workers, as long as the offshoring cost is relatively high. Once the offshoring cost becomes sufficiently small, however, unemployment increases as it becomes profitable to substitute offshored input for domestic workers. The model therefore suggests a non-monotonic relationship between the cost of offshoring and unemployment in the presence of collective bargaining. In contrast, the model predicts that offshoring unambiguously increases unemployment when wages are determined through individual bargaining. The key difference with respect to the collective bargaining case is that the individual worker does not internalize the effect of her own wage on total domestic employment, leading to a smaller wage cut, but also more unemployment in response to increased offshoring.

We contribute to the existing literature by estimating the effects of offshoring on employment transitions for a large number of European countries. To the best of our knowledge, our paper is the first empirical study that analyzes the role of collective bargaining for the employment effects of offshoring.

The rest of this paper is organized as follows. Section 2 describes the data and presents some descriptive statistics. We describe our empirical method in section 3. Results are discussed in section 4, section 5 concludes.

3.2 Data and Descriptive Evidence

This section describes data sources and the construction of the variables used in our empirical analysis.

Our microdata at the individual level come from the European Union Labour Force Survey (EU-LFS). The EU-LFS database consists of a large number of representative national household surveys covering all European countries (EU 28) as well as Norway, Iceland, and Switzerland. The dataset is processed by Eurostat and applies harmonized classifications and definitions, e.g. for the economic sector (Nomenclature of Economic Activities [NACE]) and the occupation (International Standard Classification of Occupations [ISCO]) of individual workers, which ensure comparability across countries.

The EU-LFS data includes repeated cross-sections of workers and contains information on a person's current and previous employment status, three- and two-digit occupational codes, one-digit industry codes, and some worker characteristics, e.g. gender, marital status, age, and educational attainment.

[1] See also Hummels, Munch and Xiang (2018) for a review of the literature on the labour market effects of offshoring.

In the data, yearly labour market flows can be analysed by using information on an individual's current labour market status, and the retrospectively collected labour market status in the previous year. Although these two definitions may not overlap perfectly, using both to identify labour market transitions from one year to the next is preferable to alternative approaches, which would not allow for consistent measurement across countries (For more details, see Bachmann and Felder 2021). For reasons of data availability with respect to both EU-LFS and the other data sources described below, our final sample of analysis consists of 20 European countries: Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Italy, Lithuania, Luxembourg, Netherlands, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, and the United Kingdom.

We display the labour market transition rates in the countries analysed in Figure 3.A.1 in the Appendix. In general, the transition rates from employment to unemployment (EU), shown by the dashed lines, vary from 0% to 6%, and the transition rates from unemployment to employment (UE), depicted by the solid lines, are in the range of 10% to 60%. The transition rates behave very differently across the countries in our sample. For example, some countries exhibit falling employment to unemployment transition rates over time (such as Finland and Germany), a few others display fairly constant transition rates (e.g., Italy, the Netherlands, Sweden, and the UK), and the rest show mean-preserving fluctuations in transition rates from one year to the next. For worker flow rates from unemployment to employment, we still observe heterogeneity across countries, but for most countries the rates are fairly constant over the time period analysed.

We use the World Input-Output Database (WIOD) to construct the offshoring measure.[2] We measure industry-level offshoring of industry j in country c and year t as the share of imported intermediate inputs in industry gross output (broad offshoring following the terminology of Feenstra and Hanson, 1999):[3]

$$Off_{jct} = \frac{IIMP_{jct}}{GO_{jct}} \tag{3.1}$$

Data on collective bargaining coverage are collected from the OECD/AIAS ICTWSS database (OECD and AIAS, 2021a). Collective bargaining is defined as all negotiations which take place between trade unions and employers' organisations in order to provide common standards of wages, working hours, and working conditions and terms of employment in labour markets (OECD and AIAS 2021b; ILO Convention No. 154 1981).
Bargaining coverage index measures the extent to which the terms of workers' employment are affected by collective negotiation. This indicator is a coverage rate and represents the share of employees covered by the collective agreement to total number of wage and salary-earners (Traxler, 1994).

Data on domestic production is obtained from the OECD STructural ANalysis

[2]We use the 2013 release, which covers 35 sectors and 40 countries (plus a model for the rest of the world) for the period 1995–2011. See Timmer, Dietzenbacher, Los, Stehrer and de Vries (2015) for a detailed description and some illustrative applications of this dataset.

[3]We reweight this industry-level measure to the level of occupations for our empirical analysis, as we explain below.

(STAN) database (ISIC Rev. 3)[4], in which production (or gross output) at current prices corresponds to the value of goods and services produced in a certain industry, country, and year.

We show descriptive statistics for our main variables of interest in Table 3.A.1 in the Appendix.

3.3 Methodology

Our empirical strategy is to relate the probability of making a transition from employment to unemployment, and from unemployment to employment, to our lagged measure of offshoring exposure and collective bargaining coverage as follows:

$$Pr(U_{ioct}|E_{ioc,t-1}) = F\left(\mathit{Off}_{oc,t-1}, \mathit{Off}_{oc,t-1} \times CBC_{c,2000}, X_{i,t-1}, C_{c,t-1}, \alpha_c, \delta_t, \gamma_o\right) \tag{3.2}$$

$$Pr(E_{ioct}|U_{ioc,t-1}) = F\left(\mathit{Off}_{oc,t-1}, \mathit{Off}_{oc,t-1} \times CBC_{c,2000}, X_{i,t-1}, C_{c,t-1}, \alpha_c, \delta_t, \gamma_o\right) \tag{3.3}$$

where indicator variable U_{ioct} takes on value 1 if individual i working in occupation o in country c in period $t-1$ becomes unemployed in time period t; flows from unemployment to employment (E_{ioct}) are defined analogously. $\mathit{Off}_{oc,t-1}$ denotes the level of offshoring exposure for an occupation, which we explain below. $CBC_{c,2000}$ is a country-specific measure of collective bargaining coverage in year 2000.[5] We are particularly interested in the effects of offshoring exposure and how it varies with the level of collective bargaining coverage, captured by the interaction term $\mathit{Off}_{oc,t-1} \times CBC_{c,2000}$.

In addition, we include a large number of control variables. X denotes individual characteristics, including sex, marital status, age (with the categories young: 15–29 years, middle-aged: 30–54, and elderly: 55–64), and education (with the International Standard Classification of Education [ISCED] categories low: ISCED 0–2, medium: ISCED 3–4, and high: ISCED 5–6). Furthermore, we include a vector of country-specific variables (C) which control for GDP per capita (in log terms) and the annual growth rate of real GDP. We also add country (α_c) and year (δ_t) fixed effects that control for macroeconomic changes common to all countries and permanent cross-country differences in institutions. Finally, we include occupation fixed effects, γ_o, to absorb variation specific to time-invariant features of occupations.

The variable offshoring in our econometric analysis is measured at the occupation level because the EU-LFS data contains sectoral information at the 1-digit

[4]Note that, at the 1-digit level, the ISIC Rev. 3 industry classification is equivalent to the NACE Rev. 1, which is the industry classification of the EU-LFS data

[5]We use the value of collective bargaining coverage in year 2000 in our models since for most of the countries in our sample, data on collective bargaining coverage is available from this year. Using a time invariant measure of CBC reduces endogeneity concerns. However, as a robustness check, in Table 3.A.2 in the Appendix, we allow the values of collective bargaining coverage to vary by time and obtain qualitatively similar results.

level only, which is far too broad to construct an industry-level measure of offshoring exposure. Instead, EU-LFS contains information about an individual's occupation at both 2-digit and 3-digit levels. Therefore, we are able to follow a methodology similar to Ebenstein, Harrison, McMillan and Phillips (2014) and Baumgarten, Geishecker and Görg (2013), and create an occupation-specific offshoring measure through reweighting:

$$Off_{oct} = \sum_{j=1}^{J} \frac{L_{ojc}}{L_{oc}} Off_{jct} \tag{3.4}$$

where Off_{oct} is offshoring exposure for occupation o in country c at time t. L is the level of employment, and industries are denoted by j. Thus, offshoring is aggregated across industries using the industry's share in occupation total employment as weight. These weights are time-invariant and averaged over the years 1998–2000 (or the first 3 available years in the EULFS). Moreover, similar to Ebenstein *et al.* (2014), we use a lagged measure of offshoring exposure ($Off_{oc,t-1}$) in our estimation models as it presumably takes some time for employment to adjust, and to avoid simultaneous shocks which are likely to affect offshoring exposure and employment within a given year.

A potential concern is that offshoring and domestic employment are jointly determined by domestic market conditions that are not captured by our fixed effects and control variables. To address this concern, we follow the idea of Hummels, Jørgensen, Munch and Xiang (2014) and instrument offshoring by the world export supply to countries outside of our sample, again relying on the WIOD data. Specifically, our instrument is constructed as follows:

$$ES_{jct} = \frac{\sum_l \sum_s share_{lsjc} X_{lst}^{Non-Europe}}{GO_{95}} \tag{3.5}$$

where l denotes the source industry and s the source country. $share_{lsjc}$ is the input share of a source-industry, source-country combination in the use-industry, use-country combination jc, measured in the pre-sample year 1995. $X_{lst}^{Non-Europe}$ are the time-varying exports of the source-industry, source-country combination ls to countries outside Europe. We then again reweight this measure using the procedure in Equation 3.4 above to arrive at an instrument that varies at the occupation-country-year level. This instrumental variable is likely to be correlated with the costs of offshoring, e.g. due to transport costs or variation in productivity and wages in the source countries, but is unlikely to be correlated with domestic market conditions within the countries in our sample.

3.4 Results

In this section, we display the results of our empirical analysis. As described in section 3, we start by estimating the conditional transition probability into and out of unemployment, and examine the role of CBC. In the next step, we address the possible endogeneity of offshoring.[6]

3.4.1 The impact of offshoring on labour market transitions and the role of CBC

In Panel A of Table 3.1, we present the Probit regression results for equation 3.2, which refers to the transition probability from employment to unemployment. In Panel B, we show the results for the transition probability in the reverse direction, as outlined in equation 3.3.

Before looking at the coefficients of the main variables of interest, the offshoring indicator and an interaction term, we briefly highlight some of the other estimates. The results indicate that both the likelihood of making a transition from employment to unemployment as well as the probability of re-entering the labour force is steadily decreasing in age. It can also be seen that males, married, and high-educated individuals are less likely to make a transition to unemployment but more likely to find a job out of unemployment. In addition, the coefficients on GDP and GDP per capita have the expected signs as both are associated with a decrease in the likelihood of transition to unemployment and a rise in the probability of re-entering the employment.

Turning now to the coefficient on the offshoring variable in Column 1, we see a positive and statistically significant association between offshoring and the transition rate from employment to unemployment, which is in line with the results of previous literature which document that higher exposure to offshoring increases unemployment.

Regarding the contribution of collective bargaining, it can be seen that the interaction term between offshoring and CBC is negative and statistically significant at 1% level. This implies that the positive impact of offshoring on transition into unemployment decreases with higher levels of collective bargaining coverage. To illustrate the point more clearly, Figure 3.1a depicts marginal effect of the variable offshoring for a range of different levels of CBC and different initial values of offshoring. Considering, for instance, a level of CBC equal to 30.7 (10th percentile), a 1 percentage point (pp) increase in offshoring exposure increases the probability of transition to unemployment by about 0.04 pp for initial values of offshoring exposure between the 25th and the 90th percentile. This effect is however insignificant and close to zero for the levels of CBC larger than 50th percentile. This result is broadly consistent with the theoretical model of Ranjan (2013).

As for the transition rate from unemployment to employment in the Probit regression (Column 2 of Table 3.1), we find no statistically significant relationship between offshoring and the unemployment outflow rate. Yet, the interaction term between CBC and offshoring displays a significantly negative coefficient. Figure 3.1b shows again the average marginal effects of the variable offshoring for different levels of CBC. As can be seen, at lower levels of CBC, the effect of higher exposure to offshoring on the transition rate to employment is smaller than at higher values of CBC. For instance, at 10th percentile of CBC, an increase in offshoring exposure

[6] We also experimented with different functional forms for F(.). Table 3.A.3 in the Appendix shows, for instance, estimates of linear probability models.

by 1 pp is associated with a decrease in the probability of a transition out of unemployment by about 0.01 pp (statistically insignificant). However, when the level of CBC increases to its 50th percentile, the estimated effect increases to more than 0.2 pp for low initial values of offshoring(significant at the 5% level).[7]

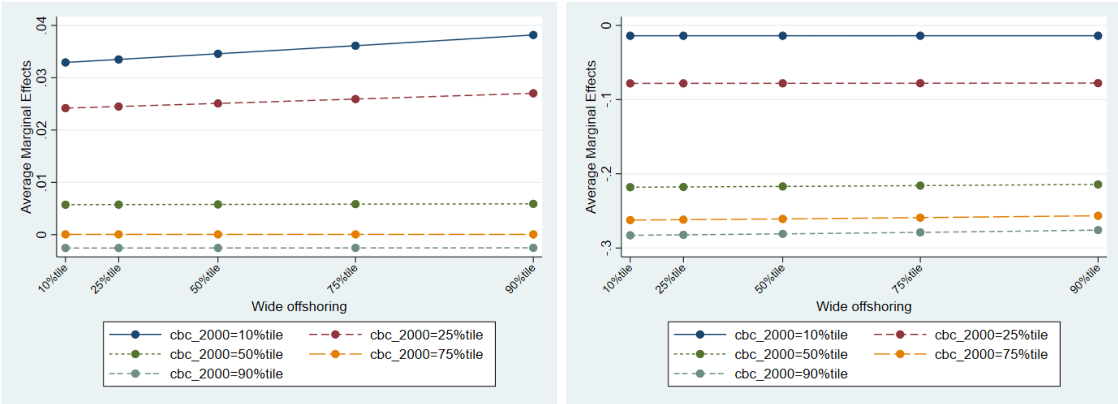
Table 3.1: Probability of becoming (un)employed in response to changes in offshoring and CBC– Probit

	Panel A: Prob (**E**→**U** Transition)	**Panel B:** Prob (**U**→**E** Transition)
	Probit 1	Probit 2
WideOffshoring	0.820***	0.301
	(0.194)	(0.424)
CBC_{2000} × WideOffshoring	-0.009***	-0.011**
	(0.003)	(0.005)
Male	-0.084***	0.070***
	(0.009)	(0.013)
Married	-0.181***	0.014*
	(0.004)	(0.008)
Age 30-54	-0.193***	-0.452***
	(0.007)	(0.016)
Age 55-65	-0.206***	-0.898***
	(0.017)	(0.032)
Medium skill	-0.105***	0.158***
	(0.006)	(0.011)
High skill	-0.158***	0.332***
	(0.009)	(0.014)
GDP_GR	-0.009***	0.024***
	(0.003)	(0.006)
GDP_PC	-0.202***	0.210***
	(0.049)	(0.075)
Observation	6,741,315	610,123

Notes:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (SE) in parentheses. SEs are clustered at the occupation(2-digit)-year level. The regressions also include full sets of country, occupation(two digit) and year dummies. CBC index includes missing data for France(FR) in 2000. We therefore conduct an imputation for this year using the first non-missing value in previous years for this country. Final sample of analysis consists of 27 occupations and 20 European countries: Austria, Belgium, Czech Republic, Germany, Denmark, Spain, Finland, France, Greece, Hungary, Italy, Lithuania, Luxembourg, Netherlands, Poland, Portugal, Sweden, Slovenia, Slovak Republic and the United Kingdom. Authors' calculations for the time period 1998-2008

[7] Table 3.A.4 in the Appendix reports average marginal effects of the variable offshoring at different percentiles of offshoring and collective bargaining coverage.

Figure 3.1: Average Marginal Effects of Wideoffshoring



(a) E to U transition, Probit

(b) U to E transition, Probit

Notes: Average Marginal Effects of wide offshoring computed at values of wide offshoring= 0.015(1%tile), 0.043(10%tile), 0.060(25%tile), 0.092(50%tile), 0.138(75%tile), 0.196(90%tile), 0.321(99%tile), 0.467(maximum); and values of CBC_{2000}=30.7(10%tile) , 47.2(25%tile), 83.25(50%tile), 94.7(75%tile), and 100(90%tile).

3.4.2 Endogeneity

A key estimation issue which we have not addressed so far is that the offshoring variable might be endogenous to employment outcomes, thus raising concerns about a potential bias in the coefficients. To deal with this concern, we instrument offshoring with world-export supply, as explained in Section 3. The results of the control function (CF) approach reported in Table 3.2 show that the magnitudes of the coefficients increase compared to the baseline specifications reported in Table 3.1. In addition, while the sign and level of statistical significance remain robust for the CF specification in Panel A, the association between interaction term and the probability of unemployment outflow is now insignificant (column 2 of Table 3.2).[8]

Note that each control function estimate in Table 3.2 requires two first-stage regressions. To assess the strength of the CF approach, we report the first-stage results at lower part of the table. As the values of Kleibergen-Paap F statistics indicate, in both panels, the F-statistic is below the conventional threshold of 10, indicating that the instruments are relatively weak. Therefore, the reported estimates in Table 3.2 should be interpreted with caution. In order to address the concern of incorrect empirical inference with a weak instrument, we employ a weak-instrument-robust test for our specifications, and use the *ivprobit* command in *Stata15* with *weakiv* (Finlay, Magnusson and Schaffer, 2014). As *weakiv* only supports the two-step estimator of *ivprobit*, we use the two-step IV probit with bootstrapped standard errors clustered at occupation-year level[9], and find Anderson-Rubin statistics of 83.15 (for Panel A)

[8]We also show marginal effects of the variable offshoring for our CF specifications in Figures 3.A.3a and 3.A.3b.

[9]IVprobit regressions are estimated with bootstrap standard errors, because *-ivprobit, twostep-* does not support *vce(cluster)* option. Standard errors are obtained by a 500-replication bootstrap of the two-step procedure

and 22.84 (for Panel B), which are significant at the 1% level (Table 3.A.5 in the Appendix).[10]. However, in further analysis, we attempt to improve the robustness of our estimations by applying other methods, such as GMM models, and using alternate tests to address remaining concerns about weak instruments.

[10]The AR statistics provide a fully robust test of the hypothesis that the coefficients on offshoring and offshoring interacted with CBC are zero

Table 3.2: Probability of becoming (un)employed in response to changes in offshoring and CBC– Control Function

	Panel A: Prob (**E**→**U** Transition)	**Panel B:** Prob (**U**→**E** Transition)
	CF	CF
	1	2
WideOffshoring	6.848***	4.652
	(1.853)	(3.319)
CBC_{2000} × WideOffshoring	-0.042***	-0.014
	(0.014)	(0.025)
Male	-0.083***	0.075***
	(0.009)	(0.013)
Married	-0.181***	0.016**
	(0.004)	(0.008)
Age 30-54	-0.195***	-0.452***
	(0.007)	(0.016)
Age 55-65	-0.214***	-0.899***
	(0.017)	(0.032)
Medium skill	-0.125***	0.148***
	(0.010)	(0.014)
High skill	-0.173***	0.321***
	(0.011)	(0.017)
GDP_GR	-0.008***	0.024***
	(0.003)	(0.006)
GDP_PC	-0.288***	0.163*
	(0.059)	(0.088)
Residual 1^{st}	-6.045***	-4.352
	(1.878)	3.405
Residual 2^{nd}	0.034**	0.001
	(0.014)	(0.024)
Observation	6,741,315	610,123
First stage results, dependent variable: Wide Offshoring		
$ESown5\_all\_ALL\_GO95$	-.0004**	-.0004**
	(0.0002)	(0.0002)
$ESown5\_all\_ALL\_GO95$ ×CBC_{2000}	.00005***	.00006***
	(.00001)	(.00001)
R-Squared	0.893	0.905
F-test of excluded instruments	12.78	14.53
Prob > F	0.000	0.000
Sanderson-Windmeijer F-test	9.66	7.00
Prob > F	0.002	0.009
First stage results, dependent variable: Wide Offshoring ×CBC_{2000}		
$ESown5\_all\_ALL\_GO95$	-.174***	-.160***
	(.021)	(.022)
$ESown5\_all\_ALL\_GO95$ ×CBC_{2000}	.009***	0.009***
	(.001)	(0.001)
R-Squared	0.878	0.887
F-test of excluded instruments	43.25	29.37
Prob > F	0.000	0.000
Sanderson-Windmeijer F-test	9.99	10.67
Prob > F	0.002	0.001
Anderson-Rubin Wald test F(2,296)	2.65	2.48
P-Val	0.072	0.086
AR Wald test chi2(2) (ivreg2)	5.33	4.97
P-Val	0.07	0.08
AR test chi2(2) (weakiv)	4.16	4.79
P-Val	0.125	0.0911
Kleibergen-Paap Wald rk F statistic	4.94	3.41
Obs.	6,741,315	610,123

Notes:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (SE) in parentheses. SEs are clustered at the occupation(2-digit)-year level. The regressions also include full sets of country, occupation(two digit) and year dummies. CBC index includes missing data for France(FR) in 2000. We therefore conduct an imputation for this year using the first non-missing value in previous years for this country. Final sample of analysis consists of 27 occupations and 20 European countries: Austria, Belgium, Czech Republic, Germany, Denmark, Spain, Finland, France, Greece, Hungary, Italy, Lithuania, Luxembourg, Netherlands, Poland, Portugal, Sweden, Slovenia, Slovak Republic and the United Kingdom. Authors' calculations for the time period 1998-2008

3.5 Conclusion

This paper investigates the effects of offshoring on employment transitions using comparable micro data across 20 European countries. Our results indicate that offshoring increases the risk that employed workers become unemployed but this effect is dampened in countries with high collective bargaining coverage. In these countries, offshoring is, however, negatively associated with transitions from unemployment to employment.

