Offshoring, Technological Change, Labour Market Institutions and the Demand for Typical and Atypical Employment in Europe

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Abstract

This paper analyses the effect on employment of two megatrends: offshoring (the international outsourcing of production stages) and technological change, in general and by type of employment in terms of typical and atypical employment, and also examines the moderating role of different labour market institutions in the EU. It is structured in two parts. The first part analyses the short-, medium- and longer-term employment effects of different types of offshoring and technological change, both in total and by type in terms of typical and atypical employment. It uses two different data samples – a total economy sample (excluding all public industries) and a manufacturing sample – to identify differences between sectors, and uses the strictness of employment protection legislation (EPL) to identify its moderating role in this context. The second part focuses on *involuntary* atypical employment, in total and by type in terms of involuntary part-time work, involuntary fixed-term work, and underemployment. It analyses the long-term effect of two specific types of technological change – automation, and software and databases – on the share of involuntary atypical employment. It identifies the specific demographic groups (by gender and age) most affected by both types of technological change and analyses the moderating effect of trade unions in this context. The results show that both megatrends have an impact on European labour markets: offshoring (only in the service sector) and information and communications technology (ICT), especially communications technology, are important drivers of the expansion of atypical employment; robotisation has a labour displacement effect, but because total employment decreases more than atypical employment, the share of atypical employment and *involuntary* atypical employment increase, affecting women and the youngest age cohort the most. Labour market institutions – EPL and trade unions – play an important moderating role.

Keywords: Offshoring, robotisation, information and communications technology, labour demand, typical and atypical employment

JEL classification: F16, F22, F66

1. Introduction

In many parts of the world, atypical, non-standard forms of employment – such as temporary employment, marginal employment, part-time employment, temporary agency work or other forms of multiparty employment relationships, bogus or dependent self-employment – have become more widespread, particularly in many advanced economies, and have spread into sectors and occupations where they did not previously exist (ILO, 2016). In the EU27, temporary contracts and self-employment expanded strongly between the late 1980s and the onset of the global financial crisis in 2007 (Eurofound, 2018). Temporary contracts increased again between 2010 and 2015, but have fallen slightly since 2020. The share of part-time employment in total employment increased from the late 1980s until the early 2000s (Buddelmeyer et al., 2004) and remained relatively stable until 2020, before falling slightly. Agency work has expanded at a lower rate but has declined since the 2007 recession, and ranges between 1% and 3% of total employment in EU member states (Spattini, 2012). In 2023, temporary workers accounted for 11.5% of total employment, the self-employed for 13.2% and part-time workers for 17.8%.[1]

Atypical forms of employment have for some time been seen as a means of increasing employment opportunities and tackling high levels of unemployment. However, their spread has become a concern for policy makers, owing to their adverse effects on 'atypical' workers. Atypical forms of employment are associated with low job security, frequent movements in and out of the labour market, low pay, and a consequent high risk of (in-work) poverty and unemployment, all of which affect workers' employability and increase the likelihood of precarious employment histories over the course of their lives (Månsson and Ottosson, 2011; Blásquez Cuesta and Moral Carcedo, 2014; Görg and Görlich, 2015; Westhoff, 2022; Mäkinen et al., 2023). Moreover, as these workers are more likely than 'typical' workers to have interrupted social insurance contribution records, or even none at all, they also have limited entitlements to benefits in the event of unemployment, illness, maternity, disability and old age (Schmid and Wagner, 2017).

Although the reasons for the spread of atypical forms of employment are complex and vary considerably across countries, the expansion of global supply chains – i.e. the international outsourcing, or offshoring, of production stages – and the emergence and diffusion of new technologies, which have progressed in tandem with atypical forms of employment, are seen as important drivers of this trend.

[1] See Eurostat: lfsi_pt_a_h and lfsi_pt_a for temporary contracts and part-time contracts, and lfsq_egaps for employment and self-employment, all for the age class 15-64 years.

From a theoretical perspective, offshoring may promote the spread of atypical forms of employment in several ways. For firms that offshore, the need to respond flexibly to fluctuations in demand and to remain competitive – by cutting costs by moving certain stages of production to low-wage countries and by using workers in non-standard forms of employment, who are often cheaper because of lower wages (Hirsch, 2005; Westhoff, 2022) or because of savings on social security and other benefits (Zeytinoglu and Cooke, 2005), and whose numbers can more cheaply be adjusted owing to lower labour adjustment costs (i.e. dismissal costs) – are key incentives not only to offshore in the first place, but also to resort to atypical forms of employment (Shire et al., 2009). Conversely, if lower-skilled and more standardised jobs are moved abroad, the quality of the remaining jobs may improve and employment may become more secure. For suppliers, offshoring can lead to lower labour standards (Nadvi, 2004; Plank et al., 2012), as there is strong competitive pressure on suppliers to reduce costs (including labour costs) or to produce within short lead times. They then seek greater numerical flexibility (Kalleberg, 2001) in their workforce through atypical forms of employment. Moreover, if task complexity in supplying firms is lower, this may make workers more substitutable, leading employers to hire workers on temporary contracts (Lakhani et al., 2013).

Similarly, technological change can also lead to an increase in atypical forms of employment by reducing workers' bargaining power: Firms, aware of the comparative advantage of labour in response to shocks, do not displace labour but minimise operating costs by shifting workers from standard to non-standard employment. Atypical forms of employment tend to increase, especially when technological change is rapid and tasks and jobs need to be adjusted more frequently, requiring more flexible work arrangements. Certain jobs – particularly less complex ones at the lower end of the skills hierarchy – may be more affected, especially if they are highly substitutable and can be easily filled by other workers with little or no loss of human capital.