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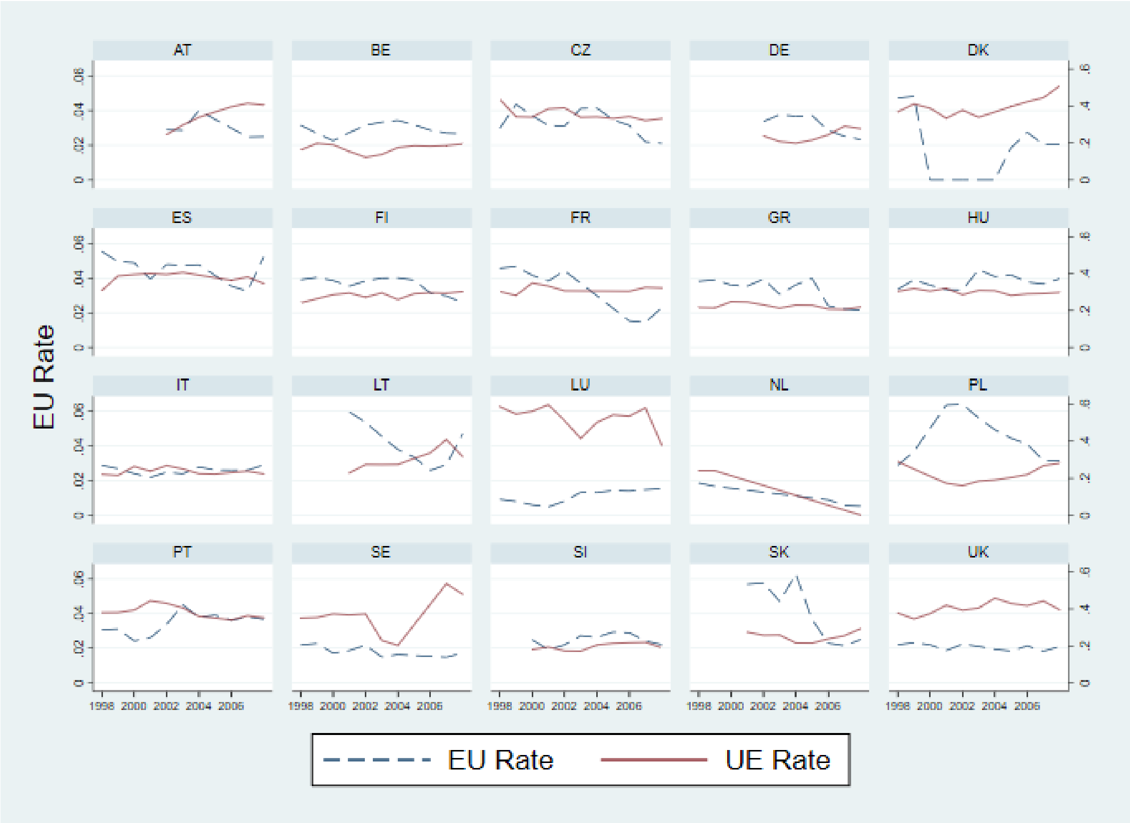
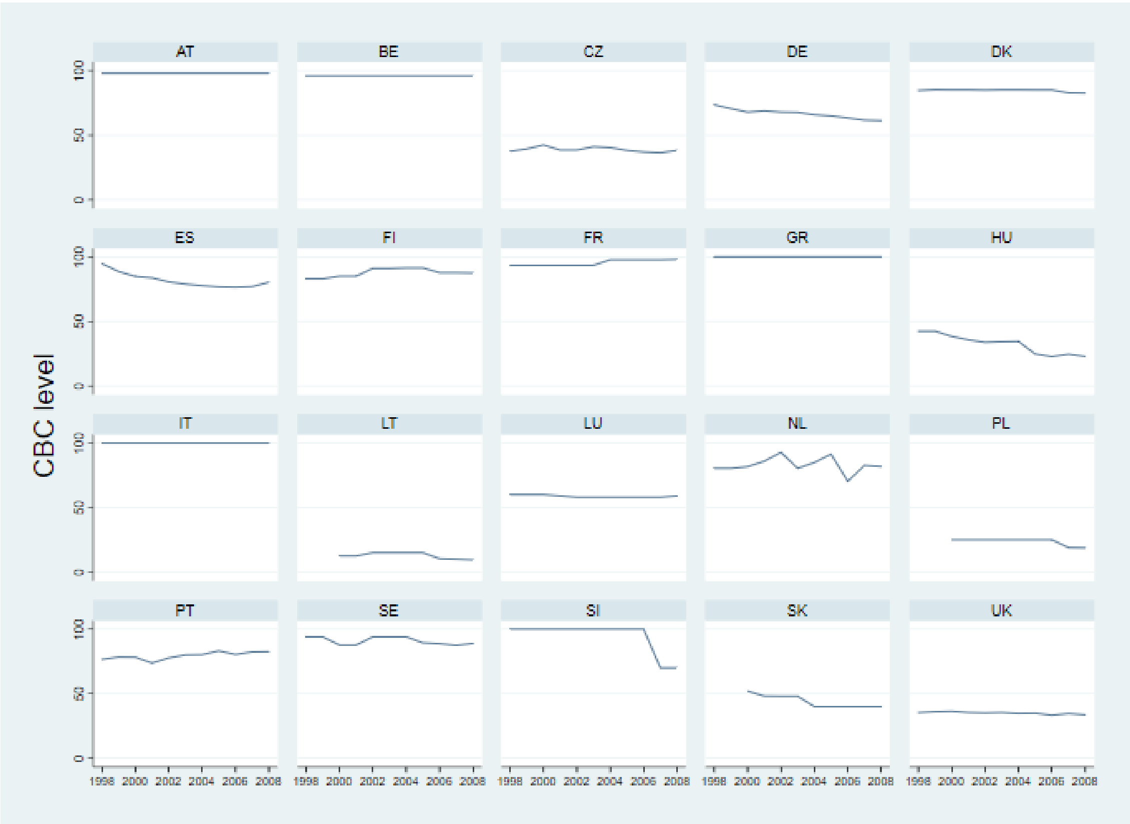
Appendix A

Figure 3.A.1: Transition rates from employment to unemployment (EU) and from unemployment to employment (UE), in (%) by country, 1998-2008



Notes: The left axis shows the scale for the EU rate, the right axis the scale for the UE rate.
Source: EU-LFS, own calculation.

Figure 3.A.2: Collective Bargaining Coverage (CBC) level in (%) by country, 1998-2008



Source: OECD/AIAS ICTWSS database (OECD and AIAS, 2021a).

Table 3.A.1: Summary statistics

Variables	**E**→**U** Sample	**U**→**E** Sample
Sex:Male	0.542	0.519
	(0.498)	(0.500)
Marital Status:Married	0.615	0.461
	(0.486)	(0.498)
Age:15-29	0.196	0.332
	(0.397)	(0.471)
Age:30-54	0.696	0.583
	(0.460)	(0.493)
Age:55-64	0.108	0.085
	(0.311)	(0.278)
Skill:Low	0.263	0.419
	(0.440)	(0.493)
Skill:Medium	0.509	0.468
	(0.500)	(0.499)
Skill:High	0.228	0.112
	(0.419)	(0.315)
2000 Collective Bargaining Coverage (CBC)	73.58	74.14
	(26.14)	(26.83)
Dummy 2000 Collective Bargaining Coverage (DCBC)	0.605	0.618
	(0.489)	(0.486)
Real GDP growth (GDP-GR)	2.683	2.788
	(2.185)	(2.256)
log GDP per capita, current prices (US dollars)	10.10	9.953
	(0.606)	(0.608)
Wide offshoring (Off_{oct})	0.106	0.104
	(0.067)	(0.067)
Lag of wide offshoring ($Off_{oc,t-1}$)	0.103	0.101
	(0.065)	(0.065)
$lESown5\_all\_ALL\_GO95_{oc,t-1}$	1.998	1.787
	(5.391)	(4.165)
Unemployment Rate	0.109	0.120
	(0.037)	(0.035)
Employment Rate	0.755	0.731
	(0.082)	(0.079)
Transition rate from employment to unemployment	0.030	
	(0.010)	
Transition rate from unemployment to employment		0.273
		(0.072)

DATA: Regression sample, authors' calculations for the time period 1998-2008.

Table 3.A.2: Probability of becoming (un)employed in response to changes in offshoring and CBC (time varying)

	Panel A: Prob (**E**→**U** Transition)		**Panel B:** Prob (**U**→**E** Transition)	
	Probit	CF	Probit	CF
WideOffshoring	0.698***	6.121***	0.054	4.718*
	(0.168)	(1.692)	(0.378)	(2.737)
CBC × WideOffshoring	-0.008***	-0.035***	-0.008*	0.008
	(0.002)	(0.011)	(0.004)	(0.015)
Observation	6,724,964	6,724,964	608,074	608,074

Notes:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (SE) in parentheses. SEs are clustered at the occupation(2-digit)-year level. The regressions also include full sets of country, occupation(two digit) and year dummies .Control variables: lagged measure of CBC, gender, age, marital status, education, GDP growth, per capita GDP. Final sample of analysis consists of 27 occupations and 20 European countries: Austria, Belgium, Czech Republic, Germany, Denmark, Spain, Finland, France, Greece, Hungary, Italy, Lithuania, Luxembourg, Netherlands, Poland, Portugal, Sweden, Slovenia, Slovak Republic and the United Kingdom. Authors' calculations for the time period 1998-2008

Table 3.A.3: Probability of becoming (un)employed in response to changes in offshoring and CBC– LPM and 2SLS

	Panel A: Prob (**E**→**U** Transition)		**Panel B:** Prob (**U**→**E** Transition)	
	LPM	2SLS	LPM	2SLS
WideOffshoring	0.087***	0.373*	0.117	1.870
	(0.016)	(9.209)	(0.155)	(1.466)
CBC_{2000} × WideOffshoring	-0.0009***	-0.003*	-0.004**	-0.007
	(0.0002)	(0.001)	(0.002)	(0.010)
Male	-0.004***	-0.004***	0.024***	0.026***
	(0.0006)	(0.0005)	(0.004)	(0.004)
Married	-0.010***	-0.010***	0.003	0.004
	(0.0004)	(0.0004)	(0.003)	(0.003)
Age 30-54	-0.015***	-0.015***	-0.163***	-0.164***
	(0.0006)	(0.0006)	(0.006)	(0.006)
Age 55-65	-0.016***	-0.016***	-0.311***	-0.312***
	(0.001)	(0.001)	(0.010)	(0.010)
Medium skill	-0.007***	-0.008***	0.009***	0.051***
	(0.0005)	(0.001)	(0.002)	(0.006)
High skill	-0.009***	-0.010***	0.113***	0.109***
	(0.0005)	(0.0008)	(0.004)	(0.006)
GDP_GR	-0.0006***	-0.0005**	0.009***	0.009***
	(0.0002)	(0.0003)	(0.002)	(0.002)
GDP_PC	-0.015***	-0.019*	0.071***	0.052
	(0.004)	(0.007)	(0.026)	(0.035)
Observation	6,741,315	6,741,315	610,123	610,123
First stage results, dependent variable: Wide Offshoring				
ESown5_all_ALL_GO95		-.0004**		-.0004**
		(0.0002)		(0.0002)
ESown5_all_ALL_GO95 $\times CBC_{2000}$		.00005***		.00006***
		(.00001)		(.00001)
R-Squared		0.893		0.905
F-test of excluded instruments		12.78		14.53
Prob > F		0.000		0.000
Sanderson-Windmeijer F-test		9.66		7.00
Prob > F		0.002		0.009
First stage results, dependent variable: Wide Offshoring $\times CBC_{2000}$				
ESown5_all_ALL_GO95		-.174***		-.160***
		(.021)		(.022)
ESown5_all_ALL_GO95 $\times CBC_{2000}$		.009***		0.009***
		(.001)		(0.001)
R-Squared		0.878		0.887
F-test of excluded instruments		43.25		29.37
Prob > F		0.000		0.000
Sanderson-Windmeijer F-test		9.99		10.67
Prob > F		0.002		0.001
Anderson-Rubin Wald test F(2,296)		2.65		2.48
P-Val		0.072		0.086
AR Wald test chi2(2) (ivreg2)		5.33		4.97
P-Val		0.07		0.08
AR test chi2(2) (weakiv)		4.16		4.79
P-Val		0.125		0.0911
Kleibergen-Paap Wald rk F statistic		4.94		3.41
Obs.		6,741,315		610,123

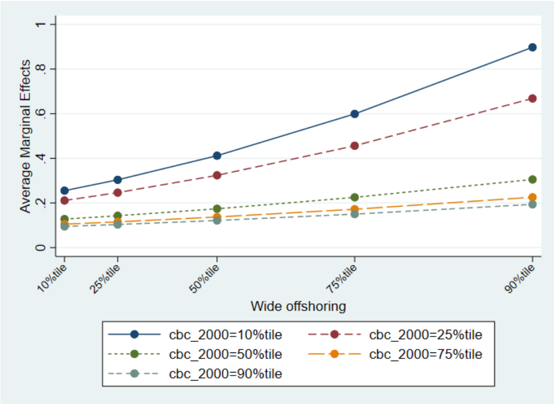
Notes:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (SE) in parentheses. SEs are clustered at the occupation(2-digit)-year level. The regressions also include full sets of country, occupation(two digit) and year dummies. CBC index includes missing data for France(FR) in 2000. We therefore conduct an imputation for this year using the first non-missing value in previous years for this country. Final sample of analysis consists of 27 occupations and 20 European countries: Austria, Belgium, Czech Republic, Germany, Denmark, Spain, Finland, France, Greece, Hungary, Italy, Lithuania, Luxembourg, Netherlands, Poland, Portugal, Sweden, Slovenia, Slovak Republic and the United Kingdom. Authors' calculations for the time period 1998-2008

Table 3.A.4: Average Marginal Effects of Wideoffshoring corresponding to Tables 3.1-3.2

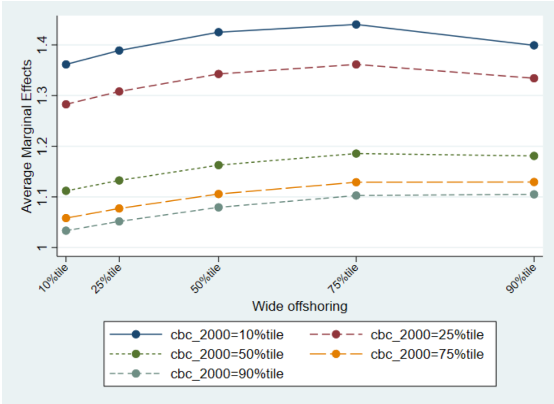
	Panel A: Prob (**E**→**U** Transition)		**Panel B:** Prob (**U**→**E** Transition)	
	Probit	CF	Probit	CF
10%WideOff & 10%CBC_{2000}	0.033***	0.255***	-0.014	1.361*
	(0.007)	(0.060)	(0.111)	(0.781)
10%WideOff & 25%CBC_{2000}	0.024***	0.211***	-0.078	1.283*
	(0.006)	(0.045)	(0.097)	(0.663)
10%WideOff & 50%CBC_{2000}	0.006	0.128***	-0.218**	1.112**
	(0.008)	(0.025)	(0.088)	(0.449)
10%WideOff & 75%CBC_{2000}	0.00006	0.105***	-0.262***	1.058***
	(0.009)	(0.023)	(0.093)	(0.405)
10%WideOff & 90%CBC_{2000}	-0.002	0.095***	-0.283***	1.033***
	(0.009)	(0.023)	(0.096)	(0.390)
25%WideOff & 10%CBC_{2000}	0.033***	0.304**	-0.014	1.389*
	(0.008)	(0.084)	(0.111)	(0.815)
25%WideOff & 25%CBC_{2000}	0.024***	0.246***	-0.078	1.308*
	(0.007)	(0.062)	(0.096)	(0.693)
25%WideOff & 50%CBC_{2000}	0.006	0.143***	-0.218**	1.132**
	(0.008)	(0.033)	(0.087)	(0.471)
25%WideOff & 75%CBC_{2000}	0.00006	0.115***	-0.262***	1.077**
	(0.009)	(0.029)	(0.092)	(0.424)
25%WideOff & 90%CBC_{2000}	-0.002	0.103***	-0.282***	1.052***
	(0.009)	(0.028)	(0.096)	(0.408)
50%WideOff & 10%CBC_{2000}	0.034***	0.411***	-0.014	1.425*
	(0.008)	(0.144)	(0.111)	(0.852)
50%WideOff & 25%CBC_{2000}	0.025***	0.324***	-0.078	1.343*
	(0.009)	(0.103)	(0.096)	(0.730)
50%WideOff & 50%CBC_{2000}	0.006	0.174***	-0.217**	1.163**
	(0.008)	(0.050)	(0.087)	(0.502)
50%WideOff & 75%CBC_{2000}	0.00006	0.137***	-0.261***	1.106**
	(0.009)	(0.042)	(0.092)	(0.451)
50%WideOff & 90%CBC_{2000}	-0.002	0.121***	-0.281***	1.079**
	(0.009)	(0.040)	(0.095)	(0.434)
75%WideOff & 10%CBC_{2000}	0.036***	0.599**	-0.014	1.440*
	(0.009)	(0.254)	(0.111)	(0.842)
75%WideOff & 25%CBC_{2000}	0.026***	0.456**	-0.078	1.361*
	(0.007)	(0.179)	(0.096)	(0.733)
75%WideOff & 50%CBC_{2000}	0.006	0.225***	-0.216**	1.185**
	(0.008)	(0.080)	(0.086)	(0.519)
75%WideOff & 75%CBC_{2000}	0.00006	0.172***	-0.259***	1.129**
	(0.009)	(0.064)	(0.090)	(0.469)
75%WideOff & 90%CBC_{2000}	-0.002	0.150**	-0.279***	1.103**
	(0.009)	(0.059)	(0.094)	(0.452)
90%WideOff & 10%CBC_{2000}	0.038***	0.898**	-0.014	1.399*
	(0.010)	(0.431)	(0.111)	(0.723)
90%WideOff & 25%CBC_{2000}	0.027***	0.668**	-0.078	1.344**
	(0.008)	(0.306)	(0.096)	(0.654)
90%WideOff & 50%CBC_{2000}	0.006	0.305***	-0.214**	1.181**
	(0.008)	(0.130)	(0.084)	(0.497)
90%WideOff & 75%CBC_{2000}	0.00006	0.225***	-0.256***	1.129**
	(0.009)	(0.100)	(0.088)	(0.456)
90%WideOff & 90%CBC_{2000}	-0.002	0.194**	-0.276***	1.105**
	(0.009)	(0.090)	(0.091)	(0.441)
Observation	6,741,315	6,741,315	610,123	610,123

Notes:This table offers the average marginal effects for the wide offshoring variable in Table **??**. The average marginal effects are computed at specified percentiles of wide offshoring and collective bargaining coverage. The values of all other covariates are as they are observed. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (SE) in parentheses. SEs are clustered at the occupation(2-digit)-year level. The regressions also include full sets of country, occupation(two digit) and year dummies. CBC index includes missing data for France(FR) in 2000. We therefore conduct an imputation for this year using the first non-missing value in previous years for this country. Final sample of analysis consists of 27 occupations and 20 European countries: Austria, Belgium, Czech Republic, Germany, Denmark, Spain, Finland, France, Greece, Hungary, Italy, Lithuania, Luxembourg, Netherlands, Poland, Portugal, Sweden, Slovenia, Slovak Republic and the United Kingdom. Authors' calculations for the time period 1998-2008

Figure 3.A.3: Average Marginal Effects of Wideoffshoring



(a) E to U transition, control function



(b) U to E transition, control function

Notes: Average Marginal Effects of wide offshoring computed at values of wide offshoring= 0.015(1%tile), 0.043(10%tile), 0.060(25%tile), 0.092(50%tile), 0.138(75%tile), 0.196(90%tile), 0.321(99%tile), 0.467(maximum); and values of CBC_{2000}=30.7(10%tile), 47.2(25%tile), 83.25(50%tile), 94.7(75%tile), and 100(90%tile).

Table 3.A.5: Probability of becoming (un)employed in response to changes in offshoring and CBC– ivprobit

	Panel A: Prob (**E**→**U** Transition)	**Panel B:** Prob (**U**→**E** Transition)
	IVProbit **Twostep**	IVProbit **Twostep**
WideOffshoring	6.848	4.652
	(4.852)	(120.75)
CBC_{2000} × WideOffshoring	-0.042	-0.014
	(0.033)	(0.747)
Male	-.083***	.075
	(0.009)	(0.155)
Married	-.181***	.016
	(0.004)	(0.049)
Age 30-54	-.195***	-.452***
	(0.007)	(0.038)
Age 55-65	-.214***	-.899***
	(0.017)	(0.033)
Medium skill	-.125***	.148
	(0.018)	(0.203)
High skill	-.173***	.321*
	(0.016)	(0.195)
GDP_GR	-.008	.024
	(0.005)	(0.150)
GDP_PC	-.288*	.163
	(0.158)	(2.851)
Observation	6,741,315	610,123
AR test chi2(2) (weakiv)	83.15	22.84
P-Val	0.000	0.000

Notes:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (SE) in parentheses. SEs are clustered at the occupation(2-digit)-year level. The regressions also include full sets of country, occupation(two digit) and year dummies.Final sample of analysis consists of 20 European countries: Austria, Belgium, Czech Republic, Germany, Denmark, Spain, Finland, France, Greece, Hungary, Italy, Lithuania, Luxembourg, Netherlands, Poland, Portugal, Sweden, Slovenia, Slovak Republic and the United Kingdom. Authors' calculations for the time period 1998-2008

Declaration of Contribution

Hereby I, Hedieh Aghelmaleki, declare that the Chapter "Offshoring, Collective Bargaining, and European Jobs" is co-authored by Daniel Baumgarten and Joel Stiebale. All authors contributed equally to the chapter.