There is a large body of literature analysing the impact of offshoring or technological change on employment, both in total and differentiated by skill level. The offshoring literature finds mixed results for the impact on total employment. Most studies find rather small effects of offshoring on domestic employment in advanced economies, whether positive or negative (Groshen et al., 2005; Landesmann and Leitner, 2023b). Some studies suggest that the impact on employment varies across industries, with employment losses in manufacturing and employment gains in services (Landesmann and Leitner, 2023b). The literature also shows that the type of offshoring matters: in addition to manufacturing offshoring, services offshoring, which has more recently gained momentum, also tends to affect domestic employment, in some instances positively (Hijzen et al., 2011; Amiti and Wei, 2005) and in others negatively (Amiti and Wei, 2006 and 2009), although the impact is smaller in magnitude (Görg and

Hanley, 2005; OECD, 2007). Moreover, offshoring to low-income countries or Central and Eastern European countries leads to job losses (Mion and Zhu, 2013; Lo Turco and Maggioni, 2012; Cadarso et al., 2008) or stronger transitions to unemployment (Liu and Trefler, 2011), while offshoring to high-income countries leads to employment gains (Ebenstein et al., 2009; Landesmann and Leitner, 2023b). However, offshoring affects different types of workers differently. It particularly hurts those with medium or low levels of education (see, for example, Hijzen et al., 2005; Crinò, 2010b and 2012; Foster-McGregor et al., 2013; Mion and Zhu, 2013 for evidence on Europe) or workers in less skilled occupations (Crinò, 2010a), but increasingly also in skilled occupations, such as managers and professionals, whose tasks have become increasingly more offshorable (Landesmann and Leitner, 2023a).

The technology literature finds similarly mixed results. Negative employment effects from robotisation and digitalisation are found by, for example, Acemoglu and Restrepo (2020), Acemoglu et al., (2020), Anton et al. (2020) and Chiacchio et al. (2018), and positive employment effects by, for example, Gaggl and Wright (2017), Ghodsi et al. (2020), Koch et al. (2021) and Gregory et al. (2022), while others find no significant effects (Autor et al., 2015; Dauth et al., 2019; Dottori, 2021; de Vries et al., 2020; Graetz and Michaels, 2018). Some studies – particularly regional studies – show that the negative employment effect is either stronger in the manufacturing sector or occurs only in that sector (see, for example, Jestl, 2024; Chiacchio et al., 2018; Dauth et al., 2019). It also shows that the three components of information and communications technology (ICT) – information technology (IT), communications technology (CT) and software and databases (DB) – have different effects, with a negative employment effect from DB but a positive employment effect from IT in the EU (Jestl, 2024). Moreover, it points towards employment polarisation (Goos and Manning, 2007), with medium-skilled occupations particularly prone to being displaced by robotisation and digitalisation that can take over routine cognitive and routine manual tasks (see, for example, Autor et al., 2003 and 2015; Autor and Dorn, 2013; Acemoglu and Restrepo, 2020; Goos et al., 2009 and 2014; Darvas and Wolff, 2016; de Vries et al., 2020; Gregory et al., 2022; Chiacchio et al., 2018). However, with artificial intelligence, highly skilled occupations could be particularly affected (Webb, 2020).

Conversely, empirical evidence on the effect of offshoring and technological change on the spread of atypical forms of employment is scarce. For instance, Rutledge et al. (2019) show for the United States that globalisation (captured by Chinese imports to the US) does not have a significant relationship with non-traditional work, while robotisation does. Specifically, they find that a one standard deviation increase in the use of industrial robots per 1,000 employees is associated with an 11% increase in non-standard employment. Similarly, Kiyota and Maruyama (2017) find for the Japanese manufacturing sector that ICT leads to an increase in demand for part-time workers, while there is no significant effect from offshoring. However, according to Machikita and Sato (2011), offshoring is associated with a shift from permanent to temporary workers in the Japanese manufacturing sector. In the European context, Nikulin and Szymczak (2020) focus on 10 Central and Eastern European countries and show that greater integration into global value chains (GVCs) increases the incidence of temporary employment contracts, predominantly in tradable sectors.

Hence, in view of the growing spread and negative consequences of atypical forms of employment, any form of labour protection plays an important role in securing better employment terms for workers. Generally, empirical evidence shows that dismissal regulation lowers job flows, not only in terms of fewer layoffs but also in terms of reduced levels of hiring (Autor et al., 2006; Boeri and Jimeno, 2005; Haltiwanger et al., 2014; Micco and Pagés, 2006) and that the use of fixed-term contracts increases when employment protection is stricter for permanent than for temporary workers (Centeno and Novo, 2012; Hijzen et al., 2017). Empirical evidence on the moderating role of labour market protection schemes is scarce, but seems to find a negative effect, reducing the positive employment effects from offshoring (Amiti and Ekholm, 2006; Milberg and Winkler, 2011). Little is known about the moderating role of forms of employment protection by type of worker – typical versus atypical – in this context.

In view of the above, this paper provides insights into the employment effects of offshoring and technological change in the EU, both in total as well as by type of employment in terms of typical and atypical employment. It also sheds light on the role of different labour market institutions in moderating the effects of both forces on the type of employment.

The paper is structured in two parts. The first part uses detailed industry-level information for a sample of EU member states for the period 2009-2018. It analyses the short-, medium- and long-term effects on employment of a set of technological changes (robotisation and the three dimensions of ICT) and different types of offshoring – narrow (intra-industry) and broad (inter-industry) offshoring, manufacturing and services offshoring, and offshoring by sourcing region from developed countries, developing countries or the 'new' EU13 member states (EU13) – both in total and by type of employment in terms of typical and atypical employment. It analyses two data samples – a total economy sample (excluding all public industries) and a manufacturing sample – to identify differences between sectors and uses information on EPL for individual and collective dismissals as well as for the hiring of temporary workers, to show whether and how legislation shapes the impact of both forces on the type of employment. The second part focuses on *involuntary* atypical employment, in total and by type in terms of involuntary part-time work, involuntary fixed-term work, and underemployment. It analyses the effect of two specific types of technological change – automation, and software and databases – on the change in the share of involuntary atypical employment (in total and by type) in a number of EU member states between 2006 and 2018. It also identifies which specific demographic groups are most affected by each type of technological change, differentiating by gender and age, and analyses the moderating effect of trade unions in this context.

The remainder of the paper is structured as follows. Section 2 analyses the effect of a set of technological changes (robotisation and the three dimensions of ICT) and different types of offshoring on employment, both in total and by type of employment in terms of typical and atypical employment. After discussing the methodological approach, the different offshoring and technology indicators and the different data sources used in the analysis, it provides a brief overview of the changes in patterns of atypical employment, offshoring and technological change between 2009 and 2018 and a detailed discussion of the results, also addressing different endogeneity issues inherent in the analysis. Section 3 analyses the effects of automation and software and databases on *involuntary* atypical employment, in total and by type, and explores which demographic groups were most affected. It discusses the data and methodology, and provides some descriptive evidence on the relationship between involuntary atypical employment and technological displacement, before a detailed discussion of the results, including the results of a decomposition analysis by gender and age group of the effects attributed to technology, and also several robustness checks. Section 4 provides a summary of the results and sets out our conclusions.

2. Effects of offshoring and technological change on total, typical and atypical employment in the EU

2.1. Methodological approach

In this part of the analysis, we employ the log-linear model of labour demand (Hamermesh, 1993).[2] We closely follow Hijzen and Swaim (2010), albeit focusing on the conditional labour demand model, where the profit-maximising level of labour demand is determined by minimising production costs conditional on output. Thus, we determine the employment effect of offshoring and technological change by holding output constant. We expect a negative impact on employment if they have a productivity-enhancing effect, as the same amount of output can be produced with fewer inputs. As is common in the literature,

[2] This allows us to interpret coefficients as elasticities.

we treat capital as quasi-fixed, to avoid measurement problems of the user cost of capital. The conditional labour demand equation can be written as follows:

$$lnL_{ict} = \alpha_0 + \alpha_w lnw_{ict} + \alpha_{ip} lnp_{ict} + \beta_y lny_{ict} + \sum_{l=1}^{L} \gamma_l lnz_{ilct} + \pi_{ic} + \varepsilon_{ict}, \qquad (1)$$

where L_{ict} refers to labour demand in industry i in country c at time t, w_{ict} and p_{ict} are the average gross annual wage of workers and the price of materials, respectively, y_{ict} is the real gross output (in 2015 prices) and z_{ilct} refers to a set of l different demand shifters, including the different measures of offshoring and technological change we use in the analysis (as discussed in detail in Section 2.2 below). As we already use different types of capital stocks as proxies for technological change, which are an integral part of the total capital stock, we exclude the total capital stock (which is usually included in standard labour demand equations) from our estimations. Furthermore, following Hijzen and Swaim (2010), we also include import penetration (IP), defined as $Imports_{ict}/(GDP_{ict} + Imports_{ict} - Exports_{ict})$ as a measure of general trade openness of an industry. Finally, π_{ic} refers to country-industry fixed effects and ε_{ict} to a random disturbance term assumed to be normally distributed with zero mean and constant variance.

Furthermore, we difference the data to account for any time-invariant fixed effects that affect the level of labour demand. Typically, in this line of literature, longer differences are used; these not only take into account lagged responses of labour demand, but also help to decrease measurement errors. However, we also use shorter differences, which allows us to determine the robustness of our results to the chosen differencing period and to produce more appropriate results if measurement errors are not an issue. Specifically, we use five different differencing periods: one year, two years, three years, five years and nine years. The conditional labour demand equation then becomes:

$$\Delta lnL_{ict} = \alpha_0 + \alpha_w \Delta lnw_{ict} + \alpha_{ip} \Delta lnp_{ict} + \beta_y \Delta lny_{ict} + \sum_{l=1}^{L} \gamma_l \Delta lnz_{ilct} + \varepsilon_{ict} \qquad (2)$$

where Δ refers to the difference of a variable.

We also estimate the model for two different types of employment, namely *typical* and *atypical* employment. In general, 'atypical' work refers to employment relationships that do not conform to the standard or 'typical' model of full-time, regular, open-ended employment with a single employer over a long time span (Eurofound, 2018). Generally, this includes part-time work, temporary work, fixed-term work, casual and seasonal work, self-employed persons, independent workers, and homeworkers. In our analysis, we focus on employees only[3] and define atypical employment as part-time work and any form of temporary work, as available in our data source (for details, see Section 2.3 below).

Furthermore, we extend the analysis in two ways. First, we differentiate between the group of 'old' EU member states (EU15) and the group of 'new' EU member states (EU13) which joined the EU in or after 2004 to better bring out differences across the countries in our analysis in terms of the impact of offshoring and technological change on employment in general and typical and atypical employment in particular. The descriptive analysis in Section 2.4 below points to important differences between the EU15 and the EU13 in this respect. For this purpose, we include in equation (2) above interaction terms between an EU15-dummy variable on the one hand, and offshoring (including the various types thereof) and technological change on the other.

Second, we also account for the role played by labour market institutions in potentially moderating the impact of both forces on employment, in total as well as by type. Specifically, we use information on the strictness of employment protection legislation (EPL) (see Section 2.3 below for a detailed discussion) on the dismissal of workers on *regular* contracts – both individual and collective dismissals – and on the hiring of workers on *temporary* contracts. Generally, countries with stricter employment protection provisions for regular workers also tend to have stricter hiring laws for workers on temporary contracts (OECD, 2020). However, as this is not the case for all the countries in our sample, we use the two indicators separately, which allows us to identify the potentially differentiated effect of the type of EPL on the type of employment. As these indicators change very little over time, we cannot use them in differenced form, but instead group the countries in our sample according to the strictness of their EPL into a group of 'strict' EPL countries in the case of above-average EPL and a group of 'weaker' EPL countries for countries with average or below-average EPL (as the reference category). Specifically, we classify Belgium, Czechia, France and Slovakia as countries with strict EPL for the dismissal of regular contracts and France, Slovakia and Spain as countries with strict EPL for the hiring of workers on temporary contracts. In the analysis, we include in equation (2) interaction terms between the individual EPL strictness dummies and offshoring and technological change.

[3] All self-employed persons are excluded.

Methodologically, we estimate the total labour demand equation by ordinary least squares (OLS) and the labour demand equations for typical and atypical employment by seemingly unrelated regression (SUR). SUR allows for the contemporaneous correlation of the error terms across the two regression equations and is thus more efficient than separate estimation by OLS. We cluster standard errors at the country-industry level to correct for within-group serial correlation in the residuals.