Signature of co-author 1 (Daniel Baumgarten): Daniel Baumgarten --

Signature of co-author 2 (Joel Stiebale): Joel Stiebale --

Chapter 4

Do labour market institutions matter? The joint impacts of technology and labour market institutions on employment structure in Europe

4.1 Introduction

Employment polarisation has been a research subject since the 1990s. Several attempts have been made to investigate the main drivers behind job polarisation in advanced economies. One of the main hypotheses proposed in recent years concerns the "Routine-Biased Technologocial Change" (RBTC) explanation which suggests that most of the recent technological advancements have been shifting labour demands away from workers in routine jobs in the middle-wage distribution while increasing demands for labour in non-routine cognitive and non-routine manual activities, which are usually performed by workers in high- and low-wage occupations, respectively. Evidence supporting the job polarisation phenomenon is provided both for the US (e.g., Autor, Levy and Murnane, 2003; Autor, Katz and Kearney, 2006a, 2008; Autor and Dorn, 2013), and for many European countries (e.g., Goos and Manning, 2007; Goos, Manning and Salomons, 2009, 2014; Michaels, Natraj and Van Reenen, 2014; Jerbashian, 2019). However, the role of labour market institutions in explaining the heterogeneity in the extent of job structure among countries has been less explored in the related literature.

Figure 4.1 plots the percentage points change in the share of total hours worked for the high-, middle-, and low-paid occupation groups across the EU countries in my sample from 1993-2007. As can be seen, the employment share (defined by hours worked) has declined in medium-wage occupations in all countries; however, the fall is particularly larger in some countries than others (e.g., Austria, Italy, and the UK). In addition, all countries have experienced a growth in the employment share of high-paid jobs; but the rise is more significant in Austria and Italy. Regarding the low-wage occupational group, no clear pattern in employment shares was observed: While some countries such as the UK and Finland experienced quite a large growth (by 6 and 3.6 percentage points, respectively), some other countries experienced only a weak increase (e.g., Germany) or a decline (e.g., Italy) in the share of employment in this occupation group.

Altogether, we see most of these EU countries show a pattern that is consistent with the routinization hypothesis; however, we find large cross-country differences in the magnitude and extent of the occupational structure of employment. Besides this, countries also differ widely in their use of labour market institutions. For instance, while the UK is often linked with more flexible institutions, which rely on markets and choose job transitions over protection, Sweden is an example of a strongly regulated country where the major worry is shielding of existing jobs. Therefore, in this paper, I examine the combined effects of technology and labour market institutions on job structures to answer the following two research questions: First, can country-specific institutional framework in labour markets explain the distinctive magnitudes of job patterns that we observe in the data? Second, how do these effects differ across worker types?

To answer these research questions, I make use of comparable microdata across 9 European countries from Eurostat's European Union Labour Force Survey (EU-LFS), which contains information on employment status, occupation, and socioeconomic characteristics at the worker level. I combine these individual-level data with the industry-level data on intensity of Information and Communication Technologies

(ICT) from the EU KLEMS database in order to capture exposure to technology. This approach allows me to examine the effects of technological change on employment shares in different occupation groups.

The first contribution of this work is that it provides further evidence on the role of labour market institutions in relation to technology and employment. This is not the only paper to address the importance of labour market institutions in this context (e.g., Goos, Manning and Salomons, 2010; Martelli, 2017; Hope and Martelli, 2019), but most of the previous studies only control for institutional variables in their specifications and/or consider other sets of variables and datasets. By contrast, in this paper, I investigate the potential impacts of interaction between the advancements of technology and labour market institutions and discuss their joint effects on employment structures among some EU countries.
Secondly, this paper contributes to the literature by examining the heterogeneous effects across different worker groups, particularly with respect to gender, age, and education using microdata from the EU-LFS.

In this study, I focus on the role of two labour market institutions (employment protection legislation and collective bargaining) that theory and previous research indicate are particularly relevant for the study of differences across countries' employment outcomes. For instance, the research considering the employment protection legislation discusses two countervailing effects: On the one hand, strict employment regulations may have positive impacts on the welfare of incumbent workers (insiders) and increase their job security by preventing them from being fired. This, in turn, can rise the value of employment for workers and increase their effort and investment in industry-specific human capital, which can have positive impacts on productivity (Bassanini and Garnero, 2013; Griffith and Macartney, 2014). On the other hand, if more stringent regulations reduce job creation and constrain the reallocation of workers to productivity-enhancing sectors and occupations, this can hinder productivity and structural changes. In fact, Aghion, Burgess, Redding and Zilibotti (2008) find that employment protection legislation affects the speed at which firms can adjust their production process through hiring and firing and the level of reallocation of resources across firms. Similarly, Haltiwanger, Scarpetta and Schweiger (2014) show that more restrictive employment regulations are associated with smaller firm-level job flows and employment adjustments, particularly in those industries and firm size classes where technological and market-driven factors require labour adjustments more regularly. Nevertheless, as mentioned, the welfare effects of lower labour market flows are ambiguous.
As regards collective bargaining, the employment and welfare effects are not clear-cut, too. On the one side, Bertola, Blau and Kahn (2007) develop a theory showing that collective bargaining increases relative wages and decreases the relative employment of workers with more elastic labour supply schedules (i.e., female, young, and elderly workers). Also, Nellas and Olivieri (2012) build a model in which collective bargaining leads to higher wages for workers in manual jobs at the cost of lower employment growth. On the other side, Ranjan (2013) sets up a model with collective bargaining where the wages are set by unions and firms choose employment. In his model, the possibility of offshoring (triggered by innovation in ICT) brings unions

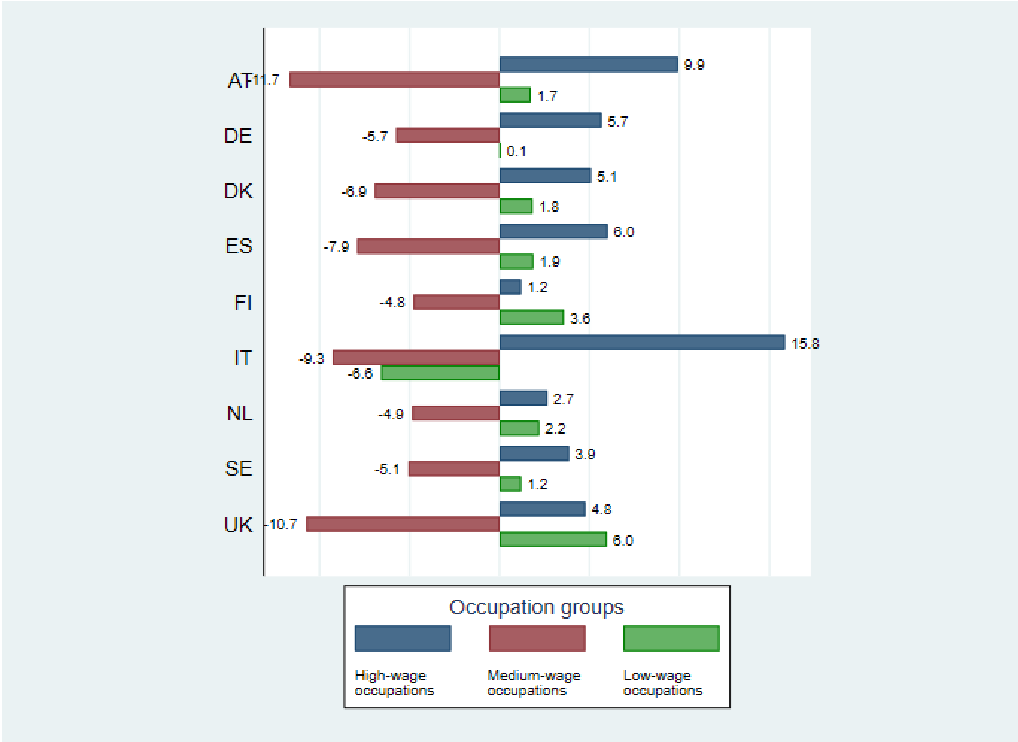
to set lower wages in the first stage, inducing firms to hire more workers. [1]
In addition, Acemoglu (2003) argues that when there is wage bargaining and rent sharing, wage push may induce technology adoption, which in turn can affect the composition and amount of labour in production. Finally, to the extent that strict employment protection regulations or higher bargaining power raise labour costs, employers may use technology more intensively to overcome distortions in the labour market and remain competitive. As a consequence, employers may put individuals out of work and lower the labour demand (Presidente, 2021).

By exploiting data for 9 European countries (Austria, Denmark, Finland, Germany, Italy, Netherlands, Spain, Sweden, and the UK) from 1993 to 2007, my results indicate robust evidence that an increase in ICT intensity, or more generally, technological growth is associated with a higher share of employment in high-wage occupations and lower share of employment in medium-wage occupations. However, strict labour market institutions, in particular, the employment protection legislation, contribute to mitigating these effects. In addition, I provide evidence of the heterogeneous effects among worker groups. For instance, my results show that higher ICT intensity has raised the share of employment in the high-wage occupations and decreased the share of employment in the low-wage occupations among females more than males, but these effects are partially alleviated by higher levels of EPL.

The rest of this paper is structured as follows. Section 2 summarizes the related literature. Section 3 introduces the data and presents descriptive evidence. Section 4 describes the identification strategy and empirical model. Section 5 shows the results and section 6 includes various robustness checks. Section 7 concludes.

[1] In the longer run, however, unemployment increases because the offshoring cost becomes sufficiently small.

Figure 4.1: Share of total hours worked, change between 1993 and 2007, percentage points



Notes: This figure shows the percentage points change in the share of total hours worked by occupation group and country, between 1993 and 2007. As the EU-LFS database does not have occupation data for some of the countries in some years, the sample Period starts from 1995 for Austria, and from 1997 for Finland and Sweden. Elaborated by the author based on Job Polarisation in Europe by Goos *et al.* (2010).

4.2 Related literature

The present work is related to three streams of literature:

First, my research is related to a large number of empirical studies that investigate how technological advancements affect employment. The first serious discussion and analysis of the so-called "routinization" hypothesis emerged during the early 2000s with the study by Autor *et al.* (2003), who found that the impact of computerisation on demand for labour depends on the extent to which tasks can be automated. Using the US data, the authors show that the use of computers leads to higher demand for workers performing non-routine cognitive tasks (which to date cannot be replaced by computers) such as managers, while it lowers the demand for workers performing routine tasks (which are replaceable by computers) such as stationary plant operators. However, the authors find no clear effect on non-routine manual tasks since computers neither strongly substitute nor strongly complement these tasks.

The hypothesis of routine biased technological change (RBTC) has also been analysed by several researchers using different data sets. For instance, Spitz-Oener

(2006) and Dustmann, Ludsteck and Schönberg (2009) document comparable evidence for Germany and find that occupations at the high end of wage distribution experienced greater increases in non-routine cognitive task inputs, whereas occupations in the middle of wage distribution used more routine task inputs. In relation to Europe, Goos *et al.* (2009) and, more recently, Jerbashian (2019) present cross-country evidence that routine-biased technological change contributes to a fall in employment shares of middle-paid occupations and increasing employment shares of high- and low-paid occupations.

The evidence of technological change and associated employment polarisation is also found in skill groups. Acemoglu and Autor (2011), for instance, use the US data and show that relative to the demand for workers with medium-level of education, the demand for workers with high- and low-levels of education has increased. Similarly, Goos and Manning (2007) suggests a pervasive pattern of polarisation for the UK, with employment growth in the highest- and lowest-skilled occupations, and declining employment in the middle of the skill distribution. Moreover, a number of studies provided cross countries evidence of a polarised employment structure. For instance, a study by Michaels *et al.* (2014) which covers 11 OECD countries find that industries with faster growth in information and communication technologies (ICT) have increased the demand for highly educated workers at the expense of the middle-educated, with almost no effect on low-educated workers.

In recent years the attention of researchers has been drawn toward a newer type of automation technology, i.e., industrial robots and how it affects the labour market. In this regard, Acemoglu and Restrepo (2020) use IFR data on the stocks of robots and show that an inverse relation exists between robots and employment and wages in the US. Dauth, Findeisen, Suedekum and Woessner (2019) also use robot data from the same source and study the adjustment of local labour markets to industrial robots for Germany. Their findings suggest that increasing the use of robots has adverse effects on employment in manufacturing, while, on the aggregate, job losses are fully offset by new jobs in services. Moreover, they show that industrial robots were more beneficial for workers who performed complementary tasks.

Second, this research is also related to a large literature on the effects of institutions on the labour market. As for the role of employment protection legislation in employment, the theory suggests that higher EPL favours incumbent employees since their dismissal becomes more costly for employers and at the same time decreases a firm's propensity to hire because employers weigh the potential cost of future lay-off costs in their hiring decisions. Hence, EPL has ambiguous effects on (un)employment and the overall effect depends on which channel dominates (Bertola, 1999; Mortensen and Pissarides, 1999). The empirical literature is also indecisive and offers inconclusive results on the impact of EPL on (un)employment. For example, while Lazear (1990) shows that EPL has a negative effect on employment, the findings of Autor, Kerr and Kugler (2007) suggest that total employment can increase with the adoption of dismissal protections. On the other side, Miles (2000) and Martin and Scarpetta (2012) found no clear association between EPL and the aggregate employment or unemployment rate.

As in the case of dismissal regulations, the employment effects of collective bargaining coverage are ambiguous, too. For example, the empirical findings of Traxler and Brandl (2011) reveal that collective bargaining coverage, in general, has neither a negative nor a positive effect on (un)employment. The authors point out that because of the important complementarities between the degree of coverage and other aspects of the bargaining system (e.g., wage coordination and centralization), the impact of individual dimensions such as bargaining coverage cannot be studied in isolation.

Further, in an attempt to explore the heterogeneous effects of labour market institutions on employment of different worker groups, Kahn (2007) studies the effect of EPL and CBC on demographic patterns of temporary employment and non-employment. His findings indicate that stronger EPL is positively associated with the relative incidence of temporary employment among some worker groups such as females, younger, and low-skilled workers, and these effects are stronger the higher the level of the collective bargaining coverage. Similarly, Autor, Donohue III and Schwab (2006b) find that the short-term impact of wrongful discharge protections in the US is largest for workers who change jobs most frequently (i.e., women, younger, and low-educated workers). Moreover, Bertola *et al.* (2007) find that collective wage-setting agreements and unionisation reduce employment more for youth, women, and older workers arguably because these population groups have better alternatives to paid jobs (for example, schooling for youth, home production for women, and retirement for older individuals).

Third, my work contributes to a recent literature that focuses on the role of labour market institutions in explaining the effects of technology on labour market outcomes. Theoretical work regarding the joint effects of technology and collective bargaining has identified two main impacts on employment and wage structures (Nellas and Olivieri, 2012): First, by maintaining a high level of manual wage, a more centralised collective bargaining process avoids employment growth in low-wage jobs. Hence, the overall employment pattern appears more similar to an upgrading trend—employment decreases in lowest and middle paid occupations and increases in highest-paid occupations—than to a polarised one. Second, technological change may generate low-skill unemployment when the union's employment target for current members (insiders) is stricter. In addition, the theoretical implications of other labour market institutions (including unemployment benefits, payroll taxes, and EPL) for the effect of technological change on labour demand have been studied by Hornstein, Krusell and Violante (2007). According to their model, the presence of labour market institutions worsens the negative effects of technological change on overall labour demand and increases unemployment and unemployment durations.

There exists some empirical literature on this topic as well. A recent study in this area is the work of Kristal and Cohen (2017) who find that declining unions and the fall in minimum wage are almost twice as important as computerisation in explaining the rising inequality within US industries. Also, in a study on four countries with different wage-setting institutions (Britain, Germany, Spain, and Switzerland), Oesch and Rodríguez Menés (2011) explain why some countries (e.g., Britain or Spain) show patterns of polarised job growth, while others (e.g., Germany or Switzerland) experience an employment structure that is more consistent with the occupational upgrading explanation. They argue that since the creation of low-wage service jobs is less profitable in countries with stricter wage-setting institutions (i.e., collective bargaining, unemployment benefits, or wage inequality), these countries tend to experience an upgrading pattern of employment. Whereas where flexible wage-setting institutions facilitate the creation of low-wage service jobs, employment polarisation occurs. Looking across a wider range of OECD countries, the findings of Hope and Martelli (2019) also highlight an important role for labour market institutions in the effects of the transition to knowledge economy on income inequality. More precisely, the results of their study suggest that a more coordinated wage bargaining, stricter EPL, and higher bargaining coverage reduce the inequality-inducing impacts of technical changes for the 90/10 wage ratio. Moreover, a recent research by Martelli (2017) provides further evidence that EPL mitigates the effects of routinization on employment structures of European countries, while union density and minimum wages have no significant effect.

4.3 Data and Descriptive Evidence

4.3.1 Data sources

The data for this study are taken from three main databases:

First, I obtain information on employment in different groups of occupations and industries and the socio-demographic characteristics from the EU-LFS database. The EU-LFS data consists of repeated cross-sections of workers and includes all EU Member States as well as Norway, Iceland, and Switzerland. The dataset is based on national household surveys conducted by the national statistical agencies of the participating countries. This means that the data are of high quality and fully representative for the resident population (Eurostat, 2018). Furthermore, the underlying surveys apply harmonised concepts and definitions for economic sectors (NACE Rev.1 at 1-digit level) and occupations (ISCO at 2- and 3-digit aggregation levels), which enables me to perform a cross-country comparison.

Following the methodology adopted in earlier studies (e.g., Goos, Manning and Salomons 2014; Jerbashian 2019), I first restrict my sample to 15-65-year-old individuals who are considered to be working age population. Next, I use the 2-digit aggregation level for occupations throughout the analysis and keep only the employed individuals, dropping the employed with no industry and/or occupation codes. I also exclude the same occupations and industries which are dropped from the analysis by Goos *et al.* (2014) due to the sample imperfections and potentially large state involvement. Following these authors, I construct an hours-weighted measure of employment[2] by multiplying the sample weights by the number of (usual) weekly hours worked in occupation groups in each sample. Finally, I assign the occupations into high-, medium- and low-wage groups based on the wage ranking of occupations in Goos *et al.* (2014)[3]. The authors rank the occupations according to their mean

[2]although the results are not affected by using persons employed instead.

[3]I use the occupations' rankings of Goos *et al.* (2014) for two reasons. First, this would facilitate the comparison of my results with those obtained in previous studies. Second, in order to rank occupations based on earnings in 1993, I would need information on the wages of individuals. However, the harmonised EU-LFS does not contain information on wages and access to further databases (including the European Community Household Panel (ECHP), the European Union

wage at the beginning of the period (1993) across the European countries. Therefore, the ranking of occupations is fixed over time. They also test the assumption that ranking does not frequently change over time within a country as well as across countries over time, and find very strong correlations. Hence, it seems unlikely that the ranking varies with exposure to technology. Table 4.A.1 in the Appendix offers the assignment of occupations into high-, medium- and low-wage groups.

Second, to construct my measures of technology, I use data from the 2008 release of EU KLEMS, supplemented with data from EU KLEMS 2011 and 2007 releases (O'Mahony and Timmer 2009). The EU KLEMS data provides cross-country comparable sector-level measures of output, labour, and capital inputs. For the empirical application, as will be explained in more detail in Section 4, I use data on value-added, capital compensation, and (non-)ICT share in total capital compensation, which can be taken directly from the EU KLEMS files. This information is available for 72 industries according to the ISIC Rev.3 industry classification. However, to merge this data with the EU-LFS database, I convert the ISIC Rev.3 to the NACE REV.1 industry classification and use the aggregated sectoral variables at a 1-digit level.

Third, I employ data on labour market institutions indicators from the OECD Stat. and OECD/AIAS ICTWSS databases (OECD, 2018; OECD and AIAS, 2021). The labour market institutional variables I adopted in the empirical analysis include employment protection legislation and collective bargaining coverage.

Employment protection legislation (EPL) refers to the rules governing the hiring and firing of workers, which are summarized by EPL indicators constructed by the OECD (OECD, 2018). These indicators measure the requirements with respect to notification, negotiation and authorisation before an employment relationship is terminated by the employer, as well as severance pay, and the definition and costs of unfair dismissal. The stricter and/or costly the requirements make the hiring or firing of a worker, the higher the value of the EPL indicator, which ranges from one to five. The OECD provides two main EPL indicators, one for regular workers, including provisions for collective dismissals, and one for temporary workers. As there are more regular workers than temporary workers in the countries I analyse, I select the EPL indicator which applies to regular workers for my analyses.

Collective bargaining is defined as "all negotiations which take place between an employer, a group of employers or one or more employers' organisations, on the one hand, and one or more workers' organisations, on the other, for: (a) determining working conditions and terms of employment; and/or (b) regulating relations between employers and workers; and/or (c) regulating relations between employers or their organisations and a workers' organisation or workers' organisations." (ILO Convention No. 154, 1981) Bargaining coverage index measures the extent to which the terms of workers' employment are affected by collective negotiation. This indicator is "the coverage rate, i.e., the number of employees covered by the collective agreement, divided by the total number of wage and salary-earners (Traxler, 1994, P.171)."

Given data availability, my primary analytic sample covers the period of 1993-

Statistics on Income and Living Conditions (EU-SILC), and the UK Labour Force Survey) was required.

2007 and is restricted to 9 European countries.[4] The list of sample countries and their years of data coverage are presented in Table 4.A.2 in the Appendix.

4.3.2 Cross Country Trends

Panel A of Table 4.1 summarizes the averages of employment shares in the different occupation groups and basic statistics of the key variables in the sample countries. Several findings are of particular importance. First, there are more workers in the high- and medium-wage occupations and less in the low-wage occupations. Second, the rates of collective bargaining coverage (CBC) and the average value of employment protection legislation (EPL) vary widely across sample countries. In terms of CBC, Austria with 98% and Sweden with 94% of wage earners being covered by a collective agreement in 1993, have a somewhat more protected wage structure than Germany with 81% and the UK with only 53%. With respect to EPL, in 1993, the UK provided the lowest level of dismissal protection (1.35), while Spain (3.55) and the Netherlands (3.49) had the highest level of protection in this year. Third, although some countries have both high value of EPL and high CB coverage rate, this is not necessarily the case that these two institutions move together. For example, the UK has the lowest CBC and EPL compared to other countries, yet the Netherlands with a relatively high EPL value has a lower coverage rate than many other countries. Forth, the mean values of ICT capital intensity are not statistically different across countries.

Panel B of Table 4.1 presents the same variables for the average changes over the sample period. All countries have experienced an increase in their value of ICT intensity and a decrease in the share of medium-wage occupation group. Similarly, the share of employment in high-wage occupations increased in almost all countries in this time window. Yet, the change of employment share in the low-wage occupation group is less clear.[5] Overall, these seem to be supportive of the routinization hypothesis, however, there are many other unobservable factors at the country level which are not yet taken into account.