However, our analysis is subject to potential endogeneity issues. For instance, an exogenous demand and/or productivity shock may affect offshoring and technology adoption which, in turn, affects labour demand in general as well as by type (typical and atypical) in particular.

Moreover, offshoring and technological change may be interrelated. Specifically, through the positive scale effect, a rise in offshoring can lead to an expansion of output and an increase in labour demand in general, including for workers whose tasks are not offshored – typically less skilled workers (Autor et al., 2003; Goos et al., 2014; Michaels et al., 2014; Becker et al., 2013), but increasingly also more skilled workers (Landesmann and Leitner, 2023a). This in turn can induce investments in (new) technologies, given the changed task specialisation towards more knowledge-intensive activities (Saad, 2017). Conversely, technology adoption that tends to substitute for less skilled workers (Autor et al., 2003), can make offshoring less attractive (Carbonero et al., 2018).

We address these endogeneity issues through instrumental variables (IV) estimation and test several instruments. For offshoring, we use a shift-share instrument and, following Wright (2010), construct a variable that comprises the composition of intermediate imports from different developing countries at the industry level three years prior to the estimation period and augment this alternatively with output growth, aggregate intermediate input growth and hours worked.[4] We use this instrument in two different forms: first, in logarithmic and differenced form, and second, as a Paasche-like index in which we sought to make full use of the change in intermediate input purchases from each individual developing country over the entire observation period by first taking the logs and differences of the intermediate input purchases in each industry from each developing country and then weighting and summing over all countries.

For technological change, we follow Acemoglu and Restrepo (2020) and instrument each of the indicators for technological change with their average in all available advanced economies. Specifically, for IT, CT and DB, we use the average of each ICT asset type in other countries, excluding the country for which the

[4] The construction of this variable used three databases: WIOD release 2016, plus the upcoming WIOD release available to the authors regarding imported intermediate inputs (at the industry level) and output growth, while hours worked was taken from EU-LFS statistics.

instrument is calculated. Because the EU-KLEMS from which we take the data for IT, CT and DB also provides information on other EU countries, we also include other EU countries (with full information on all three ICT asset types) not included in our country sample. In view of the heterogeneity of the country sample analysed, we use two different groups of countries from which the instrument is calculated (i.e. 'other countries'), referring to (i) the EU15, and (ii) the EU13 (which, owing to the limited availability of detailed employment data, includes in addition to the three countries in our sample – Czechia, Poland and Slovakia – only the larger of the remaining EU13 countries, namely Hungary, Romania and Bulgaria). All in all, we test nine instruments for each endogenous ICT asset type.

Similarly, for robot density, we rely on International Federation of Robotics (IFR) data and use as instrument the average robot density in that industry in other countries, again excluding the country for which the instrument is calculated.[5] We again use different groups of countries from which the instrument is calculated (i.e. 'other countries'). But, because Switzerland is included in the IFR data, we also use an EU16 sample which comprises the EU15 plus Switzerland, in addition to the EU15 and the EU13 samples (as defined above). Moreover, we use employment before the start of the estimation period to guarantee that any changes in robot density solely stem from changes in the stock of robots, and construct for each of the three aforementioned country groups various instruments based on three different base years for employment: 2006, 2007 and 2008. Hence, all in all, we tested 12 different instruments for robot density.

We use the same approach to account for the endogeneity of total employment as well as of employment by type (typical and atypical). Methodologically, we use a standard IV approach for total employment and a multiple-equation generalised method of moments (GMM) approach for typical and atypical employment.

With respect to the possible interrelationship between offshoring and technological change, we use the results from the first stage IV regressions for both variables. These show not only the relevance of the tested instruments, but also the relationship between them (when an endogenous variable is regressed on its instrument(s) plus all other variables).

We discuss the results from the IV estimations in Section 2.6.

[5] Data are taken from the World Robotics Industrial Robots statistics from the IFR.

2.2. Offshoring and technological change

Offshoring is measured using information from international input-output tables (IOTs), which can be used to measure purchases of intermediate inputs by each sector and country from each sector and country. In our analysis, we distinguish various offshoring measures. Our initial indicator of offshoring – *total offshoring* – is a measure of *total* imported intermediate purchases by industry i in country c:

$$IIM_{i,c}^{T} = \frac{\sum_{j=1}^{J} O_{j,c}}{GO_{i,c}}, \tag{3}$$

where $O_{j,c}$ refers to imported intermediate purchases by industry i from industry j in country c and GO refers to gross output of industry i in country c. This initial offshoring measure is further broken down along three different dimensions:

First, following Feenstra and Hanson (1999), we differentiate between *narrow (N)* and *broad (B)* offshoring. Narrow offshoring considers only imports of intermediates in each industry from the same industry, while broad offshoring considers imports of intermediates from all industries but its own. In this respect, narrow offshoring better captures the essence of international production fragmentation, which, by definition, takes place within the industry. Narrow and broad offshoring are defined as follows:

$$IIM_{i,c}^{N} = \frac{O_{j=i,c}}{GO_{i,c}} \quad \text{and} \quad IIM_{i,c}^{B} = \frac{\sum_{j=1,j\neq i}^{J} O_{j,c}}{GO_{i,c}}. \tag{4}$$

Second, we differentiate between *manufacturing (M)* and *services (S)* offshoring, to account for the growing importance of services offshoring over the past two decades (Jensen and Kletzer, 2005). Manufacturing and services offshoring are defined as follows:

$$IIM_{i,c}^{M} = \frac{\sum_{m=1}^{M} O_{m,c}}{GO_{i,c}} \quad \text{and} \quad IIM_{i,c}^{S} = \frac{\sum_{s=1}^{S} O_{s,c}}{GO_{i,c}}, \tag{5}$$

where M and S are the subset of manufacturing and service industries, respectively.