As for institutional variables, we observe a general decreasing trend in most of the sample countries: The levels of EPL for regular workers increased slightly in Germany and the UK, remained constant in Italy, and decreased in other countries.

[4]The final year of my analysis is 2007, as the EU KLEMS database has several definitional changes and major revisions in later releases. Moreover, the ISCO classification, in the EU-LFS database, underwent a major revision in 2011 and the ISCO-88 was replaced by the ISCO-08. This in turn may affect the accuracy of occupations' rankings which are based on the ISCO-88 classification. Nevertheless, I use the 2017 release of the EU KLEMS data to analyse 1996 – 2015 separately in some of the robustness checks

[5]A closer inspection of the data reveals that all sample countries have experienced an increase in their total employed number over the period of analysis (i.e., more people became employed). Yet, due to the lack of data on previous occupations' status, it is not feasible to determine whether changes in employment shares of different occupation groups at the country level are because people change occupations or more people become employed. Nevertheless, we can interpret the average negative changes in an occupation category as the existence of switch in occupational category. In fact, the data shows that although the average change in the total number of employed across all occupations is positive, the average change in the number of employed in medium-wage occupation group is negative for Denmark, Sweden, and the UK, indicating that workers indeed change occupation categories as well.

Likewise, data on changes in bargaining coverage rates from 1993 to 2007 shows that there has been a drop in bargaining coverage for seven out of nine countries in my sample. There are only two countries, namely Austria and Finland, where bargaining coverage remained stable or increased over these years.

Table 4.1: Summary statistics by country

Panel A	Average employment shares			Basic statistics in 1993				
Country	High Wage	Medium Wage	Low Wage	CBC	EPL	$\frac{ICTcapital}{value-added}$	$\frac{Non-ICTcapital}{value-added}$	ln(value-added)
AT	34.83	42.60	22.57	98	2.67	0.033	0.309	9.966
						(0.037)	(0.123)	(0.621)
DE	40.69	40.96	18.35	80.8	2.50	0.031	0.235	12.30
						(0.030)	(0.153)	(0.775)
DK	41.56	34.85	23.58	83	1.52	0.047	0.220	9.705
						(0.036)	(0.146)	(0.601)
ES	33.49	40.57	25.93	92.0	3.55	0.040	0.312	11.11
						(0.042)	(0.110)	(0.610)
FI	41.90	35.04	23.06	83	2.37	0.043	0.260	9.423
						(0.069)	(0.197)	(0.785)
IT	34.10	41.49	24.41	82	3.02	0.031	0.282	11.74
						(0.031)	(0.134)	(0.725)
NL	48.30	34.40	17.30	81.9	3.49	0.040	0.271	10.64
						(0.031)	(0.111)	(0.643)
SE	42.84	36.03	21.13	94.0	2.64	0.045	0.225	10.13
						(0.037)	(0.161)	(0.709)
UK	42.47	36.63	20.89	52.7	1.35	0.049	0.217	11.84
						(0.032)	(0.115)	(0.663)
Panel B	Average changes over the sample period, by Country							
Country	High Wage	Medium Wage	Low Wage	CBC	EPL	$\frac{ICTcapital}{value-added}$	$\frac{Non-ICTcapital}{value-added}$	ln(value-added)
AT	0.769	-0.716	-0.053	0	-0.025	0.0005	0.0041	0.044
DE	-0.038	-0.111	0.150	-1.59	0.006	0.0006	0.0036	0.028
DK	0.501	-0.540	0.039	-0.44	-0.003	0.0006	-0.0016	0.046
ES	0.577	-0.490	-0.087	-0.7	-0.079	0.0002	0.0034	0.056
FI	0.215	-0.345	0.130	0.39	-0.019	0.0032	0.0044	0.055
IT	0.942	-0.474	-0.468	-0.17	0	0.0005	0.0040	0.031
NL	0.115	-0.243	0.128	-0.2	-0.009	0.0006	0.0017	0.054
SE	0.225	-0.398	0.173	-0.35	-0.013	0.0016	0.0022	0.039
UK	0.224	-0.545	0.321	-1.29	0.011	0.0014	-0.0008	0.060

Notes:Columns 2-4 of panel A offer the averages of employment shares in high-, medium- and low-wage occupations in the sample countries. Averages are taken across sample industries and period. Columns 5-9 of panel A summarise some basic statistics for other main variables. Standard deviations are reported in parentheses. Panel B offers the average change in variables over the sample period in each country. The EU-KLEMS variables report means weighted by 1993 share of each country's employment.

4.3.3 Cross Industry Trends

Table 4.2 breaks down the data by industry. In general, the manufacturing sector has a higher share of employment in middle-wage occupations and lower shares of employment in high- and low-wage occupations as compared to service sectors. The values of ICT capital intensity for 1993 indicate that financial intermediation and transport, storage, and communication sectors are ahead of other industries in their initial share of ICT-capital in value-added, whereas hotels and restaurant and construction sectors had the lowest ICT's share of the value-added.

In addition, we observe some variations in the ICT-intensity evolution across industries: while in some industries, such as electricity, gas, and water supply as well as real estate, renting and business activities, there was almost no change in ICT intensity, financial intermediation and hotels and restaurants sectors had the highest increase in their ICT intensity.

Table 4.2: Summary Statistics by Industry

	Panel A						Panel B					
	Average employment shares			Basic statistics in 1993			Average changes over the sample period, by Industry					
Industry name	High wage	Medium Wage	Low Wage	$\frac{ICTCapital}{VA}$	$\frac{Non-ICTCapital}{VA}$	ln(VA)	High wage	Medium Wage	Low Wage	$\frac{ICTCapital}{VA}$	$\frac{Non-ICTCapital}{VA}$	ln(VA)
Manufacturing	25.81	65.16	9.032	0.029	0.235	11.37	5.02	-4.74	-0.282	0.008	0.081	0.44
				(0.012)	(0.058)	(0.962)						
Electricity, Gas and Water Supply	32.29	60.21	7.495	0.032	0.613	9.270	10.2	-7.73	-2.475	-0.001	0.105	0.418
				(0.018)	(0.089)	(0.913)						
Construction	16.38	75.07	8.556	0.002	0.149	10.15	0.88	-2.32	1.432	0.011	0.053	0.64
				(0.016)	(0.112)	(1.032)						
Wholesale and Retail Trade; Repair of Goods	37.14	31.13	31.73	0.031	0.183	10.87	2.25	-1.92	-0.34	0.013	0.041	0.5
				(0.016)	(0.065)	(0.978)						
Hotels and Restaurants	34.06	7.103	58.83	-0.014	0.102	9.237	-5.43	0.128	5.31	0.027	0.077	0.62
				(0.042)	(0.103)	(1.241)						
Transport, Storage, and Communication	20.79	69.28	9.928	0.086	0.226	10.37	4.48	-8.12	3.642	0.014	0.08	0.55
				(0.032)	(0.087)	(0.883)						
Financial Intermediation	47.90	49.81	2.290	0.1	0.265	10.07	13.54	-13.17	-0.381	0.085	-0.033	0.47
				(0.080)	(0.083)	(1.04)						
Real Estate, Renting, and Business Activities	61.15	25.12	13.73	0.039	0.588	11.19	4.51	-5.15	0.63	-0.001	-0.074	0.78
				(0.016)	(0.080)	(1.095)						
Health and Social Work	59.77	11.15	29.08	0.013	0.129	10.30	-0.54	-1.646	2.19	0.003	-0.018	0.66
				(0.007)	(0.064)	(0.922)						
Other Community and Personal Service Activities	46.98	20.08	32.94	0.04	0.216	9.707	-3.25	0.57	2.67	0.003	-0.019	0.573
				(0.027)	(0.094)	(1.042)						

Notes:As the EU-LFS database does not have occupation data for Austria before 1995 and for Finland and Sweden before 1997, industry-level employment shares are averaged across the following countries: Denmark, Germany, Spain, Italy, the Netherlands, and the UK. Industry values are simple unweighted averages across all countries.

4.4 Econometric strategy

The empirical strategy of this paper closely follows the existing literature. However, I additionally look at how employment shares of different occupational groups vary by the type and level of institutional variables, i.e., EPL and CBC. In order to analyse the differential effects of the technology on employment shares in the high-, middle- and low-wage occupations in countries with more rigid labour institutions compared to countries with fewer regulations, I set up empirical models of the following forms for each occupation group:

$$EmploymentShare_{cit} = \beta_1 ln(\frac{ICT}{VA})_{cit} + \beta_2 ln(\frac{NICT}{VA})_{cit} + \beta_3 ln(VA)_{cit} + \beta_4 ln(\frac{ICT}{VA})_{cit} \times EPL_{ct} + \alpha_{c,t} + \gamma_{c,i} \tag{4.1}$$

$$EmploymentShare_{cit} = \beta_1 ln(\frac{ICT}{VA})_{cit} + \beta_2 ln(\frac{NICT}{VA})_{cit} + \beta_3 ln(VA)_{cit} + \beta_4 ln(\frac{ICT}{VA})_{cit} \times CBC_{c,t} + \alpha_{c,t} + \gamma_{c,i} \tag{4.2}$$

Where $EmploymentShare_{cit}$ is the share of employment in one of the occupation groups, country c, industry i (1-digit NACE), and year t. As a measure of technology change, I use logarithms of ICT-capital intensity, i.e., $ln(\frac{ICT}{VA})_{cit}$. ICT-capital intensity is calculated by multiplying capital compensation by the share of ICT assets in total capital compensation and dividing by nominal value-added. In addition, the model includes $ln(\frac{NICT}{VA})_{cit}$, which denotes the non-ICT intensity (and computed analogously to ICT intensity) and $ln(VA)_{cit}$, which is the log of value-added.[6] I am particularly interested in the effects of ICT intensity and how it varies with the level of employment protection and collective bargaining coverage. These terms are captured by the interaction term $ln(\frac{ICT}{VA})_{cit} \times EPL_{c,t}$ in equation 4.1 and $ln(\frac{ICT}{VA})_{cit} \times CBC_{c,t}$ in equation 4.2.[7] Moreover, I allow for unobserved heterogeneity between industry-by-country pairs($\gamma_{c,i}$), and add country-by-year dummies ($\alpha_{c,t}$) to absorb all country-time specific factors. The regressions are estimated by OLS [8] with robust standard errors[9].

In the next step, I analyse the heterogeneous effects for workers of different characteristics by re-estimating the employment shares of occupations within each

[6]When comparing nominal variables (such as value-added at current prices or compensation of capital) across countries, I convert them to U.S. dollars using annual nominal exchange rates from the Penn World Table version 9.1 (See Feenstra, Inklaar and Timmer 2015) https://www.rug.nl/ggdc/productivity/pwt/.

[7]As a robustness test, I also considered using lagged values of EPL and CBC to reduce potential concerns regarding the endogeneity of institutional variables. As documented in Table 4.A.3 in the Appendix, the findings remain very similar to those of Table 4.3 in the Results section.

[8]I also tried estimating the specifications in 4.1 and 4.2 with beta regression model, which is a specific type of fractional response models for dependent variables that vary between 0 and 1. Thus, the main difference with respect to the dependent variables in the OLS estimations is that the employment shares are in the range of 0 and 1 instead of 0 and 100%. Using this method does not change my findings; however, I only rely on the OLS estimation strategy, which is also employed in prior literature

[9]Similar to Jerbashian (2019), I also considered estimations with two-way clustered standard errors at industry- and country-year-level. As the results turn out to be very similar, I only report the results with robust standard errors.

gender, age and education group.

In the robustness tests, I consider augmenting equations 4.1 and 4.2 in various ways: First, I consider some sample restrictions. Second, I re-estimate the previous models in long differences. Third, I use an instrumental variable approach to address the potential endogeneity of my technological variable, ICT intensity. Fourth, I include some control variables, measured in initial year, such as R&D and relative wages of workers in different skill groups as well as additional fixed effects. Last, I re-estimate my specifications with the newer release of EUKLEMS data to cover more recent years [10] and consider using some other aspects of technical change beside ICT to test whether the results are sensitive to the choice of technology measure.

4.5 Results

In this section, I present the results of my empirical analysis. I start with the estimation of the specifications 4.1 and 4.2 for the shares of employment in high-, medium- and low-wage occupations. In the second step of my analysis, I investigate the heterogeneous effects on different worker groups.

4.5.1 The role of ICT and labour market institutions in explaining employment structures

My first set of results for the shares of employment in high-, medium- and low-wage occupations is reported in Table 4.3. Panel A presents the baseline results with no interaction effects, showing how the change in capital intensity (ICT and non-ICT) and value-added are related to the employment shares of each occupation group. Looking at the estimated coefficients of the ICT intensity, we find that, as expected, higher ICT capital intensity is associated with a higher demand for high-wage occupations (column 1) and lower demand for medium-wage occupations (column 2). The results further indicate a shrinking employment share in the lowest-wage occupation group in response to higher ICT capital intensity. These results are generally in line with the routinization hypothesis and confirm previous findings in the literature with respect to the impacts of technology on the occupational structure of employment.

As far as other variables in these specifications are concerned, some interesting results can be observed. For example, the insignificant coefficient on non-ICT capital in all occupation groups suggests that there is no sign of a direct relationship between the non-ICT component of capital and employment shares in the different wage groups. Moreover, the coefficients on value-added indicate that faster-growing industries reduced their demand for workers in high-wage occupations and increased their share of workers in medium-wage occupations. This seems to contrast the findings by Michaels *et al.* (2014), which report increasing (decreasing) demand for high-skilled (medium-skilled) workers in industries that experience higher growth

[10] Because the measures of ICT intensity and occupational groups become less reliable for analysing more recent period, due to major revisions and definitional changes in later releases of EU KLEMS as well as major revision in occupational classifications (in 2011) in the EU-LFS data, I cannot confidently extend my analysis to the present and use that as the main specification.

in value-added. However, a higher value-added may be related to the increase in non-capital inputs, such as energy, material, or services, which can increase the demand for workers in related occupations such as plant operators, clerks, or other service-related jobs (which are more present in medium-and low-wage occupations), as compared to workers who are in managerial and professional jobs (which are mainly high-wage occupations)

Turning now to the main focus of the paper — the contribution of labour market institutions in explaining labour market effects of technology— I start by looking at the interaction term between ICT intensity and EPL. It can be seen from Panel B of Table 4.3 that the interaction terms are statistically significant at 1% level for all occupation groups, suggesting that ICT growth affects the employment shares of occupation groups to a divergent extent in countries with different levels of EPL.

In order to assess the magnitude of these effects, it is useful to compute the amount of change in employment shares with a percentage increase in ICT intensity for a range of different values of EPL. As can be seen in Figure 4.2a, it appears that the change in the employment share of high-wage occupations in response to a percentage change in ICT intensity decreases for higher values of EPL. For instance, for a level of EPL equal to 1.4, a percentage increase[11] in ICT intensity increases the employment share in the high-wage occupations by about 4.7 pp.[12] The effect is, however, smaller when the value of EPL equals 2.3 and is insignificant for levels of EPL above the median.

Similarly, Figure 4.2b shows that at lower levels of EPL, the negative impact of ICT growth on the employment share of medium-wage occupations is larger than at higher values of EPL. As an example, for a value of EPL equal to 1.4, an increase in ICT intensity by 1 percent results in a decrease in the employment share of medium-wage occupations by about 2 pp. However, the impact decreases to almost 0.53 pp, when the EPL level increases to 2.6.[13]

Finally, Figure 4.2c reveals that more ICT intensity is associated with a lower share of employment in low-wage occupations. However, higher values of EPL reduce the negative impact of technology on the employment shares of workers in low-wage occupations such that no significant effects can be found for EPL values that are larger than 2.

Taken together, these results imply that employment protection regulations play an important role in determining the extent to which ICT growth affects employment shares. More specifically, EPL seems to mitigate the impact of ICT on the occupational structure of employment.

The next part of the analysis is concerned with the role of collective bargaining coverage. Panel C of Table 4.3 shows OLS results of the models, which include interaction terms between collective bargaining coverage and ICT intensity measures.

[11]A 1% increase is about 1 log point

[12]The average employment share in the high-wage occupation group is 40%. Hence, the size of this marginal effect is equivalent to about 12% of the mean employment share in the high-wage occupation group. This suggests that ICT has quantitatively important effects, particularly for low values of EPL.

[13]The average employment share in the middle-wage occupation group is about 39%. Thus, the size of these marginal effects are equivalent to about 5 and 1% of the mean employment share in the middle-wage occupation group, respectively.

The results indicate that more extensive coverage by centralised collective bargaining has no significant effect on the impact of ICT growth on employment shares of workers in high- and medium-wage occupations, whereas, as coverage rate increases, the impact of ICT intensity on employment shares in low-wage occupations gets more and more negative. More precisely, as shown in Figure 4.3, the average marginal effect of ICT intensity ranges from an insignificant value of -0.28 pp in the 10th percentile of CBC (i.e., cbc value of 36.4) to a significant value of -2.25 pp in the 90th percentile (i.e., cbc level of 98). This evidence is therefore broadly consistent with the theoretical predictions and findings of Nellas and Olivieri (2012), who argue that a more centralised collective bargaining process prevents employment growth in low-wage jobs.

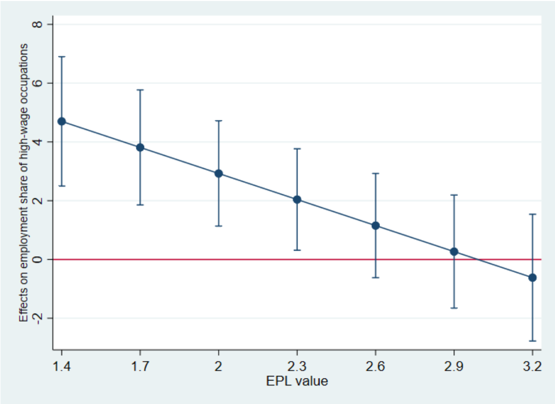
Considering the aim of unions and bargaining agreements which is to achieve the highest-paid wage that is compatible with the employment target for covered members (Nellas and Olivieri, 2012), a possible explanation for this result may be that the earnings of workers in low-paid occupations has increased to the detriment of their employment. While it is not possible to further investigate the relationships of this interaction term and wages, since wages information is not available in the EU-LFS data, it has been shown that the impact of the knowledge economy on income inequality is dampened by high collective bargaining coverage (Hope and Martelli, 2019). The lower wage inequality associated with higher bargaining coverage may point towards higher wages for workers covered by collective agreements, who are more likely to be unskilled workers in low-wage occupations at the expense of their employment.

Table 4.3: Main results for the change in employment shares in high-, medium- and low-wage occupations

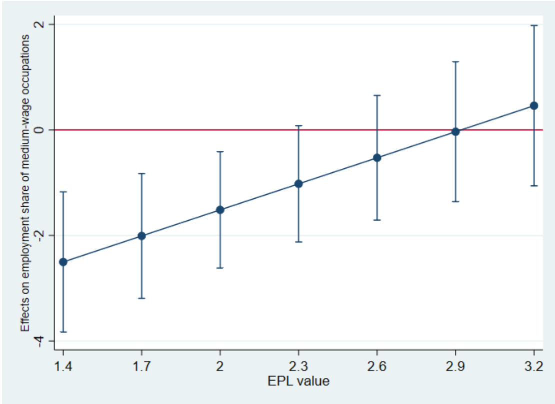
	Panel A *Baseline*			**Panel B** *ICT*EPL*			**Panel C** *ICT*CBC*		
OLS	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage
$ln(ICTint)$	2.995***	-1.553***	-1.442**	8.835***	-4.805***	-4.029***	3.235*	-4.117**	0.882
	(0.875)	(0.558)	(0.631)	(1.961)	(1.238)	(1.192)	(1.901)	(1.695)	(1.218)
$ln(NICTint)$	-1.222	0.701	0.522	-1.570**	0.894*	0.676	-1.537**	1.123**	0.414
	(0.658)	(0.441)	(0.469)	(0.773)	(0.488)	(0.517)	(0.714)	(0.484)	(0.549)
$ln(VA)$	-7.835***	6.169***	1.666	-6.605***	5.484***	1.121	-7.114***	6.043***	1.071
	(1.494)	(1.210)	(1.135)	(1.530)	(1.222)	(1.149)	(1.538)	(1.280)	(1.120)
EPLreg$\times ln(ICTint)$				-2.954***	1.645***	1.309***			
				(0.754)	(0.514)	(0.470)			
CBC$\times ln(ICTint)$							0.001	0.031	-0.032*
							(0.025)	(0.019)	(0.017)
Country-Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Country-Industry FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1,223	1,223	1,223	1,223	1,223	1,223	1,175	1,175	1,175
R-Squared	0.961	0.986	0.976	0.963	0.986	0.976	0.962	0.986	0.977

Using the EU-KLEMS 2009 release (O'Mahony, Mary and Marcel P. Timmer, 2009), this table offers the results for the shares of employment in high-, medium- and low-wage occupations. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Coefficients estimated by OLS with robust standard errors in parentheses. The regressions also include full sets of country-year and country-industry dummies.Final sample of analysis consists of 9 European countries: Austria, Germany, Denmark, Spain, Finland, Italy, Netherlands, Sweden, and the United Kingdom. Author's calculations for the period from 1993-2007.

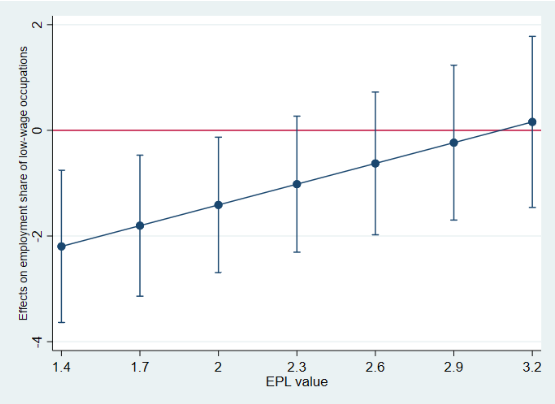
Figure 4.2: Average Marginal Effects of ICT intensity, with 95% CIs



(a)



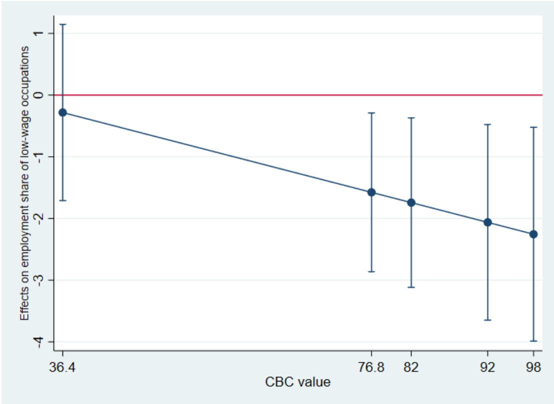
(b)



(c)

Notes: Figures 4.2a, 4.2b, and 4.2c show the changes in employment share of high, medium, and low-wage occupations for a percentage change in the ICT intensity when EPL is held constant at different values. Elaborated by the author based on the results in columns 1-3 of panel B in Table 3.

Figure 4.3: Average Marginal Effects of ICT intensity, with 95% CIs



Notes: This figure shows the change in employment share of low-wage occupations for a percentage change in the ICT intensity when CBC is held constant at different values (i.e, at 10, 25, 50, 75, 90th percentile of CBC). Elaborated by the author based on the results in column 3 of panel C in Table 3.

4.5.2 Exploring worker heterogeneity

My estimates so far considered the impacts of technological growth and labour market institutions on changes in employment shares, irrespective of worker types. Yet, the response to the technological change can greatly vary across different demographic groups. In order to analyse this heterogeneity, I re-estimate the specifications 4.1 and 4.2 for the shares of employment in high-, medium- and low-wage occupations within each gender, age, and education group.

As a first step, I estimate the impact of adapting ICT on employment shares for workers of different gender groups. The results are reported in Table 4.4. They are largely consistent with the findings for the employment shares in occupation groups in Table 4.3, with some differences among worker groups. For instance, the results of Panels A–C show that, in general, the impact of ICT intensity on employment share among females is about two times larger than among males. Moreover, testing of the significant differences between men and women in the direct impact of ICT on employment shares indicates no significant difference between these groups for medium-wage occupations, while there are significant differences in high- and low-wage occupations (at least at the 5% level). A possible explanation for these results, as noted by Jerbashian (2019), is that females tend to have a comparative advantage in performing tasks which require communication and social skills, and these tasks are more present in high-paying/cognitive occupations.
In addition, Panel B shows that a higher employment protection legislation limits the effect of ICT on the shares of employment for both women and men. However, the difference between men and women is only significant for the low-wage occupation group. More specifically and as depicted in Figures 4.4e and 4.4f, it is only at very low values of EPL that ICT has a slight negative significant effect (at the 10% level) on the share of employment in low-wage occupations among males. This is while the negative and significant impact of ICT on the employment shares of women in

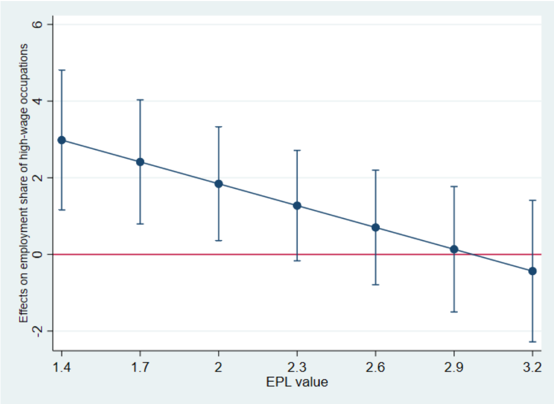
low-wage occupations is persistent for all levels of EPL below 2. Lastly, the results in Panel C show that collective bargaining coverage has no significant influence on the impact of ICT on employment shares in the two gender groups.

Table 4.4: Change in employment shares in high-, medium- and low-wage occupations within gender groups

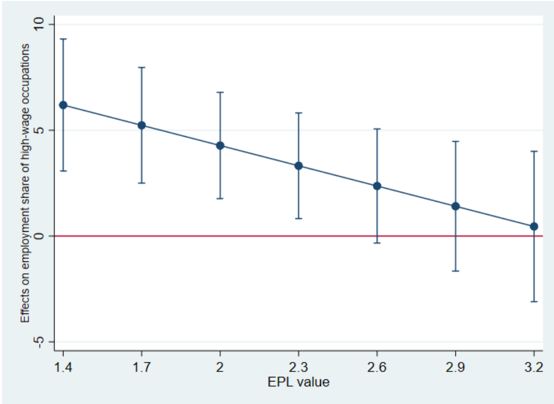
	Within males								
	A: No interaction			***B: ICT*EPL***			***C: ICT*CBC***		
OLS	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage
$ln(ICTint)$	1.887***	-1.237***	-0.650	5.642***	-3.549***	-2.093**	1.481	-2.442	0.961
	(0.732)	(0.498)	(0.574)	(1.645)	(1.252)	(0.962)	(1.415)	(1.533)	(1.067)
$ln(NICTint)$	-0.442	0.177	0.265	-0.666	0.315	0.351	-0.570	0.388	0.182
	(0.562)	(0.416)	(0.442)	(0.639)	(0.453)	(0.471)	(0.590)	(0.450)	(0.504)
$ln(VA)$	-8.306***	6.315***	1.991*	-7.515***	5.828***	1.687	-7.888***	6.494***	1.394
	(1.428)	(1.219)	(1.067)	(1.451)	(1.231)	(1.078)	(1.464)	(1.273)	(1.045)
EPLreg$\times ln(ICTint)$				-1.899***	1.169**	0.730**			
				(0.644)	(0.550)	(0.373)			
CBC$\times ln(ICTint)$							0.008	0.014	-0.022
							(0.017)	(0.018)	(0.013)
Observations	1,223	1,223	1,223	1,223	1,223	1,223	1,175	1,175	1,175
R-Squared	0.974	0.986	0.968	0.975	0.986	0.968	0.975	0.987	0.968
	Within females								
$ln(ICTint)$	4.352***	-2.403**	-1.949***	10.65***	-5.138**	-5.517***	4.110	-3.897*	-0.213
	(1.238)	(0.995)	(0.702)	(3.009)	(2.296)	(1.510)	(2.679)	(2.268)	(1.465)
$ln(NICTint)$	-1.940**	1.204	0.736	-2.315**	1.367*	0.948	-2.305**	1.550**	0.755
	(0.949)	(0.736)	(0.553)	(1.065)	(0.778)	(0.612)	(0.995)	(0.753)	(0.668)
$ln(VA)$	-7.725***	6.462***	1.263	-6.397***	5.886***	0.511	-6.597***	5.932**	0.665
	(2.414)	(2.293)	(1.465)	(2.441)	(2.279)	(1.517)	(2.410)	(2.341)	(1.519)
EPLreg$\times ln(ICTint)$				-3.189**	1.384	1.805***			
				(1.260)	(0.994)	(0.637)			
CBC$\times ln(ICTint)$							0.009	0.017	-0.025
							(0.034)	(0.026)	(0.021)
Observations	1,223	1,223	1,223	1,223	1,223	1,223	1,175	1,175	1,175
R-Squared	0.882	0.955	0.971	0.885	0.955	0.971	0.885	0.955	0.972

Using EU-KLEMS 2009 release (O'Mahony, Mary and Marcel P. Timmer, 2009), this table offers the results for the shares of employment in high-, medium- and low-wage occupations. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Coefficients estimated by OLS with robust standard errors in parentheses. The regressions also include full sets of country-year and country-industry dummies.Final sample of analysis consists of 9 European countries: Austria, Germany, Denmark, Spain, Finland, Italy, Netherlands, Sweden, and the United Kingdom. Author's calculations for the period from 1993-2007.

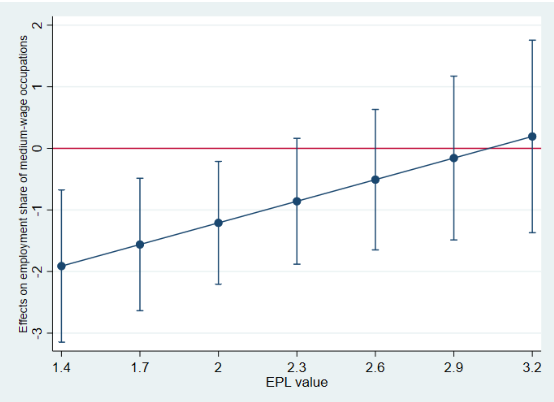
Figure 4.4: Average Marginal Effects of ICT intensity, with 95% CIs



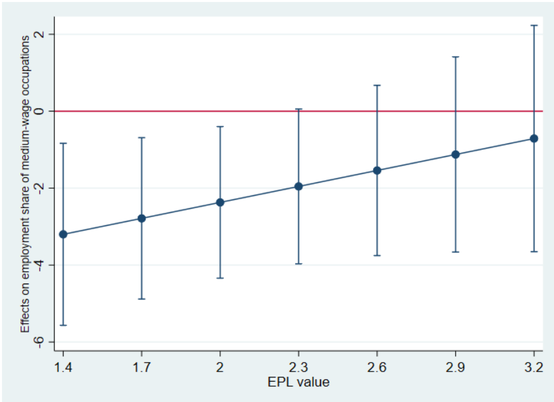
(a) males



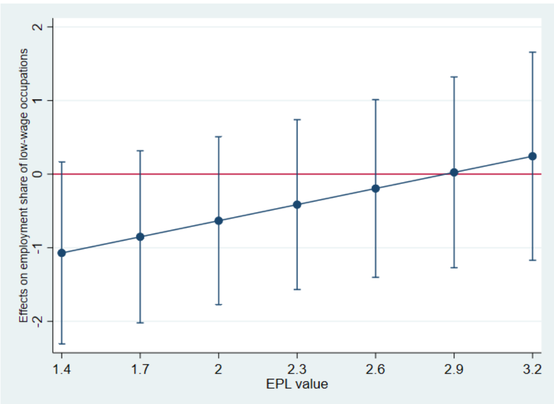
(b) females



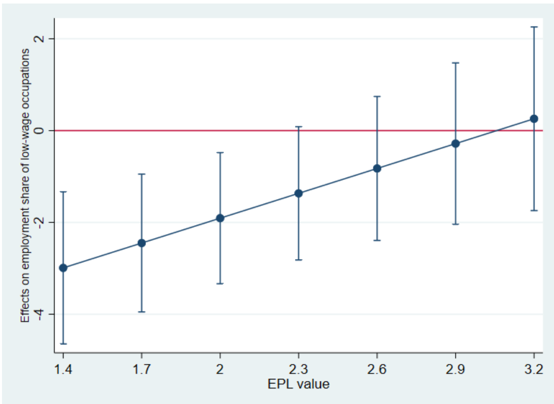
(c) males



(d) females



(e) males



(f) females

Notes: Figures 4.4a- 4.4f show the change in the share of employment in high, medium, and low-wage occupations among men and women for a percentage change in the ICT intensity when EPL is held constant at different values. Elaborated by the author based on the results in columns 1-3 of Panel B in Table 4.

Next, I investigate the differential impact of ICT growth on employment shares across different age groups. The results presented in Table 4.5 show that an increase in ICT intensity is associated with an increase in the share of employment in high-wage occupations and a reduction of employment share in medium- and low-wage occupations among all age categories. However, this effect is smaller and statistically insignificant for young workers in middle-wage occupations. A possible explanation for this result may be that as younger workers have completed their education more recently than older ones, they tend to have relatively higher (analytical) skills than older individuals and could be less affected by the loss of competence. Also, comparing the estimated coefficients between the three age groups reveals that the negative impact of ICT on the share of employment in the low-wage occupations is significantly stronger for older workers than for the middle-aged ones. This could be because older workers are likely to be less physically fit in performing non-routine manual tasks, including service works related to assisting or caring for others.
In contrast to ICT growth, higher intensity of traditional (non-ICT) capital is associated with employment gains for younger workers in medium-wage occupations and for older workers in low-paid jobs, suggesting that relatively low-tech machines may complement routine and non-routine manual tasks.
If we now turn to the coefficients on the interaction terms in Panel B, we see that higher employment protection contributes to offsetting the impact of ICT. However, it plays a less important role for young and old workers in low- and medium-paid occupations, respectively. Finally, Panel C shows the effect of adding the two-way interaction term between collective bargaining coverage (CBC) and ICT intensity in the model. The results show that high levels of collective bargaining lead to a higher employment share of young people in medium-wage jobs at the expense of the low-paid ones.

Lastly, I examine whether individuals with different skills experienced different or similar patterns of occupational change. The classification of individuals into three skill groups are based on their levels of education: low-skilled (individuals with primary or lower secondary education), medium-skilled (individuals with upper and post-secondary education and/or a completed apprenticeship), and high-skilled (individuals with tertiary education). According to data, the number of high-skilled individuals who work in high-, medium-, and low-wage occupations is 829,738, 192,225, and 81,047, respectively.
From the results provided in Table 4.6, it seems that falling employment shares of medium-wage occupations are more profound for medium- and low-skilled workers than for high-skilled ones. Also,the rise in ICT intensity has a larger effect on the share of employment in high- and low-paid jobs for medium-skilled workers than the other two skill groups.
The findings in Panel B imply that employment protection legislations disproportionately protect the jobs of high- and medium-skilled workers in medium-wage occupations, as indicated by the positive and significant two-way interaction terms between EPL and ICT.
As for the role of collective bargaining , the results in Panel C show that the effects of ICT intensity on employment shares in low-paid occupations are more negative and stronger the higher the collective bargaining coverage level. In contrast, it seems

that high levels of centralised collective bargaining lead to a lower negative impact on the employment share of medium-wage occupations. This effect is stronger, especially for high-skilled workers in this occupation category.

Taken together, the results imply that labour market institutions, particularly the employment protection legislation, can moderate the impact of technology on the occupational structure of employment. Consequently, rather than showing a uniform pattern of polarisation, as argued by Goos *et al.* (2009, 2014), countries seem to reveal the heterogeneous extent of occupational patterns depending on their institutional frameworks.

Table 4.5: Change in employment shares in high-, medium- and low-wage occupations within age groups

	Within young								
	A: No interaction			***B: ICT*EPL***			***C: ICT*CBC***		
OLS	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage
$ln(ICTint)$	3.001***	-1.349	-1.652**	9.044***	-5.637***	-3.407**	3.217	-5.777***	2.560*
	(1.052)	(0.934)	(0.696)	(2.242)	(1.703)	(1.475)	(2.105)	(2.093)	(1.518)
$ln(NICTint)$	-1.739**	1.409**	0.330	-2.100**	1.665**	0.435	-2.122**	2.059***	0.062
	(0.775)	(0.669)	(0.572)	(0.894)	(0.704)	(0.610)	(0.846)	(0.746)	(0.631)
$ln(VA)$	-1.852	1.165	0.687	-0.577	0.260	0.317	-0.393	0.558	-0.165
	(2.247)	(2.275)	(1.640)	(2.269)	(2.297)	(1.651)	(2.374)	(2.455)	(1.562)
EPLreg$\times ln(ICTint)$				-3.056***	2.168**	0.888			
				(0.840)	(0.638)	(0.583)			
CBC$\times ln(ICTint)$							0.001	0.056**	-0.057***
							(0.027)	(0.024)	(0.020)
Observations	1,222	1,222	1,222	1,222	1,222	1,222	1,174	1,174	1,174
R-Squared	0.914	0.961	0.974	0.915	0.961	0.974	0.915	0.960	0.975
	Within medium-age								
$ln(ICTint)$	2.643***	-1.656**	-0.987	9.001***	-5.628***	-3.374***	2.630	-3.872*	1.242
	(1.022)	(0.741)	(0.693)	(2.368)	(1.692)	(1.215)	(2.280)	(2.107)	(1.402)
$ln(NICTint)$	-0.568	0.391	0.177	-0.946	0.627	0.319	-0.857	0.817	0.039
	(0.797)	(0.582)	(0.532)	(0.925)	(0.654)	(0.571)	(0.852)	(0.622)	(0.645)
$ln(VA)$	-11.28***	9.715***	1.561	-9.937***	8.879***	1.058	-10.89***	9.818***	1.071
	(1.911)	(1.673)	(1.246)	(1.963)	(1.690)	(1.272)	(2.009)	(1.780)	(1.280)
EPLreg$\times ln(ICTint)$				-3.216***	2.009***	1.208**			
				(0.910)	(0.674)	(0.481)			
CBC$\times ln(ICTint)$							0.005	0.025	-0.030
							(0.029)	(0.023)	(0.020)
Observations	1,223	1,223	1,223	1,223	1,223	1,223	1,175	1,175	1,175
R-Squared	0.947	0.977	0.966	0.948	0.977	0.966	0.947	0.977	0.966
	Within old								
$ln(ICTint)$	3.778***	-1.555***	-2.222**	9.171***	-3.213***	-5.958***	4.170**	-2.961**	-1.209
	(1.058)	(0.582)	(0.874)	(2.010)	(1.145)	(1.648)	(1.833)	(1.323)	(1.306)
$ln(NICTint)$	-1.852**	0.473	1.380**	-2.173***	0.571	1.602**	-2.119***	0.671	1.448**
	(0.750)	(0.456)	(0.609)	(0.828)	(0.474)	(0.664)	(0.812)	(0.489)	(0.673)
$ln(VA)$	-6.811***	4.964***	1.847	-5.674***	4.615***	1.060	-5.998***	4.915***	1.083
	(1.754)	(1.312)	(1.346)	(1.793)	(1.333)	(1.377)	(1.800)	(1.371)	(1.340)
EPLreg$\times ln(ICTint)$				-2.728***	0.839*	1.890***			
				(0.746)	(0.490)	(0.636)			
CBC$\times ln(ICTint)$							-0.002	0.017	-0.015
							(0.024)	(0.016)	(0.017)
Observations	1,223	1,223	1,223	1,223	1,223	1,223	1,175	1,175	1,175
R-Squared	0.936	0.981	0.952	0.937	0.981	0.953	0.936	0.981	0.953

Notes: Using the EU-KLEMS 2009 release (O'Mahony, Mary and Marcel P. Timmer, 2009), this table offers the results for the shares of employment in high-, medium- and low-wage occupations. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Coefficients estimated by OLS with robust standard errors in parentheses. The regressions also include full sets of country-year and country-industry dummies.Final sample of analysis consists of 9 European countries: Austria, Germany, Denmark, Spain, Finland, Italy, Netherlands, Sweden, and the United Kingdom. Author's calculations for the period from 1993-2007.

Table 4.6: Change in employment shares in high-, medium- and low-wage occupations within skill groups

	Within low-skilled								
	A: No interaction			***B: ICT*EPL***			***C: ICT*CBC***		
OLS	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage
$ln(ICTint)$	2.133*	-1.909*	-0.225	5.607**	-3.377*	-2.230	2.354	-4.243*	1.888
	(1.129)	(0.999)	(0.880)	(2.319)	(1.750)	(1.728)	(2.538)	(2.503)	(1.595)
$ln(NICTint)$	0.135	0.596	-0.731	-0.074	0.685	-0.611	-0.010	0.734	-0.723
	(0.909)	(0.772)	(0.718)	(0.985)	(0.806)	(0.766)	(0.959)	(0.868)	(0.793)
$ln(VA)$	-8.071***	3.192	4.879**	-7.300***	2.866	4.434**	-7.429***	4.154	3.275*
	(1.873)	(2.374)	(1.959)	(1.913)	(2.425)	(2.001)	(1.997)	(2.533)	(1.960)
EPLreg$\times ln(ICTint)$				-1.770**	0.748	1.022			
				(0.785)	(0.625)	(0.645)			
CBC$\times ln(ICTint)$							-0.003	0.031	-0.028*
							(0.026)	(0.026)	(0.017)
Observations	1,174	1,174	1,174	1,174	1,174	1,174	1,126	1,126	1,126
R-Squared	0.882	0.968	0.963	0.883	0.968	0.963	0.881	0.968	0.965
	Within medium-skilled								
$ln(ICTint)$	4.906***	-1.789**	-3.117***	9.924***	-5.089***	-4.836**	3.003	-4.127***	1.124
	(1.303)	(0.670)	(1.013)	(2.584)	(1.199)	(2.015)	(2.709)	(1.332)	(2.167)
$ln(NICTint)$	-1.689*	1.323**	0.366	-1.991*	1.521***	0.469	-1.713	1.656***	0.056
	(0.999)	(0.523)	(0.827)	(1.080)	(0.536)	(0.851)	(1.102)	(0.562)	(0.913)
$ln(VA)$	-9.049***	4.299**	4.750***	-7.936***	3.567**	4.369***	-8.762***	4.284**	4.477***
	(2.110)	(1.697)	(1.585)	(2.142)	(1.707)	(1.593)	(2.133)	(1.720)	(1.618)
EPLreg$\times ln(ICTint)$				-2.557**	1.681***	0.876			
				(1.032)	(0.477)	(0.838)			
CBC$\times ln(ICTint)$							0.028	0.029*	-0.057*
							(0.038)	(0.015)	(0.031)
Observations	1,174	1,174	1,174	1,174	1,174	1,174	1,126	1,126	1,126
R-Squared	0.926	0.980	0.968	0.927	0.980	0.968	0.929	0.981	0.969
	Within high-skilled								
$ln(ICTint)$	1.282	0.004	-1.286	5.673***	-3.259**	-2.413	2.634	-2.737*	0.103
	(0.868)	(0.677)	(0.807)	(1.831)	(1.272)	(1.501)	(1.852)	(1.491)	(1.204)
$ln(NICTint)$	-0.428	0.019	0.409	-0.692	0.215	0.477	-0.796	0.420	0.376
	(0.676)	(0.524)	(0.629)	(0.741)	(0.540)	(0.658)	(0.719)	(0.566)	(0.676)
$ln(VA)$	-2.313	2.187	0.126	-1.339	1.463	-0.124	2.091	2.506	-0.415
	(1.953)	(1.672)	(1.130)	(1.973)	(1.685)	(1.113)	(2.069)	(1.797)	(1.127)
EPLreg$\times ln(ICTint)$				-2.238***	1.663***	0.574			
				(0.779)	(0.614)	(0.550)			
CBC$\times ln(ICTint)$							-0.015	0.034*	-0.019*
							(0.021)	(0.018)	(0.011)
Observations	1,174	1,174	1,174	1,174	1,174	1,174	1,126	1,126	1,126
R-Squared	0.913	0.914	0.929	0.914	0.915	0.929	0.913	0.913	0.929

Using the EU-KLEMS 2009 release (O'Mahony, Mary and Marcel P. Timmer, 2009), this table offers the results for the shares of employment in high-, medium- and low-wage occupations. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Coefficients estimated by OLS with robust standard errors in parentheses. The regressions also include full sets of country-year and country-industry dummies.Final sample of analysis consists of 9 European countries: Austria, Germany, Denmark, Spain, Finland, Italy, Netherlands, Sweden, and the United Kingdom. Author's calculations for the period from 1993-2007.