Third, we differentiate by sourcing country. Specifically, following the classification of countries in the 2009 World Development Report (World Bank, 2009) according to income levels, we differentiate between *developed countries* (those classified as high-income countries in 2009), *developing countries* (those not classified as high-income countries in 2009) and the group of *new EU13 member states (EU13)* which, with the exceptions of Cyprus, Malta, Slovakia and Slovenia, are not classified as high-income countries in 2009. From a European perspective, this further differentiation of the group of EU13 countries is important as they are strongly integrated with the EU and are important source countries for intermediate inputs. Our measures of offshoring to developed, developing and EU13 countries are defined as follows:

$$IIM_{i,c}^{Devd} = \frac{\sum_{x=1}^{X} O_{x,c}}{GO_{i,c}}, \quad IIM_{i,c}^{Devg} = \frac{\sum_{y=1}^{Y} O_{y,c}}{GO_{i,c}} \quad \text{and} \quad IIM_{i,c}^{EU13} = \frac{\sum_{z=1}^{Z} O_{z,c}}{GO_{i,c}} \qquad (6)$$

Moreover, we identify the effect of technological change on the labour demand of workers and distinguish two different technology measures: (i) information and communications technology (ICT) and its three components, IT, CT and DB;[6] and (ii) industrial robots, defined as the stock of industrial robots per 1,000 employees.

2.3. Data sources

We construct our database from six different data sources. First, we use the *EU Statistics on Income and Living Conditions (EU-SILC)* for key labour market-related information such as total employment, further broken down into typical and atypical employment, and annual gross wages, defined as cash or near cash income per employee. We focus on employees aged 15-64 – but exclude the self-employed – and use information on current economic status (i.e. employees working part-time) and type of contract (i.e. temporary jobs/work contracts of limited duration) of the main job to identify atypical employment. The EU-SILC is a standardised annual survey on income, poverty, social exclusion and living conditions in the EU that has been conducted since 2003/2004 in an ever-increasing number of EU countries and EU candidate countries, plus Iceland, Norway and Switzerland. In general, Eurostat provides standardised and anonymised EU-SILC microdata from scientific use files (SUF) in cross-sectional and longitudinal form for all countries that have agreed to their publication. However, these microdata are available only at the very

[6] IT refers broadly to computer hardware, CT to telecommunications equipment, and DB to intangible computer software and databases.

rough one-digit industry level. Some industries are even combined into larger aggregated industry groups, such as manufacturing (NACE-C), which is grouped together with mining and quarrying (NACE-B), electricity, gas, steam and air conditioning supply (NACE-D) and water supply, sewerage, waste management and remediation activities (NACE-E) into a NACE-B-E aggregate. Particularly for the manufacturing sector, which has borne the brunt of past offshoring activities and plays a key role in the generation and adoption of new technologies, this broad industry classification is a major constraint on the analysis, as it conceals the differentiated and industry-specific effects of offshoring and technological change. In view of this, we contacted national statistical offices to acquire the detailed – but anonymised – national EU-SILC data that are collected at the detailed two-digit industry level. We focused on the larger EU member states whose data coverage allows for meaningful analysis at the detailed two-digit industry level. We also included Switzerland as a non-EU member state. In total, we received detailed national EU-SILC data from eight countries – Austria (AT), Belgium (BE), France (FR) and Spain (ES) as old EU member states and Switzerland (CH) as a non-EU member state; Czechia (CZ), Poland (PL) and Slovakia (SK) as new EU member states – and for different time periods. From the detailed national EU-SILC data, we constructed a balanced sample for the period 2009-2018.

Second, we take trade-related data from the 2020 release of the World Input-Output Database (WIOD),[7] which combines detailed information on national production activities and international trade. It provides information on international linkages of production processes and structures of final goods trade across 38 industries (NACE Rev.2, A38) and 50 countries, comprising all 27 EU member states (as of 2020), the United Kingdom, the six Western Balkan countries, Ukraine and 15 other major countries in the world, plus an estimate for the rest of the world over the period 2005-2018. We use information for both domestic and imported inputs at the one- and two-digit industry level to construct the different offshoring measures (as discussed above) for 2009-2018.

Third, information on input prices, real gross output and the real capital stock (in 2015 prices) of IT, CT and DB is taken from the *EU-KLEMS Growth and Productivity Accounts* 2021 release. It is available for all 27 EU member states (as of 2020) plus Norway, Japan, the US and the UK for the period 1995-2019, for 40 detailed industries (plus 23 industry aggregates), according to the NACE Rev.2 industry classification. Because Switzerland is not included in the EU-KLEMS, we have taken information on input prices and real gross output from Eurostat's national accounts data. However, for Switzerland there is no information

[7] As constructed by The Vienna Institute for International Economic Studies (wiiw).

on capital stocks in total and by asset type. For Poland, net capital stocks, both total and by asset type, are available only for the total economy (i.e. all NACE activities). We have imputed the missing data, using information on the capital stock by asset type for the total economy and the shares at the more detailed NACE level of EU reference countries.[8]

Fourth, information on industrial robots is taken from the *World Robotics Industrial Robots statistics*. These are compiled and published by the International Federation of Robotics (IFR)[9] and are available for the period 1993-2022.[10] The robots data is collected from nearly all industrial robot suppliers worldwide and supplemented with (secondary) data provided by several national robot associations.[11] The robots database includes data on the number of robots (stocks and flows) delivered to each industry, by country and year. Data are available for 11 broad manufacturing industries, further disaggregated to two- and three-digit industries[12]; six broad non-manufacturing industries, at the section level; and one 'unspecified' category. The last of these does not correspond to any industry class but contains all data where the exact industry in which the robots are used is either unknown or cannot be disclosed for compliance reasons. To make full use of the data, we split the 'unspecified' category and allocated the data to the 11 broad manufacturing industries and the six broad non-manufacturing industries according to their share in the total, similar to Acemoglu and Restrepo (2020).

Fifth, information on employment by detailed industry (used to compute the robot density) is taken from the *Structural Business Statistics* (SBS) available from Eurostat,[13] which provide details of the structure, economic activity and performance of businesses over time. Information on employment is available for all EU member states, Iceland, Norway and Switzerland, as well as some candidate and potential candidate countries at the one- and two-digit industry level, according to the NACE Rev.2 industry classification for the period 2006-2020.

[8] For Poland, we used CZ and SK as reference countries.