4.6 Robustness checks

In this section, I present several robustness checks for my main results, on the effects of technological progress and labour market institutions on employment shares of high-, medium-, and low-wage occupations.

4.6.1 Sample restriction

Imports Trade openness and import competition can be associated with increases in the shares of employment in high-wage occupations and decreases in the share for low-wage occupations (Michaels, Natraj and Van Reenen 2014; Autor, Dorn and Hanson 2015). However, Panels A–C of Table 4.7 show that the impact of ICT growth remains very similar when excluding the manufacturing industry, i.e., the tradable sector, from the sample.

Offshoring As argued by Goos *et al.* (2014), offshoring is another important factor which can affect the structure of employment. To confirm that highly offshorable occupations do not significantly affect my estimates, similar to Jerbashian (2019), I have excluded from the sample those occupations with an offshorability index above the 75th percentile of the score proposed by Goos *et al.* (2014). As shown in Panels D–F of Table 4.7, exclusion of those occupations has no significant effect on the employment estimates.

The role of individual countries To make sure that the findings are not driven by individual countries, I sequentially exclude one country at a time from the sample and re-estimate the same specification in levels as in Table 4.3. Thus, for instance, I re-estimate the model in levels with Austria excluded, and then include Austria but exclude Germany, and continue in this way. Tables 4.A.4–4.A.6 in the Appendix report the estimation results. Although the statistical significance varies somewhat across some specifications, the overall effects remain fairly stable.

Table 4.7: Imports and Offshoring

	Panel A			Panel B			Panel C		
	Baseline			***ICT*EPL***			***ICT*CBC***		
W/o Manufacturing Sector	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage
$ln(ICTint)$	3.010***	-1.577***	-1.432**	9.010***	-4.837***	-4.173***	3.441*	-4.202**	0.760
	(0.891)	(0.569)	(0.642)	(1.949)	(1.227)	(1.194)	(1.907)	(1.684)	(1.234)
$ln(NICTint)$	-1.279*	0.726	0.553	-1.638**	0.921*	0.717	-1.619**	1.162**	0.456
	(0.668)	(0.448)	(0.480)	(0.780)	(0.492)	(0.527)	(0.727)	(0.490)	(0.564)
$ln(VA)$	-7.674***	6.084***	1.590	-6.248***	5.309***	0.939	-6.744***	5.909***	0.834
	(1.774)	(1.473)	(1.352)	(1.810)	(1.480)	(1.372)	(1.845)	(1.578)	(1.350)
EPLreg$\times ln(ICTint)$				-3.042***	1.653***	1.390***			
				(0.751)	(0.511)	(0.473)			
CBC$\times ln(ICTint)$							-0.001	0.031*	-0.030*
							(0.025)	(0.019)	(0.018)
Observations	1,098	1,098	1,098	1,098	1,098	1,098	1,055	1,055	1,055
R-Squared	0.959	0.985	0.976	0.961	0.985	0.976	0.961	0.985	0.977
	Panel D			**Panel E**			**Panel F**		
W/o Offshorable Occupations	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage
$ln(ICTint)$	3.098***	-1.671***	-1.427**	9.172***	-4.583***	-4.590***	2.438	-3.308***	0.870
	(0.891)	(0.560)	(0.665)	(1.931)	(1.169)	(1.340)	(1.693)	(1.248)	(1.379)
$ln(NICTint)$	-1.339**	0.747*	0.592	-1.700**	0.920**	0.780	-1.608**	1.046**	0.562
	(0.681)	(0.437)	(0.508)	(0.787)	(0.466)	(0.569)	(0.763)	(0.474)	(0.599)
$ln(VA)$	-7.707***	5.613***	2.093	-6.427***	5.000***	1.427	-6.563***	5.667***	0.896
	(1.689)	(1.275)	(1.449)	(1.71)	(1.287)	(1.466)	(1.687)	(1.344)	(1.396)
EPLreg$\times ln(ICTint)$				-3.073***	1.473***	1.600***			
				(0.743)	(0.494)	(0.534)			
CBC$\times ln(ICTint)$							0.013	0.019	-0.032*
							(0.023)	(0.014)	(0.019)
Observations	1,223	1,223	1,223	1,223	1,223	1,223	1,175	1,175	1,175
R-Squared	0.961	0.986	0.972	0.962	0.986	0.972	0.962	0.986	0.974

Notes: Using the EU-KLEMS 2009 release (O'Mahony, Mary and Marcel P. Timmer, 2009), this table offers the results for the shares of employment in high-, medium- and low-wage occupations in the sample industries. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Coefficients estimated by OLS with robust standard errors in parentheses. The regressions also include full sets of country-year and country-industry dummies.Final sample of analysis consists of 9 European countries: Austria, Germany, Denmark, Spain, Finland, Italy, Netherlands, Sweden, and the United Kingdom. The following occupations fall into the category of highly offshorable jobs: Physical, mathematical and engineering science professionals (ISCO-88=21); Other professionals (ISCO-88=24); Office clerks (ISCO-88=41); Precision, handicraft, craft printing and related trades workers (ISCO-88=73); Other craft and related trades workers (ISCO-88=74); Stationary plant and related operators (ISCO-88=81); Machine operators and assemblers (ISCO-88=82). Author's calculations for the period from 1993-2007.

4.6.2 long differences

I have so far estimated the models in levels. However, adjustments to technology shocks may be slow, and as noted by Michaels *et al.* (2014), there may be issues of measurement error when estimating in levels. Therefore, as a further robustness check, I re-estimate the equations 4.1 and 4.2 by OLS in long (five-year overlapping) differences. This is a demanding estimation since the specifications are already in differences and so most of the variation in ICT changes stem from country-industry differences. As can be seen in Panel A of Table 4.8, the coefficients on ICT changes have the same sign but become smaller in magnitude. In addition, while the coefficient on ICT change is still weakly significant (at 10% level) for the high-wage occupation group, the ones for the middle- and low-wage occupations become statistically insignificant.

Given that institutional variables have no or very little variation over the years, in order to analyse the interaction between technological development and institutions in the long-difference estimations, I construct two dummy variables for EPL and CBC, taking on the value of unity if the levels are above their median and zero otherwise.

Panel B displays the results of specifications which include ICT growth interaction with EPL dummy. The estimates in column 1 suggest that, while in the long-run, employment in high-wage occupations increases with ICT growth in countries that have weak protection mandates, this effect is negative but statistically insignificant in countries with strong employment protection. Moreover, according to column 2, the negative effect of ICT growth is insignificant in both high and low EPL countries. Also, the average marginal effects of the variable ICT, corresponding to coefficients in Column 3, imply that ICT increase is associated with a significant increase in the share of employment in low-wage occupations in countries with strict employment protection.

Panel C turns the focus to the potential impact of collective bargaining coverage, but here we find no significant difference between countries with high and low levels of collective bargaining.[14]

[14]In other (not reported) robustness checks, I considered estimating the regression equations in ten- and three-year differences, and obtained qualitatively similar results to those obtained in Table 4.8.

Table 4.8: Long-difference

	Panel A *Baseline*			Panel B *ICT*EPL*			Panel C *ICT*CBC*		
OLS	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage
$\Delta ln(ICTint)$	1.565*	-0.418	-1.147	2.516**	-0.399	-2.118**	1.118	-2.134	1.017
	(0.917)	(0.608)	(0.734)	(1.128)	(0.609)	(0.991)	(2.028)	(1.552)	(2.047)
$\Delta ln(NICTint)$	-1.232	0.579	0.653	-0.855	0.586	0.269	-1.283	0.384	0.898
	(0.780)	(0.508)	(0.557)	(0.794)	(0.490)	(0.687)	(0.789)	(0.478)	(0.602)
$\Delta ln(VA)$	-1.528	-0.105	1.633	-1.463	-0.104	1.566	-1.375	0.485	0.890
	(2.082)	(1.957)	(1.582)	(2.105)	(1.963)	(1.671)	(2.053)	(1.943)	(1.475)
DEPLreg$\times\Delta ln(ICTint)$				-4.509***	-0.092	4.601***			
				(1.431)	(1.322)	(1.503)			
DCBC$\times\Delta ln(ICTint)$							0.557	2.139	-2.696
							(2.173)	(1.521)	(2.197)
Country-Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Country-Industry FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	865	865	865	865	865	865	865	865	865
R-Squared	0.522	0.454	0.462	0.533	0.454	0.478	0.522	0.456	0.464

Using the EU-KLEMS 2009 release (O'Mahony, Mary and Marcel P. Timmer, 2009), this table offers the results for the shares of employment in high-, medium- and low-wage occupations. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Coefficients estimated by OLS with robust standard errors in parentheses. The regressions also include full sets of country-year and country-industry dummies.Final sample of analysis consists of 9 European countries: Austria, Germany, Denmark, Spain, Finland, Italy, Netherlands, Sweden, and the United Kingdom. Author's calculations for the period from 1993-2007.

4.6.3 Instrumental variable

I identify the joint effects of ICT and institutional variables on the share of employment in different wage groups by controlling for a large set of variables, including country-time and country-industry fixed effects, as well as other types of technology and innovation that could affect the variables of interest (see subsection 4.6.4 for inclusion of more control variables in long difference estimations). In addition, I re-estimate the regression equations in five-year differences to account for unobserved factors that are constant over time and could bias the results. Nevertheless, one might still get concerned about the remaining omitted variables, measurement errors or reverse causality. Concerning the latter, for instance, it might be that the higher use of technology is due to an increasing industries' demand for employment of different tasks, and not the other way around. In order to address these issues, I conduct an IV approach similar to Michaels *et al.* (2014) and use the industry-level measure of IT intensity in the U.S. in the initial year as an instrument for ICT intensity over the whole sample. The idea behind this instrumental strategy is that the steep reduction in quality-adjusted IT prices disproportionately affects sectors, which have a greater potential to use such inputs. As argued by Michaels *et al.* (2014), the United States is a country widely considered as the technological leader and so its initial IT intensity can be seen as an indicator of this potential.

Panels A–C of Table 4.A.8 in the Appendix summarise the results of the IV specifications. The estimations of the 2SLS models are larger but generally in line with OLS estimates that only include country-year fixed effects (Table 4.A.7 in the Appendix). As the lower part of Table 4.A.8 shows, the sign of the first-stage regression coefficients, corresponding to Panel A, is as expected positive. However, the F-statistic of this instrument is below the critical value (6.45). Moreover, once the interaction terms between ICT growth and institutional variables are included, both the F-tests of excluded instruments and the Kleibergen-Paap statistics become even lower, which could cast doubts on the consistency of 2SLS results[15].

4.6.4 Additional controls

R&D As previously mentioned omitted variables might be another issue, as this would cause endogeneity problems. More precisely, it could be that the identified effects in Tables 4.3 or 4.A.7 are not because of ICT upgrading but rather because of other indirect measures of task-based technical change or innovation. To test this hypothesis, and similar to Michaels *et al.* (2014), I control for the initial R&D intensity of a sector, measured by R&D expenditure over value-added, in my regression equations. However, including the R&D data from the OECD ANBERD database would imply losing several observations since the OECD ANBERD data set does not have R&D data for some countries and industries. Hence, in Table 4.9, I first re-run the specifications of Panels A–C of Table 4.A.7, but for the sample for which data on R&D is available, yet excluding R&D intensity itself. This allows me to disentangle the effect of using this particular sample from the effect of R&D inclusion. Panels A–C of Table 4.9 indicate that this lowers the number of observations to 312, and

[15]In Table 4.A.9 in the Appendix, I also computed the magnitude of ICT effects in long-difference and IV models

the coefficients on ICT, although insignificant, show different signs as in our baseline specification. Panels D–F of Table 4.9 then add the R&D intensity variable into the above specifications. Although the effects are perhaps imprecisely estimated, the coefficient on R&D is significant for the changes in employment shares of medium- and low-wage occupations. These results may suggest a distinct role for indirect measures of technology or innovation, which is proxied by R&D.

Relative wages Although all my specifications include country-year fixed effects to absorb the impacts of other omitted labour market institutions that are national in scope, one might still get concerned about some reforms regarding relative wages which may vary across industries. Moreover, if relative wage rates vary across industries and are correlated with ICT changes, the assumed specification would be incorrect and omitted variable can raise concerns about a potential bias in the coefficients. However, as shown in Michaels *et al.* (2014), wages might just as well be dependent variables for ICT changes too. Therefore, to address this issue more cautiously, I include the level of initial wage bill share of medium- and low-skill workers in 1993 as further controls into my long difference specifications. The information on wage bill shares are obtained from the EU-KLEMS database and they are defined as the share of the hourly wage of each skill category (i.e., high, medium, and low) out of the total hourly wage. Panels A–C of Table 4.10 demonstrate that the results remain quite robust to this sensitivity check, although the coefficient on ICT for the medium wage in Panel A becomes insignificant.

Additional fixed effect So far, I have followed previous literature on the selection of fixed effects variables (for example, Michaels *et al.*, 2014; Jerbashian, 2019). However, in these additional estimates, I allow for all possible two-way interactions between country, industry, and time. The results, depicted in Table 4.A.10 in the appendix, show that ICT effects are robust to the inclusion of industry-year fixed effects in both levels (Panels A–C) and long-difference (Panels D–F) estimations. In Panels G–I of Table 4.A.10, I additionally include the full sets of country-industry dummies to my long-difference models. As already mentioned, this is a demanding estimation since the specifications are already in differences, and so most of the variation in ICT changes stem from country-industry differences. The results indicate that, including country-industry dummies, the coefficients on ICT change have the same sign but become smaller in magnitude and significance.

Table 4.9: R&D and Sample Restriction

	Panel A *Baseline*			Panel B *ICT*EPL*			Panel C *ICT*CBC*		
OLS	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage
$\Delta ln(ICTint)$	-1.055	0.296	0.760	-0.696	1.195	-0.499	-4.400	-3.122	7.522*
	(1.049)	(0.837)	(0.788)	(1.044)	(0.835)	(0.786)	(4.494)	(2.563)	(3.996)
$\Delta ln(NICTint)$	0.622	-0.487	-0.135	0.401	-1.041*	0.640***	0.253	-0.864	0.611
	(0.736)	(0.608)	(0.562)	(0.758)	(0.608)	(0.584)	(0.743)	(0.597)	(0.577)
$\Delta ln(VA)$	-4.124**	3.327***	0.797	-3.955**	3.749**	0.206	-3.820**	3.638**	0.182
	(1.699)	(1.484)	(1.334)	(1.667)	(1.522)	(1.219)	(1.657)	(1.518)	(1.211)
DEPLreg$\times\Delta ln(ICTint)$				-1.988	-4.967**	6.955*			
				(4.001)	(2.276)	(3.548)			
DCBC$\times\Delta ln(ICTint)$							3.938	4.024	-7.962*
							(4.712)	(2.568)	(4.251)
Observations	312	312	312	312	312	312	312	312	312
R-Squared	0.300	0.326	0.205	0.301	0.336	0.224	0.303	0.331	0.226
	Panel D			**Panel E**			**Panel F**		
Adding R&D intensity	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage
$\Delta ln(ICTint)$	-0.941	-0.173	1.114	-0.407	0.250	0.156	-5.119	-0.953	6.072*
	(1.076)	(0.800)	(0.807)	(1.013)	(0.789)	(0.751)	(4.499)	(2.649)	(3.522)
$\Delta ln(NICTint)$	0.551	-0.195	-0.356	0.222	-0.456	0.234	0.062	-0.287	0.225
	(0.748)	(0.592)	(0.567)	(0.735)	(0.588)	(0.559)	(0.719)	(0.578)	(0.552)
$\Delta ln(VA)$	-3.695*	1.562	2.133	-3.366*	1.822	1.543	-3.164*	1.661	1.503
	(1.974)	(1.423)	(1.729)	(1.924)	(1.500)	(1.637)	(1.905)	(1.494)	(1.628)
$ln(R\&Dint)_{1993}$	0.119	-0.488***	0.369**	0.143	-0.468***	0.325**	0.159	-0.480***	0.321**
	(0.176)	(0.082)	(0.172)	(0.171)	(0.090)	(0.164)	(0.170)	(0.090)	(0.163)
DEPLreg$\times\Delta ln(ICTint)$				-2.825	-2.234	5.059*			
				(3.903)	(2.427)	(3.045)			
DCBC$\times\Delta ln(ICTint)$							4.964	0.928	-5.892
							(4.658)	(2.702)	(3.687)
Observations	312	312	312	312	312	312	312	312	312
R-Squared	0.302	0.389	0.240	0.304	0.391	0.249	0.307	0.389	0.251

Notes: Using the EU-KLEMS 2009 release (O'Mahony, Mary and Marcel P. Timmer, 2009), this table offers the results for the shares of employment in high-, medium- and low-wage occupations. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Coefficients estimated by OLS with robust standard errors in parentheses. The regressions also include full sets of country-year dummies.Final sample of analysis consists of 6 European countries: Germany, Spain, Finland, Italy, Netherlands, and the United Kingdom. Author's calculations for the period from 1993-2007.

Table 4.10: Adding Initial Wage Bill Shares

	Panel A			**Panel B**			**Panel C**		
	Baseline			***ICT*EPL***			***ICT*CBC***		
	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage
$\Delta ln(ICTint)$	2.917***	-0.865	-2.052**	3.942***	-1.013*	-2.929**	3.067***	-2.220*	-0.848
	(1.111)	(0.564)	(0.922)	(1.444)	(0.580)	(1.212)	(1.286)	(1.212)	(1.099)
$\Delta ln(NICTint)$	-1.172	0.510	0.663	-0.927	0.474	0.453	-1.145	0.263	0.882
	(0.740)	(0.467)	(0.532)	(0.862)	(0.453)	(0.679)	(0.766)	(0.449)	(0.601)
$\Delta ln(VA)$	-5.645***	3.719**	1.926	-5.289***	3.667**	1.622	-5.698***	4.199***	1.499
	(1.879)	(1.521)	(1.432)	(1.891)	(1.549)	(1.416)	(1.802)	(1.512)	(1.347)
Δ1993 Medium-skill wage bill share	0.064**	-0.062***	-0.002	0.060**	-0.061***	0.001	0.064**	-0.058***	-0.006
	(0.027)	(0.019)	(0.018)	(0.026)	(0.019)	(0.019)	(0.027)	(0.019)	(0.019)
Δ1993 Low-skill wage bill share	-0.037**	0.020**	0.017*	-0.039***	0.020**	0.019*	-0.037***	0.019**	0.018*
	(0.090)	(0.010)	(0.010)	(0.015)	(0.010)	(0.010)	(0.015)	(0.010)	(0.010)
$DEPLreg \times \Delta ln(ICTint)$				-4.571**	0.662	3.910**			
				(2.117)	(1.199)	(1.541)			
$DCBC \times \Delta ln(ICTint)$							-0.201	1.820	-1.619
							(1.730)	(1.261)	(1.510)
Observations	865	865	865	865	865	865	865	865	865
R-Squared	0.312	0.233	0.195	0.326	0.234	0.210	0.312	0.236	0.196

Notes: Using the EU-KLEMS 2009 release (O'Mahony, Mary and Marcel P. Timmer, 2009), this table offers the results for the shares of employment in high-, medium- and low-wage occupations. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Coefficients estimated by OLS with robust standard errors in parentheses. The regressions also include full sets of country-year dummies.Final sample of analysis consists of 9 European countries: Austria, Germany, Denmark, Spain, Finland, Italy, Netherlands, Sweden, and the United Kingdom. Author's calculations for the period from 1993-2007.

4.6.5 More recent period

My analysis so far covered only the period from 1993-2007 to make the results comparable to previous studies and follow existing literature as close as possible. In this subsection, however, I use the 2017 release of the EUKLEMS database (Van Ark and Jäger 2017), which covers more recent years, i.e., up to 2015. Note that because of several changes in measurement and data construction as well as industry classification, the 2008 and 2017 releases of the EUKLEMS database are not directly comparable to each other.[16] Nevertheless, the latter can be used to examine whether the results hold in light of more recent ICT developments.

Panels A–C of Table 4.11 report re-estimates of equations 4.1 and 4.2 for 1996-2015, which is the period for which data on all variables were available. In general, the results are consistent with the pattern prevailing in 1993-2007: higher ICT intensity is associated with a higher (lower) share of employment in high (medium) wage occupations and no clear trend for low wage occupations. In addition, as in earlier decades, stricter dismissal regulations constrain the impact of ICT on the occupational structure of employment, while the results do not reveal a large role for collective bargaining coverage.

The lower part of Table 4.11 summarizes the results of re-estimating the regression equations in long differences. As in earlier decades, I estimate here the regression equation in five-year differences; however, I also tried changes of 10 and 20 years (not reported). As compared to Panel A of Table 4.A.7, the coefficients on ICT growth are smaller and statistically insignificant at conventional levels in Panel D of Table 4.11[17]. One possible explanation for weaker results in the more recent period may be that ICT technologies might have a smaller growth during the more recent period than in earlier decades (pre 2007), since the fixed costs of ICT adoption have already fallen dramatically during the past decades and nowadays other types of technologies such as industrial robots are widely used (Stiebale, Suedekum and Woessner 2020)[18].

Also, in line with the estimates for earlier decades, the interaction terms between institutional variables and ICT intensity display that countries with high levels of EPL have lower degrees of job polarisation, while there seems to be no considerable heterogeneity across countries with different rates of collective bargaining coverage.

[16]Also, the 2017 release of the EUKLEMS database does not include the information on (non-)ICT shares in total compensation (variable CAPIT in the 2008 release) any more. I obtained information on this variable by contacting the EUKLEMS support team and received this data (on 08.10.2020) from "Robert Stehrer", who is working for the EUKLEMS support team.

[17]The estimated coefficients on ICT growth using 10- and 20-year changes are larger and significant compared to the obtained coefficients when using 5-year changes

[18]Although not reported in Table 4.11, the estimates for ICT intensity are indeed somewhat weaker and insignificant for the post-2007 period.

Table 4.11: More recent decade

	Panel A *Baseline*			**Panel B** *ICT*EPL*			**Panel C** *ICT*CBC*		
OLS	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage
$ln(ICTint)$	1.450*	-1.878***	0.431	11.55***	-8.464***	-3.101**	2.104*	-4.015***	1.915*
	(0.787)	(0.649)	(0.543)	(1.950)	(1.441)	(1.344)	(1.699)	(1.383)	(0.974)
$ln(NICTint)$	-0.115	-0.047	0.162	2.269**	-1.601**	-0.671	-0.129	-0.0002	0.129
	(0.901)	(0.761)	(0.655)	(1.003)	(0.774)	(0.669)	(0.905)	(0.755)	(0.649)
$ln(VA)$	-9.069***	6.022***	3.049***	-9.785***	6.489***	3.300***	-9.043***	5.937***	3.108***
	(1.321)	(1.239)	(1.121)	(1.341)	(1.203)	(1.143)	(1.321)	(1.245)	(1.119)
EPLreg$\times ln(ICTint)$				-4.727***	3.081***	1.652***			
				(0.803)	(0.560)	(0.605)			
CBC$\times ln(ICTint)$							0.009	0.029*	-0.020*
							(0.021)	(0.017)	(0.012)
Country-Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Country-Industry FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1,727	1,727	1,727	1,727	1,727	1,727	1,727	1,727	1,727
R-Squared	0.909	0.969	0.961	0.912	0.970	0.961	0.909	0.969	0.961
	Panel D			**Panel E**			**Panel F**		
OLS	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage
$\Delta ln(ICTint)$	0.016	-0.538	0.517	1.177	-1.512*	0.337	0.848	-0.625	-0.220
	(0.806)	(0.714)	(0.564)	(1.027)	(0.844)	(0.734)	(0.993)	(0.819)	(0.722)
$\Delta ln(NICTint)$	0.325	-0.527	0.197	0.848	-0.966	0.116	0.426	-0.537	0.107
	(0.935)	(0.773)	(0.701)	(1.025)	(0.800)	(0.774)	(0.927)	(0.766)	(0.697)
$\Delta ln(VA)$	-6.768***	2.279	4.511***	-7.228***	2.665*	4.582***	-6.822***	2.285	4.558***
	(1.658)	(1.387)	(1.361)	(1.681)	(1.397)	(1.385)	(1.661)	(1.388)	(1.362)
DEPLreg$\times\Delta ln(ICTint)$				-2.436**	2.046**	0.378			
				(1.237)	(0.821)	(0.948)			
DCBC$\times\Delta ln(ICTint)$							-1.673	0.175	1.483*
							(1.026)	(0.737)	(0.796)
Country-Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1,367	1,367	1,367	1,367	1,367	1,367	1,367	1,367	1,367
R-Squared	0.199	0.141	0.168	0.201	0.144	0.168	0.200	0.141	0.170

Notes: Using the EU-KLEMS 2017 release (Jäger and Van Ark 2017), this table offers the results for the shares of employment in high-, medium- and low-wage occupations. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Coefficients estimated by OLS with robust standard errors in parentheses. The regressions in panels A–C also include full sets of country-year and country-industry dummies. The regressions in panels D–F also include full sets of country-year dummies. Final sample of analysis consists of 9 European countries: Austria, Germany, Denmark, Spain, Finland, Italy, Netherlands, Sweden, and the United Kingdom. Author's calculations for the period from 1996-2015.

4.6.6 Other technologies

As a final robustness check, I repeat the analysis using an alternative form of technological change besides ICT to test whether the results are sensitive to the choice of technology measure. For this purpose, I use the 2008 release of the EU KLEMS database (O'Mahony and Timmer 2009) and consider the price of information technologies and IT dependence, in the spirit of Jerbashian (2019). However, I limit my analysis to the same 9 European countries listed in Table 4.A.2 in the Appendix.

First, to assure that my setting is consistent with Jerbashian (2019)'s study, I replicate his regression and estimate the baseline model of the following form with OLS:

$$EmploymentShare_{cit} = \beta(ITdep_i \times (\frac{1}{ITprice}_{ct})) + \alpha_{c,t} + \gamma_{c,i} + \epsilon_{c,i,t} \tag{4.3}$$

Where, as before, $EmploymentShare_{cit}$ is the share of employment in one of the occupation groups, country c, industry i, and year t. $ITdep_i$ denotes the share of IT capital compensation out of value-added in US industries, averaged over the sample period (1993-2007). $\frac{1}{ITprice}$ stands for the inverse of IT price and $ITprice$ itself is defined as the price of investment in IT, which is normalized with the price of value-added in each industry and is averaged across industries (see also Jerbashian (2019) for more details on definition and construction of variables). Moreover, I include country-year ($\alpha_{c,t}$) and country-industry ($\gamma_{c,i}$) fixed effects and use robust standard errors, similar to my previous specifications[19].

In addition, I also employ an instrumental variable approach to tackle endogeneity issues. In particular, following Jerbashian (2019), I use the prices of communication technologies ($CTprice$), e.g., telephones and other communication infrastructure, as an instrument for IT price. The idea behind this instrument is that the same technological change and production growth that led to a decline in prices of information technology could also decrease the prices of communication technologies. Yet, communication technologies are unlikely to imply a high degree of complementarity or substitution with labour and are therefore unlikely to affect structures directly (Jerbashian 2019).
As can be seen from the lower parts of Table 4.12, which present the first stage results of the 2SLS estimation, a possible advantage of considering this alternative measure of technology over ICT could be that here the relevant instrumental variable is stronger as the F-statistics reflect. Yet, in models with the interaction term, we might still have some inconsistency in the IV estimates since the correlation between the instrument and the endogenous variables is weak in some specifications.

Panels A and D of Table 4.12 present the results of my replication exercise. As in Jerbashian (2019), I find that, in both OLS and 2SLS estimations, lower IT prices are associated with higher demand for workers in the high-wage occupation

[19] Following Jerbashian (2019), I have also experimented with using two-way clustered standard errors at industry- and country-year-level. Using this gives slightly smaller standard errors; however, as the overall results turn out to be very similar, I only report the results with robust standard errors, which are more consistent with earlier regression estimations used in this paper.

group at the expense of the middle-wage occupations, with little effect on low-wage occupation group.

Next, I investigate the contribution of labour market institutions, i.e., EPL and CBC, in shaping the employment structure.
Panels B and E of Table 4.12 display the results of the specifications which include interaction with EPL. The overall estimates in both panels suggest that stricter dismissal regulations limit the direct effect of technology on the occupational pattern, although the coefficient on the interaction term is not statistically significant for the low-wage category of occupation.

Turning to the impact of collective bargaining (Panels C and F), the coefficient on interaction terms is significant for high- and medium-wage occupation groups in Panel C. This seems to be contrary to earlier results (e.g. Panel C of Table 4.3) which suggest no role for collective bargaining for these two categories of occupations. However, once we instrument for IT prices, the coefficients provide a similar conclusion to those obtained previously (Panel F).

Overall, these results appear supportive of my prior findings on the joint impacts of ICT improvements and labour market institutions.

Table 4.12: Other technologies: IT price and IT dependence

	Panel A *Baseline*			**Panel B** *Interaction with EPL*			**Panel C** *interaction with CBC*		
OLS	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage
$ITdep \times (\frac{1}{ITprice})$	0.278***	-0.271***	-0.008	0.547***	-0.455***	-0.091	0.056	-0.020	-0.036
	(0.027)	(0.023)	(0.018)	(0.091)	(0.080)	(0.056)	(0.075)	(0.070)	(0.046)
EPLreg$\times ITdep \times (\frac{1}{ITprice})$				-0.116***	0.080**	0.036			
				(0.037)	(0.031)	(0.027)			
CBC$\times ITdep \times (\frac{1}{ITprice})$							0.003***	-0.003***	0.0004
							(0.001)	(0.001)	(0.0007)
	Panel D			**Panel E**			**Panel F**		
2SLS	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage
$ITdep \times (\frac{1}{ITprice})$	0.284***	-0.252***	-0.032*	0.885***	-0.699***	-0.186**	0.191**	-0.181**	-0.009
	(0.030)	(0.029)	(0.018)	(0.174)	(0.151)	(0.094)	(0.084)	(0.085)	(0.052)
EPLreg$\times ITdep \times (\frac{1}{ITprice})$				-0.278***	0.207***	0.071			
				(0.075)	(0.065)	(0.044)			
CBC$\times ITdep \times (\frac{1}{ITprice})$							0.001	-0.0009	-0.0003
							(0.001)	(0.001)	(0.0008)
Observations	1,250	1,250	1,250	1,250	1,250	1,250	1,200	1,200	1,200
R-Squared	0.963	0.988	0.977	0.964	0.988	0.977	0.965	0.988	0.978
First stage results, dependent variable: $ITdep \times (\frac{1}{ITprice})$									
$ITdep \times (\frac{1}{CTprice})$	5.695***	5.695***	5.695***	8.757***	8.757***	8.757***	11.60***	11.60***	11.60***
	(0.701)	(0.701)	(0.701)	(1.567)	(1.567)	(1.567)	(1.074)	(1.074)	(1.074)
EPL$\times$ $ITdep \times (\frac{1}{CTprice})$				-1.438	-1.438	-1.438			
				(0.903)	(0.903)	(0.903)			
CBC$\times$ $ITdep \times (\frac{1}{CTprice})$							-0.079***	-0.079***	-0.079***
							(0.015)	(0.015)	(0.015)
F test of excluded instruments	66.04	66.04	66.04	87.64	87.64	87.64	102.62	102.62	102.62
First stage results, dependent variable: EPL$\times ITdep \times (\frac{1}{ITprice})$ **or CBC**$\times ITdep \times (\frac{1}{ITprice})$									
$ITdep \times (\frac{1}{CTprice})$				6.366	6.366	6.366	465.60***	465.60***	465.60***
				(4.159)	(4.159)	(4.159)	(90.27)	(90.27)	(90.27)
EPL$\times$ $ITdep \times (\frac{1}{CTprice})$				2.787	2.787	2.787			
				(2.403)	(2.403)	(2.403)			
CBC$\times$ $ITdep \times (\frac{1}{CTprice})$							-0.781	-0.781	-0.781
							(1.356)	(1.356)	(1.356)
F test of excluded instruments				46.01	46.01	46.01	48.01	48.01	48.01
Kleibergen-Paap Wald rk F statistic	66.04	66.04	66.04	12.68	12.68	12.68	20.57	20.57	20.57

Notes: Using the EU-KLEMS 2009 release (O'Mahony, Mary and Marcel P. Timmer, 2009), this table offers the results for the shares of employment in high-, medium- and low-wage occupations in the sample industries. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Coefficients estimated by OLS with robust standard errors in parentheses. The regressions also include full sets of country-year and country-industry dummies.Final sample of analysis consists of 9 European countries: Austria, Germany, Denmark, Spain, Finland, Italy, Netherlands, Sweden, and the United Kingdom. Author's calculations for the period from 1993-2007.

4.7 Conclusion

Whilst some research has been carried out on employment polarisation in developed countries, there have been only a few empirical investigations into the role of labour market institutions. In this paper, I exploit data for 9 European countries to examine the joint impact of ICT investments and labour market institutions (particularly the employment protection legislation and collective bargaining coverage) on employment shares in high-, medium-, and low-wage occupations. In addition, I look into the potential differences between different socio-demographic groups to identify which groups of workers might benefit more from stronger labour market institutions. Thus, although this analysis remains descriptive and cannot assert any causal effect, it contributes to a better understanding of the driving forces behind different employment structures, and the role of labour market policies.

In general, the findings of this study support the hypothesis of routinization. In particular, the results suggest that an increase in ICT intensity implies a rise in the share of employment in high-wage occupations and a decline in the share of employment in medium-wage occupations. I also find some, albeit less robust, evidence for negative effects of ICT on the share of employment in low-wage occupations, which suggests that the overall pattern of the employment structure in European countries appears more similar to an occupational upgrading than to a polarisation. This evidence is thus more consistent with the findings of Oesch and Rodríguez Menés (2011) as well as Nellas and Olivieri (2012) than to a pervasive polarisation pattern found in Goos *et al.* (2014). Furthermore, the results show that the effects of ICT on employment shares are mitigated by stricter employment protection. Moreover, I find no significant and robust pattern with respect to the role of collective bargaining coverage in altering the effects of ICT on employment shares. Finally, my results highlight important differences among worker groups. For instance, the findings indicate that the effect of ICT on the share of employment in high- and low-wage occupations among women is about two times larger than among men. Besides, stricter dismissal regulation weakens the impact of ICT on employment shares for both gender types; however, the role of EPL seems to be significantly stronger for females in low-wage occupations as compared to males in the same occupation group. Similarly, my results show a differentiated impact for workers in different age and skill groups.

The results of my study have a number of important implications for economic policy.
Employment protection regulations seem to have played a role in altering the occupational structure of employment. Moreover, the evidence suggests that this role may be stronger among some workers groups. Although a higher EPL might benefit incumbent workers through providing higher employment security, it reduces firms' flexibility in hiring new workers and hence could come at the cost of 'outsider' individuals. In addition, if more restrictive employment regulations tend to curb direct job-to-job transitions of workers, they can play a major negative role in reallocating labour to the most productive uses. Therefore, the overall contribution of labour market institutions is not limited to employed individuals in specific occupations, however with the available data and methodology used in this paper, it was not

possible to quantify their importance for flows into another job or re-employment.

The analysis presented in this work has some limitations that suggest further possibilities for future work. First, both technological change and institutional variables have a lot of measurement issues, which make verifying a causal relationship difficult. This study was also limited by the absence of strong instrumental variables for ICT, especially for specifications with interactions between institutional variables and ICT. Thus, future studies could explore different instrumental variables in order to identify the causal impacts of technology and labour market institutions on employment patterns. Second, major revisions to the industry definitions and data construction in the more recent releases of EUKLEMS data, as well as the EU-LFS major revision in occupational classifications in 2011, do not allow me to have a direct comparison between the results obtained for the 1993-2007 period and those for later years. Also, due to limited access to further databases with wage information (including the European Community Household Panel (ECHP), the European Union Statistics on Income and Living Conditions (EU-SILC), and the UK Labour Force Survey), the ranking of occupations and comparing them with those obtained in previous studies was not possible in this study. In this regard, future research might put more emphasis on recent decades and use data on workers' wages in order to re-rank occupations for later years in more detailed categories.

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Appendix A

Table 4.A.1: List of occupations

Occupation Name and Wage group	ISCO-88 Code
High Wage Occupations	
Corporate Managers	12
Physical, Mathematical, and Engineering Science Professionals	21
Life Science and Health Professionals	22
Other Professionals	24
General Managers	13
Physical and Engineering Science Associate Professionals	31
Other Associate Professionals	34
Life Science and Health Associate Professionals	32
Medium Wage Occupations	
Stationary-plant and Related Operators	81
Metal, Machinery, and Related Trades Workers	72
Drivers and Mobile-plant Operators	83
Office Clerks	41
Precision, Handicraft, Printing, and Related Trades Workers	73
Extraction and Biulding Trades Workers	71
Customers Services Clerks	42
Machine Operators and Assemblers	82
Other Craft and Related Trades Workers	74
Low Wage Occupations	
Labourers in Mining, Construction, Manufacturing, and Transport	93
Personal and Protective Services Workers	51
Models, Salespersons, and Demonstrators	52
Sales and Services Elementary Occupations	91

Notes:Source: Goos *et al.* (2010, 2014).

Table 4.A.2: Sample countries and period

Country code	Country	Sample period
AT	Austria	1995-2007
DE	Germany	1993-2007
DK	Denmark	1993-2007
ES	Spain	1993-2007
FI	Finland	1997-2007
IT	Italy	1993-2007
NL	Netherlands	1993-2007
SE	Sweden	1997-2007
UK	The united kingdom	1993-2007

Table 4.A.3: Main results for the change in employment shares in high-, medium- and low-wage occupations

	ICT*EPL			***ICT*CBC***		
OLS	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage
$ln(ICTint)$	8.977***	-5.008***	-3.969***	2.836	-3.677**	0.841
	(1.809)	(1.146)	(1.100)	(1.867)	(1.575)	(1.270)
$ln(NICTint)$	-1.631**	0.936*	0.694	-1.561**	1.107**	0.455
	(0.783)	(0.495)	(0.517)	(0.792)	(0.516)	(0.610)
$ln(VA)$	-6.315***	5.291***	1.024	-6.864***	6.232***	0.632
	(1.539)	(1.230)	(1.154)	(1.586)	(1.334)	(1.183)
lagEPLreg$\times ln(ICTint)$	-2.979***	1.720***	1.258***			
	(0.649)	(0.447)	(0.408)			
lagCBC$\times ln(ICTint)$				0.008	0.025	-0.033*
				(0.025)	(0.017)	(0.018)
Country-Year FE	✓	✓	✓	✓	✓	✓
Country-Industry FE	✓	✓	✓	✓	✓	✓
Observations	1,223	1,223	1,223	1,106	1,106	1,106
R-Squared	0.963	0.984	0.976	0.963	0.986	0.976

Using EU-KLEMS 2009 release (O'Mahony, Mary and Marcel P. Timmer, 2009), this table offers the results for the shares of employment in high-, medium- and low-wage occupations in sample industries. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Coefficients estimated by OLS with robust standard errors in parentheses. The regressions also include full sets of country-year and country-industry dummies.Final sample of analysis consists of 9 European countries: Austria, Germany, Denmark, Spain, Finland, Italy, Netherlands, Sweden, and the United Kingdom. Author's calculations for the period from 1993-2007.

Table 4.A.4: Robustness to excluding individual countries from the sample

W/o Austria	***Baseline***			***ICT*EPL***			***ICT*CBC***		
OLS	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage
$ln(ICTint)$	2.999***	-1.632***	-1.366**	7.209***	-3.368***	-3.841***	1.936	-3.634**	1.698
	(0.917)	(0.579)	(0.655)	(1.850)	(1.166)	(1.233)	(1.951)	(1.700)	(1.334)
$ln(NICTint)$	-0.847	0.539	0.308	-1.220	0.693	0.527	-0.962	0.952*	0.010
	(0.734)	(0.468)	(0.520)	(0.819)	(0.500)	(0.578)	(0.717)	(0.502)	(0.600)
$ln(VA)$	-8.048**	5.729***	2.319**	-7.079***	5.329***	1.749	-7.460**	5.586***	1.874
	(1.536)	(1.181)	(1.176)	(1.572)	(1.201)	(1.211)	(1.546)	(1.250)	(1.158)
$EPLreg \times ln(ICTint)$				-2.183***	0.900*	1.283**			
				(0.733)	(0.485)	(0.529)			
$CBC \times ln(ICTint)$							0.018	0.024	-0.043**
							(0.026)	(0.019)	(0.019)
Observations	1,093	1,093	1,093	1,093	1,093	1,093	1,045	1,045	1,045
R-Squared	0.964	0.989	0.976	0.965	0.989	0.977	0.965	0.989	0.977
W/o Germany	***Baseline***			***ICT*EPL***			***ICT*CBC***		
OLS	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage
$ln(ICTint)$	3.228***	-1.605***	-1.622**	9.013***	-4.813***	-4.199***	3.044	-3.895**	0.851
	(0.916)	(0.578)	(0.658)	(1.934)	(1.246)	(1.178)	(1.902)	(1.656)	(1.255)
$ln(NICTint)$	-1.407**	0.701	0.705	-1.761	0.898*	0.863	-1.512**	1.072**	0.439
	(0.691)	(0.462)	(0.489)	(0.803)	(0.509)	(0.536)	(0.740)	(0.498)	(0.569)
$ln(VA)$	-8.440**	7.481***	0.959	-7.248***	6.820***	0.428	-7.958***	7.006***	0.953
	(1.639)	(1.313)	(1.254)	(1.668)	(1.318)	(1.267)	(1.669)	(1.375)	(1.239)
$EPLreg \times ln(ICTint)$				-2.937***	1.628***	1.308***			
				(0.743)	(0.518)	(0.465)			
$CBC \times ln(ICTint)$							0.004	0.028	-0.032*
							(0.025)	(0.018)	(0.018)
Observations	1,085	1,085	1,085	1,085	1,085	1,085	1,055	1,055	1,055
R-Squared	0.959	0.985	0.975	0.961	0.985	0.975	0.960	0.985	0.975
W/o Denmark	***Baseline***			***ICT*EPL***			***ICT*CBC***		
OLS	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage
$ln(ICTint)$	1.621*	-0.082	-1.539*	7.431***	-2.872**	-4.559***	1.868	-2.302	0.433
	(0.916)	(0.472)	(0.813)	(2.153)	(1.225)	(1.452)	(1.808)	(1.413)	(1.357)
$ln(NICTint)$	-0.458	-0.242	0.700	-1.157	0.094	1.063*	-0.850	0.192	0.658
	(0.671)	(0.403)	(0.562)	(0.788)	(0.451)	(0.618)	(0.809)	(0.468)	(0.689)
$ln(VA)$	-7.696***	5.589***	2.106*	-6.324***	4.930***	1.393	-6.904***	5.446***	1.459
	(1.452)	(1.127)	(1.170)	(1.480)	(1.133)	(1.181)	(1.500)	(1.177)	(1.168)
$EPLreg \times ln(ICTint)$				-2.654***	1.274**	1.380***			
				(0.747)	(0.500)	(0.484)			
$CBC \times ln(ICTint)$							0.002	0.026*	-0.028
							(0.023)	(0.015)	(0.018)
Observations	1,073	1,073	1,073	1,073	1,073	1,073	1,025	1,025	1,025
R-Squared	0.963	0.987	0.975	0.964	0.987	0.975	0.964	0.987	0.975