[9] See https://ifr.org/worldrobotics

[10] The IFR measures 'multipurpose industrial robots' based on ISO 8373: 2012 (§ 2.9) as '*an automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications*' (see IFR, 2018: p.29).

[11] Such as the national robot associations of North America (RIA), Japan (JARA), Denmark (DIRA), Germany (VDMA, R+A), Italy (SIRI), South Korea (KAR), Spain (AER), Russia (RAR) and China (CRIA).

[12] Data at the three-digit level are available only for the electronics and automotive industries (ISIC 26, 27 and 29), which are also the main users of industrial robots.

[13] Source: sbs_na_sca_r2 (Eurostat).

Finally, information on the strictness of employment protection legislation (EPL) is taken from the *OECD Employment Protection Legislation Database*.[14] The indicators quantify the costs and procedures associated with the dismissal of individual workers – or groups of workers – and the use of temporary contracts.[15] Different versions of the indicators are available for different time horizons. Given the time horizon of our analysis (2009-2018), we use version 3 of the EPL which begins in 2008 and ends in 2019.

Because of certain data limitations (e.g. no information on real capital stocks at the detailed two-digit industry level for industries G and H for Belgium, France and Spain), we use an industry classification scheme that closely follows the EU-KLEMS 2020 release, but is less detailed in some service industries. The list of industries is provided in Table A.1 in the Annex. In the analysis, we use all industries except for the public-sector industries O, P, Q, R-S, T and U, and industries D-E.

In our analysis, we use two different data samples: (i) the *total economy sample* (comprising all industries except NACE O-T and D-E) and (ii) a *manufacturing sample* (comprising all manufacturing sectors from NACE 10 to 33) which is available at the more detailed two-digit industry level. Furthermore, because information on the three ICT asset types is available for all industries, while information on industrial robots is mainly available for the manufacturing sector, we use these two types of technological change indicators differently in the two samples: in our estimations for the total economy sample, we use the three ICT asset types, while in our estimations for the manufacturing sample we use robot density (in addition to all other indicators mentioned in equation (1) above). And as there is no information on total capital stocks and capital stocks by asset type for Switzerland, Switzerland is excluded from the analysis of the total sample but included in the analysis of the manufacturing sample.

2.4. Descriptive analysis

This section provides a brief descriptive account of the key variables of interest. For instance, Figure 1 below shows the shares and growth in the shares of workers in atypical employment in total employment – the latter in terms of percentage-point changes between 2009 and 2018 – across industries, excluding those industries not covered in our analysis (D-E, O, P, Q, R, S, T and U). It shows that in many industries, the share of atypical employment is above 20%. This is particularly the case in Poland, where the share of

[14] Source: https://stats.oecd.org/Index.aspx?DataSetCode=EPL_OV

[15] The former takes account of the following four aspects of dismissal regulations: procedural requirements, notice period and severance pay, the regulatory framework for unfair dismissals, and enforcement of unfair dismissal regulations. The latter refers to hiring regulations of temporary work agency contracts and fixed-term contracts.

atypical employment exceeds 20% in almost all industries. By contrast, in both Czechia and Slovakia, the share of atypical employment is below 20% in all industries, except industry I (accommodation and food service activities). Moreover, in all the countries studied, the share of atypical employment tends to be relatively high in industry A (agriculture, forestry and fishing) and is generally higher in service industries than in manufacturing industries. Among service industries, industry I stands out as having the highest share of employees in atypical employment.

Between 2009 and 2018, the share of atypical employment changed differently across countries in the sample. In the EU15, it declined in only few industries – notably in 58-60 (publishing, audio-visual and broadcasting activities) in Austria, B (mining and quarrying) in Spain, and 19 (coke and refined petroleum products) in France – while in Switzerland and the EU13, it declined in the majority of industries. Hence, in Czechia and Slovakia, the share of atypical employment was not only low in 2009, but continued to fall in most industries until 2018. By contrast, many industries, particularly in the EU15, also experienced an increase in the share of atypical employment, although this was rather moderate, at less than 10 percentage points in most cases. The increase in the share of atypical employment was particularly high in some French manufacturing industries, at more than 20 percentage points.

As regards offshoring, Figure 2 below shows that total offshoring was relatively low in Switzerland in 2009, but higher and of a similar magnitude in the other countries in the sample. However, total offshoring was generally more pronounced in manufacturing than in services, with industry 19 (coke and refined petroleum products) being particularly dependent on importing intermediate inputs.

However, between 2009 and 2018, average offshoring growth rates were somewhat higher in several service industries, most notably in industry 61 (telecommunications), K (financial and insurance activities), and L (real estate activities), suggesting some catching-up of services relative to manufacturing in terms of their reliance on imported intermediate inputs.