Notes: Using the EU-KLEMS 2009 release (O'Mahony, Mary and Marcel P. Timmer, 2009), this table offers the results for the shares of employment in high-, medium- and low-wage occupations in the sample industries. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Coefficients estimated by OLS with robust standard errors in parentheses. The regressions also include full sets of country-year and country-industry dummies. Author's calculations for the period from 1993-2007

Table 4.A.5: Robustness to excluding individual countries from the sample, continued

W/o Spain	***Baseline***			***ICT*EPL***			***ICT*CBC***		
OLS	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage
ln(ICTint)	3.400***	-1.488**	-1.912***	8.651***	-5.714***	-2.938*	1.502	-3.348**	1.846
	(0.964)	(0.582)	(0.700)	(2.802)	(1.761)	(1.561)	(1.617)	(1.445)	(1.358)
ln(NICTint)	-1.435**	0.706	0.730	-1.627**	0.859*	0.767	-1.443	1.025**	0.418
	(0.715)	(0.456)	(0.520)	(0.795)	(0.512)	(0.532)	(0.763)	(0.495)	(0.592)
ln(VA)	-7.273***	6.647***	0.626	-6.640***	6.138***	0.502	-7.040**	6.951***	0.089
	(1.664)	(1.380)	(1.293)	(1.711)	(1.395)	(1.289)	(1.710)	(1.442)	(1.294)
EPLreg×ln(ICTint)				-2.760**	2.221***	0.539			
				(1.241)	(0.787)	(0.730)			
CBC×ln(ICTint)							0.028	0.022	-0.050**
							(0.024)	(0.016)	(0.020)
Observations	1,073	1,073	1,073	1,073	1,073	1,073	1,035	1,035	1,035
R-Squared	0.963	0.986	0.975	0.964	0.986	0.975	0.963	0.986	0.975
W/o Finland	***Baseline***			***ICT*EPL***			***ICT*CBC***		
OLS	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage
ln(ICTint)	2.697***	-2.049***	-0.648	8.706***	-5.152***	-3.554***	6.452***	-4.217**	-2.234**
	(0.692)	(0.634)	(0.574)	(1.516)	(1.357)	(0.895)	(1.515)	(1.773)	(0.937)
ln(NICTint)	-1.901***	0.851*	1.050**	-2.317***	1.066*	1.251***	-2.763**	1.274**	1.487
	(0.522)	(0.499)	(0.432)	(0.596)	(0.553)	(0.418)	(0.585)	(0.553)	(0.434)
ln(VA)	-6.835**	6.257***	0.578	-5.521***	5.578***	-0.057	-5.348***	6.026***	-0.678
	(1.490)	(1.279)	(1.114)	(1.516)	(1.296)	(1.093)	(1.545)	(1.380)	(1.041)
EPLreg×ln(ICTint)				-3.088***	1.595***	1.494***			
				(0.591)	(0.521)	(0.373)			
CBC×ln(ICTint)							-0.048**	0.027	0.020*
							(0.018)	(0.021)	(0.011)
Observations	1,126	1,126	1,126	1,126	1,126	1,126	1,078	1,078	1,078
R-Squared	0.965	0.986	0.978	0.967	0.986	0.979	0.967	0.986	0.979
W/o Italy	***Baseline***			***ICT*EPL***			***ICT*CBC***		
OLS	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage
ln(ICTint)	3.149***	-2.098***	-1.051*	9.017***	-5.300**	-3.717***	3.424*	-4.810***	1.386
	(0.917)	(0.615)	(0.607)	(1.919)	(1.165)	(1.235)	(1.916)	(1.522)	(1.224)
ln(NICTint)	-1.400**	1.307***	0.093	-1.724**	1.484***	0.240	-1.685**	1.699***	-0.014
	(0.690)	(0.465)	(0.473)	(0.804)	(0.498)	(0.531)	(0.741)	(0.494)	(0.551)
ln(VA)	-6.444***	5.859***	0.585	-5.248***	5.206***	0.042	-5.577***	5.737***	-0.160
	(1.491)	(1.239)	(1.030)	(1.532)	(1.249)	(1.060)	(1.528)	(1.297)	(1.027)
EPLreg×ln(ICTint)				-3.015***	1.645***	1.369***			
				(0.746)	(0.488)	(0.488)			
CBC×ln(ICTint)							0.0007	0.034**	-0.035**
							(0.025)	(0.017)	(0.017)
Observations	1,073	1,073	1,073	1,073	1,073	1,073	1,045	1,045	1,045
R-Squared	0.962	0.987	0.977	0.964	0.987	0.982	0.964	0.987	0.982

Notes:Using the EU-KLEMS 2009 release (O'Mahony, Mary and Marcel P. Timmer, 2009), this table offers the results for the shares of employment in high-, medium- and low-wage occupations in the sample industries. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Coefficients estimated by OLS with robust standard errors in parentheses. The regressions also include full sets of country-year and country-industry dummies. Author's calculations for the period from 1993-2007.

Table 4.A.6: Robustness to excluding individual countries from the sample, continued

W/o Netherlands	***Baseline***			***ICT*EPL***			***ICT*CBC***		
OLS	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage
$ln(ICTint)$	3.131***	-1.588***	-1.542**	8.454***	-4.788***	-3.665***	3.146	-4.190**	1.044
	(0.928)	(0.583)	(0.665)	(2.017)	(1.275)	(1.237)	(2.162)	(1.838)	(1.282)
$ln(NICTint)$	-1.087	0.668	0.419	-1.381*	0.845*	0.536	-1.380*	1.111**	0.269
	(0.717)	(0.463)	(0.508)	(0.815)	(0.506)	(0.544)	(0.761)	(0.506)	(0.585)
$ln(VA)$	-8.946***	6.300***	2.646**	-7.669***	5.532***	2.137*	-8.269***	6.170***	2.100*
	(1.609)	(1.299)	(1.211)	(1.646)	(1.312)	(1.222)	(1.653)	(1.382)	(1.191)
$EPLreg{\times}ln(ICTint)$				-2.764***	1.662***	1.102**			
				(0.802)	(0.549)	(0.512)			
$CBC{\times}ln(ICTint)$							0.004	0.031	-0.035*
							(0.028)	(0.020)	(0.018)
Observations	1,073	1,073	1,073	1,073	1,073	1,073	1,025	1,025	1,025
R-Squared	0.957	0.985	0.975	0.959	0.986	0.975	0.958	0.985	0.976
W/o Sweden	***Baseline***			***ICT*EPL***			***ICT*CBC***		
OLS	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage
$ln(ICTint)$	3.000***	-1.618***	-1.382**	9.108***	-5.140***	-3.967***	3.573*	-4.785***	1.212
	(0.922)	(0.588)	(0.659)	(1.880)	(1.186)	(1.201)	(1.990)	(1.618)	(1.311)
$ln(NICTint)$	-1.310*	0.916**	0.394	-1.709**	1.146**	0.563	-1.693**	1.468**	0.224
	(0.697)	(0.459)	(0.504)	(0.812)	(0.496)	(0.557)	(0.780)	(0.506)	(0.596)
$ln(VA)$	-8.086***	6.126***	1.960*	-6.832***	5.403***	1.429	-7.321***	5.978***	1.344
	(1.535)	(1.233)	(1.178)	(1.574)	(1.239)	(1.191)	(1.585)	(1.306)	(1.154)
$EPLreg{\times}ln(ICTint)$				-3.134***	1.808***	1.326***			
				(0.734)	(0.503)	(0.481)			
$CBC{\times}ln(ICTint)$							-0.003	0.039**	-0.036**
							(0.027)	(0.018)	(0.019)
Observations	1,114	1,114	1,114	1,114	1,114	1,114	1,066	1,066	1,066
R-Squared	0.956	0.985	0.973	0.958	0.986	0.974	0.957	0.986	0.974
W/o UK	***Baseline***			***ICT*EPL***			***ICT*CBC***		
OLS	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage
$ln(ICTint)$	3.413***	-1.545**	-1.868**	13.87***	-7.145***	-6.725***	15.81***	-17.46***	1.649
	(1.038)	(0.622)	(0.760)	(2.113)	(1.478)	(1.450)	(3.797)	(3.166)	(2.658)
$ln(NICTint)$	-0.543	0.485	0.058	0.039	0.173	-0.212	-0.622	0.188	0.434
	(0.839)	(0.543)	(0.642)	(0.729)	(0.512)	(0.608)	(0.818)	(0.509)	(0.657)
$ln(VA)$	-9.309***	5.929***	3.380**	-7.468***	4.944***	2.525*	-9.066***	7.014***	2.053
	(1.933)	(1.621)	(1.485)	(1.805)	(1.597)	(1.419)	(1.930)	(1.720)	(1.431)
$EPLreg{\times}ln(ICTint)$				-4.845***	2.594***	2.250***			
				(0.834)	(0.633)	(0.514)			
$CBC{\times}ln(ICTint)$							-0.135***	0.176***	-0.041
							(0.043)	(0.035)	(0.030)
Observations	1,074	1,074	1,074	1,074	1,074	1,074	1,026	1,026	1,026
R-Squared	0.961	0.986	0.976	0.964	0.986	0.976	0.963	0.987	0.976

Notes: Using the EU-KLEMS 2009 release (O'Mahony, Mary and Marcel P. Timmer, 2009), this table offers the results for the shares of employment in high-, medium- and low-wage occupations in the sample industries. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Coefficients estimated by OLS with robust standard errors in parentheses. The regressions also include full sets of country-year and country-industry dummies. Author's calculations for the period from 1993-2007.

Table 4.A.7: Long-difference

	Panel A *Baseline*			**Panel B** *ICT*EPL*			**Panel C** *ICT*CBC*		
OLS	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage
$\Delta ln(ICTint)$	3.263***	-1.135*	-2.128**	4.311***	-1.314**	-2.996**	4.531***	-3.333***	-1.197
	(1.084)	(0.583)	(0.909)	(1.411)	(0.607)	(1.197)	(1.395)	(1.243)	(1.123)
$\Delta ln(NICTint)$	-1.404*	0.652	0.751	-1.158	0.610	0.547	-1.164	0.237	0.927
	(0.736)	(0.479)	(0.527)	(0.850)	(0.465)	(0.663)	(0.711)	(0.442)	(0.575)
$\Delta ln(VA)$	-5.888***	4.033***	1.855	-5.480***	3.963***	1.517	-6.319***	4.780***	1.539
	(1.822)	(1.497)	(1.399)	(1.845)	(1.530)	(1.377)	(1.732)	(1.478)	(1.306)
DEPLreg$\times\Delta ln(ICTint)$				-4.704**	0.803	3.901***			
				(2.107)	(1.242)	(1.503)			
DCBC$\times\Delta ln(ICTint)$							-1.724	2.989**	-1.265
							(1.790)	(1.274)	(1.542)
Country-Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	865	865	865	865	865	865	865	865	865
R-Squared	0.288	0.209	0.193	0.303	0.209	0.208	0.289	0.215	0.194

Using the EU-KLEMS 2009 release (O'Mahony, Mary and Marcel P. Timmer, 2009), this table offers the results for the shares of employment in high-, medium- and low-wage occupations in the sample industries. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Coefficients estimated by OLS with robust standard errors in parentheses. The regressions also include full sets of country-year dummies.Final sample of analysis consists of 9 European countries: Austria, Germany, Denmark, Spain, Finland, Italy, Netherlands, Sweden, and the United Kingdom. Author's calculations for the period from 1993-2007.

Table 4.A.8: Instrumental Variable Estimations

	Panel A			Panel B			Panel C		
2SLS	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage
$\Delta ln(ICTint)$	50.32***	-47.53**	-2.796	51.04**	-48.33*	-2.717	7.413	-17.97	10.56
	(19.21)	(18.92)	(4.117)	(23.80)	(26.48)	(5.476)	(44.21)	(36.31)	(11.14)
$\Delta ln(NICTint)$	-27.30**	26.19**	1.119	-6.013	2.558	3.454	-67.74	54.04	13.70
	(11.01)	(10.71)	(2.185)	(15.87)	(16.95)	(2.245)	(70.07)	(57.10)	(14.53)
$\Delta ln(VA)$	8.054	-9.711	1.657	10.83	-12.79	1.961	50.44	-38.91	-11.53
	(8.932)	(8.509)	(1.775)	(16.25)	(17.53)	(2.671)	(64.79)	(52.46)	(13.89)
DEPLreg$\times\Delta ln(ICTint)$				-124.03	137.63	-13.60			
				(94.60)	(107.45)	(21.69)			
DCBC$\times\Delta ln(ICTint)$							117.80	-81.14	-36.66
							(157.88)	(128.95)	(33.68)
First stage results, dependent variable: $\Delta ln(ICTint)$									
$(\frac{CAP-IT}{VA})_{US,93}$	1.900**	1.900**	1.900**	4.749***	4.749***	4.749***	3.230**	3.230**	3.230**
	(0.748)	(0.748)	(0748)	(1.433)	(1.433)	(1.433)	(1.336)	(1.336)	(1.336)
DEPL$\times$ $(\frac{CAP-IT}{VA})_{US,93}$				-5.110***	-5.110***	-5.110***			
				(1.541)	(1.541)	(1.541)			
DCBC$\times$ $(\frac{CAP-IT}{VA})_{US,93}$							-2.130	-2.130	-2.130
							(1.566)	(1.566)	(1.566)
F test of excluded instruments	6.45	6.45	6.45	5.74	5.74	5.74	3.65	3.65	3.65
First stage results, dependent variable: DEPL$\times\Delta ln(ICTint)$ **or DCBC**$\times\Delta ln(ICTint)$									
$(\frac{CAP-IT}{VA})_{US,93}$				0.893*	0.893*	0.893*	0.462	0.462	0.462
				(0.522)	(0.522)	(0.522)	(0.818)	(0.818)	(0.818)
DEPL$\times$ $(\frac{CAP-IT}{VA})_{US,93}$				-1.581**	-1.581**	-1.581**			
				(0.746)	(0.746)	(0.746)			
DCBC$\times$ $(\frac{CAP-IT}{VA})_{US,93}$							0.369	0.369	0.369
							(1.148)	(1.148)	(1.148)
F test of excluded instruments				2.35	2.35	2.35	0.67	0.67	0.67
Kleibergen-Paap Wald rk F statistic	6.45	6.45	6.45	0.76	0.76	0.76	0.47	0.47	0.47
Country-Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	865	865	865	865	865	865	865	865	865

Using the EU-KLEMS 2009 release (O'Mahony, Mary and Marcel P. Timmer, 2009), this table offers the results for the shares of employment in high-, medium- and low-wage occupations in the sample industries. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Coefficients estimated by OLS with robust standard errors in parentheses. The regressions also include full sets of country-year.Final sample of analysis consists of 9 European countries: Austria, Germany, Denmark, Spain, Finland, Italy, Netherlands, Sweden, and the United Kingdom. Author's calculations for the period from 1993-2007.

Magnitudes

To give some idea of the magnitude of the effect of ICT in long difference estimations, similar to Michaels *et al.* (2014), I perform some back of the envelope calculations for the share of employment in high-wage occupations. Column 1 of the table below reports calculations which refer to the baseline OLS specification (first column in Panel A of Table 4.A.7). The estimates indicate that ICT explains about 5.7% of the increase in the employment share in high-wage occupations. Column 2 shows equivalent calculations for the specification that includes interaction with EPL (Column1 in Panel B of Table 4.A.7). Here, ICT alone accounts for almost 7.5% of the increase in the employment share of high-wage occupation, and ICT interacted with EPL explains about 8% of the decrease in employment share. Likewise, columns 3 and 4 report calculations referring to the IV specifications of high-wage occupation groups in Panels A and B of Table 4.A.8, respectively. Column 3 estimates that the mean contribution of ICT is more than 10 times larger in IV estimates with no interaction with EPL, and the estimations in Column 4 suggest an ICT contribution of 89% and 215% for the model with interaction term. However, we may have some serious concerns for the estimation results of the IV specifications, as the first stage results for IV are quite weak in general.

Table 4.A.9: Contribution of ICT changes to Changes in the employment share of High-wage occupations

Panel used and method	1 A-OLS	2 B-OLS	3 D-IV	4 E-IV
Δ (High-wage employment share)	1.750	1.750	1.750	1.750
$\Delta ln(ICTint)$	0.0304	0.0304	0.0304	0.0304
Coefficient on ICT	3.263	4.311	50.32	51.04
Coefficient on ICT×EPL		4.704		124.03
Mean×ICT coefficient	0.099	0.131	1.529	1.552
Mean×coefficient of ICT×EPL		0.143		3.77
Mean contribution of ICT (in%)	5.66	7.49	87	89
Mean contribution of ICT×EPL (in%)		8.17		215

Numbers for Δ (High-wage employment share) refer to the coefficient on the constant, suggesting that on average, there is a 1.75 percentage point increase in the employment share of high-wage occupations.$\Delta ln(ICTint)$ is the average of log(ICT inetnsity) change across all industries.

Table 4.A.10: Additional fixed effects

	Panel A			Panel B			Panel C		
OLS	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage
$ln(ICTint)$	3.291***	-1.676***	-1.615**	6.601***	-1.760**	-4.841***	1.298	-2.147**	0.849
	(0.885)	(0.503)	(0.722)	(1.584)	(0.854)	(1.355)	(1.436)	(0.955)	(1.344)
$ln(NICTint)$	-1.218*	0.773**	0.444	-1.461**	0.780*	0.681	-1.086	0.861**	0.225
	(0.676)	(0.386)	(0.563)	(0.724)	(0.403)	(0.622)	(0.728)	(0.437)	(0.633)
$ln(VA)$	-3.885**	2.039	1.845	-3.204*	2.022	1.181	-3.914**	2.127	1.787
	(1.575)	(1.467)	(1.381)	(1.642)	(1.505)	(1.443)	(1.628)	(1.619)	(1.414)
$EPLreg \times ln(ICTint)$				-1.659***	0.042	1.616***			
				(0.598)	(0.374)	(0.528)			
$CBC \times ln(ICTint)$							0.027	0.006	-0.033*
							(0.020)	(0.012)	(0.018)
Industry-Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Country-Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Country-Industry FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1,223	1,223	1,223	1,223	1,223	1,223	1,175	1,175	1,175
R-Squared	0.971	0.991	0.978	0.972	0.991	0.978	0.962	0.991	0.979
	Panel D			Panel E			Panel F		
OLS	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage
$\Delta ln(ICTint)$	3.833***	-1.291**	-2.542**	4.263***	-1.047*	-3.216***	4.493***	-1.715	-2.778*
	(1.100)	(0.583)	(1.007)	(1.311)	(0.591)	(1.243)	(1.424)	(1.281)	(1.452)
$\Delta ln(NICTint)$	-1.547*	0.736	0.811	-1.394*	0.823	0.571	-1.405*	0.644	0.761
	(0.799)	(0.498)	(0.623)	(0.824)	(0.488)	(0.768)	(0.831)	(0.483)	(0.632)
$\Delta ln(VA)$	-3.860*	2.853	1.007	-3.872*	2.846	-2.107	-4.140**	3.033	1.107
	(2.155)	(1.934)	(1.642)	(2.177)	(1.954)	(1.754)	(2.138)	(1.938)	(1.586)
$DEPLreg \times \Delta ln(ICTint)$				-2.108	-1.202	3.310**			
				(1.936)	(1.367)	(1.616)			
$DCBC \times \Delta ln(ICTint)$							-0.925	0.595	0.330
							(1.943)	(1.395)	(1.837)
Industry-Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Country-Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	865	865	865	865	865	865	865	865	865
R-Squared	0.436	0.395	0.298	0.438	0.396	0.307	0.436	0.395	0.298
	Panel G			Panel H			Panel I		
OLS	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage	High wage	Medium wage	Low wage
$\Delta ln(ICTint)$	2.136**	-0.232	-1.905**	2.802**	-0.240	-2.561**	2.522	-1.466	-1.056
	(1.055)	(0.673)	(0.822)	(1.249)	(0.666)	(1.031)	(2.102)	(1.809)	(1.939)
$\Delta ln(NICTint)$	-1.249	0.263	0.986	-.932	0.258	0.674	-1.203	0.116	1.087*
	(0.838)	(0.537)	(0.602)	(0.860)	(0.522)	(0.716)	(0.841)	(0.507)	(0.634)
$\Delta ln(VA)$	-3.419	4.767*	-1.347	-3.402	4.767*	-1.364	-3.511	5.060*	-1.549
	(2.813)	(2.713)	(1.773)	(2.847)	(2.716)	(1.884)	(2.853)	(2.742)	(1.828)
$DEPLreg \times ln(ICTint)$				-3.398**	0.046	3.351**			
				(1.522)	(1.181)	(1.324)			
$DCBC \times ln(ICTint)$							-0.482	1.543	-1.061
							(2.239)	(1.797)	(2.092)
Industry-Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Country-Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Country-Industry FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	865	865	865	865	865	890	890	890	890
R-Squared	0.586	0.512	0.555	0.592	0.512	0.563	0.586	0.513	0.555

Notes:Using the EU-KLEMS 2009 release (O'Mahony, Mary and Marcel P. Timmer, 2009), this table offers the results for the shares of employment in high-, medium- and low-wage occupations. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Coefficients estimated by OLS with robust standard errors in parentheses. Final sample of analysis consists of 9 European countries: Austria, Germany, Denmark, Spain, Finland, Italy, Netherlands, Sweden, and the United Kingdom. Author's calculations for the period from 1993-2007.

Eidesstattliche Versicherung

Ich, Frau Hedieh Aghelmaleki, versichere an Eides statt, dass die vorliegende Dissertation von mir selbstständig, und ohne unzulässige fremde Hilfe, unter Beachtung der "Grundsätze zur Sicherung guter wissenschaftlicher Praxis an der Heinrich-Heine-Universität Düsseldorf" erstellt worden ist.

Düsseldorf, den

Unterschrift