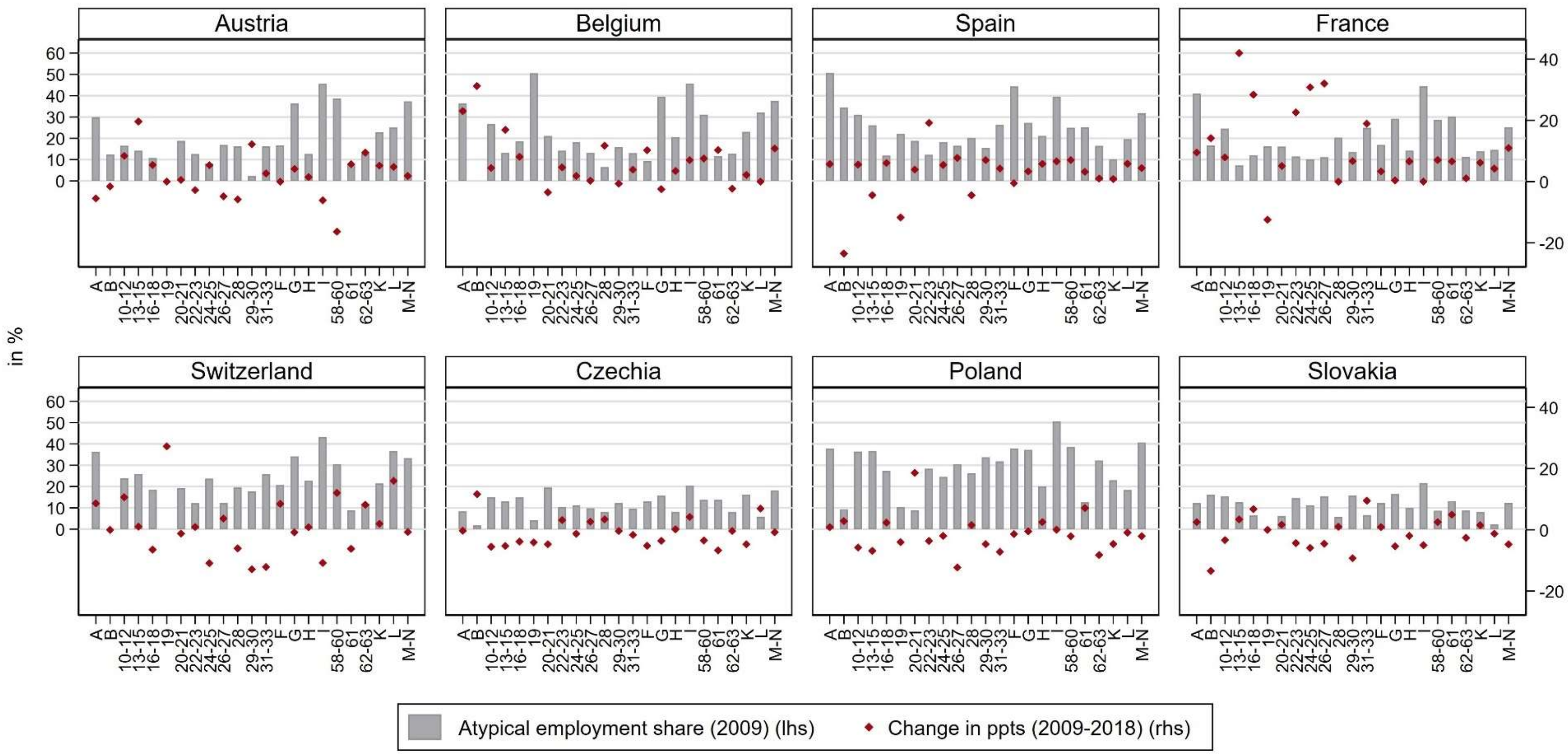
Robot density was generally higher in the manufacturing industries of the EU15 than the EU13 in 2009. A notable exception is industry 29-30 (transport equipment) in Slovakia, where the robot density was similar to that in France or Switzerland. Generally, robot density in industry 29-30 (transport equipment) was much higher in 2009 than in the remaining manufacturing industries (Figure 3). However, other manufacturing industries also show a relatively high degree of robot density, such as industry 22-23 (rubber and plastics products, and other non-metallic mineral products) and 24-25 (basic metals and fabricated metal products). Robot density was also relatively high in industry 10-12 (food, beverages and tobacco) in Belgium, Spain and Switzerland.

Except for industry 13-15 (textiles, wearing apparel, leather and related products) in Spain and industry 29-30 (transport equipment) in France, robot density increased in all manufacturing industries in all countries in the sample between 2009 and 2018. In general, however, average robot density growth rates were higher in the EU13 than in the EU15 (and also Switzerland) and higher in those industries where the degree of robot density was low in 2009, especially 13-15 (textiles, wearing apparel, leather and related products), 16-18 (wood and paper products, printing and reproduction of recorded media) and 20-21 (chemicals and chemical products), depending on the country. Hence, a catching-up process is under way.

Finally, as regards the three ICT asset types (IT, CT and DB), Figure 4 shows that ICT use was generally higher in the EU15 than in the EU13 in 2009. Furthermore, it was higher in the services industries, with some industries standing out – depending on the country – such as industry 61 (telecommunications), 62-63 (IT and other information services), K (financial and insurance activities) and M-N (professional, scientific and technical activities).

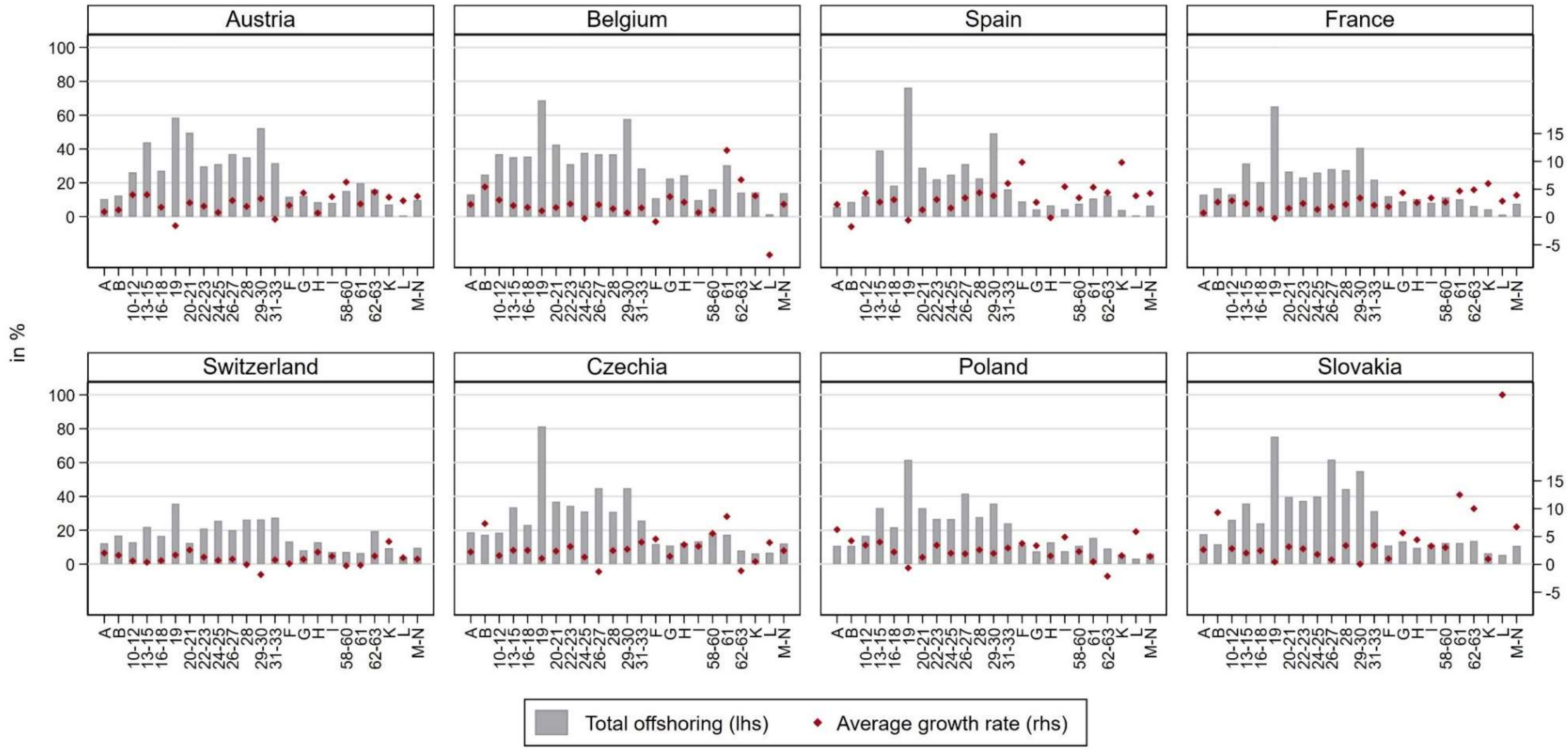
Although the average growth rates of IT, CT and DB were quite different between 2009 and 2018, it is nevertheless possible to make some general observations. With the exception of Slovakia, the average growth rates in DB were mostly positive, but generally of relatively low magnitude (except for Poland, where relatively high average growth rates occurred in many industries); the average growth rates of CT were more muted than those of IT, but only in the OMS; the growth rates of CT were rather low and uniform in France and Spain, but higher in the other countries.

Figure 1. Atypical employment share in 2009 (lhs) and absolute change (in percentage points) between 2009 and 2018 (rhs)



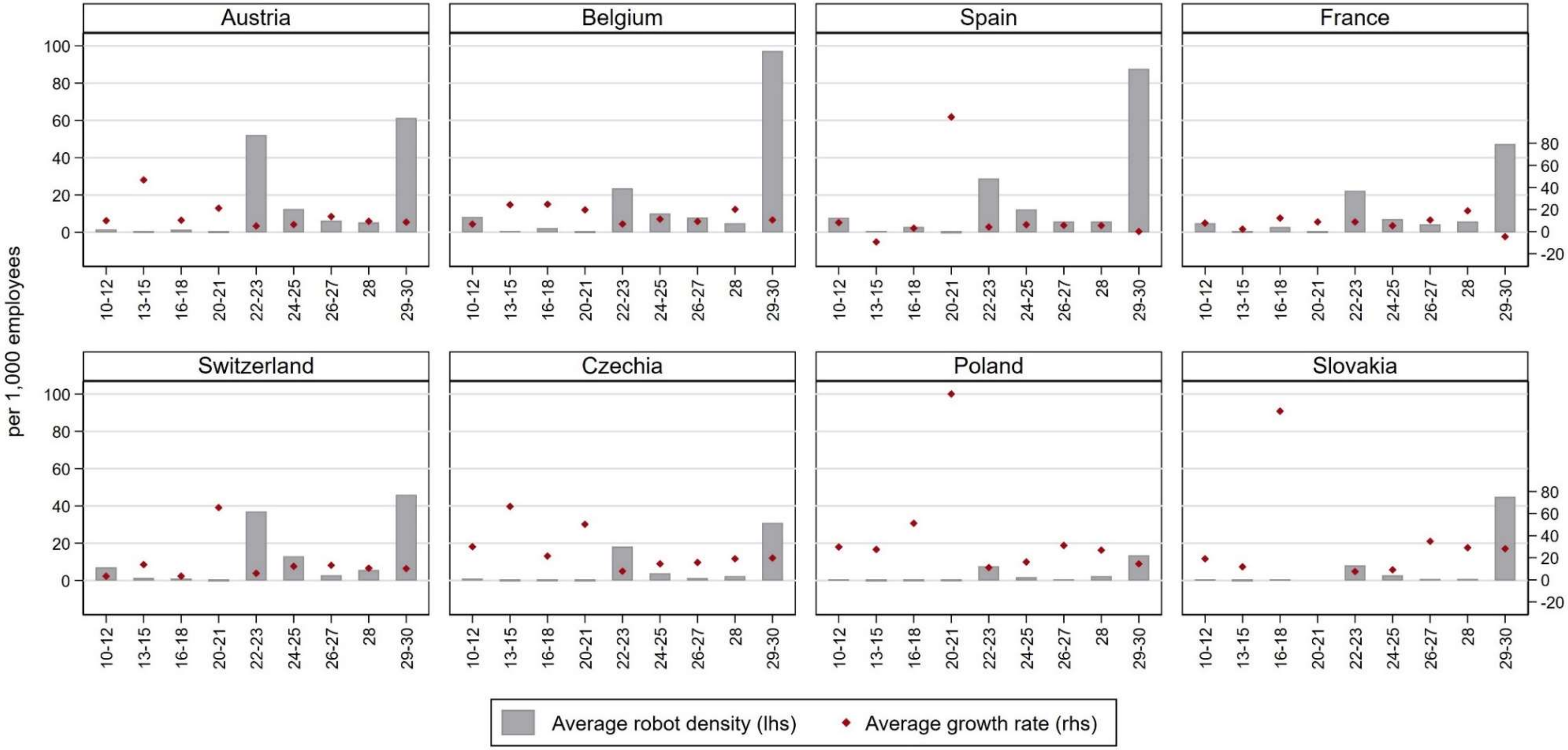
Note: The grey bar refers to the atypical employment share in 2009; the red diamonds to the change (in ppts) between 2009 and 2018. A refers to agriculture, forestry and fishing; B to mining and quarrying; 10-12 to food products, beverages and tobacco; 13-15 to textiles, wearing apparel, leather and related products; 16-18 to wood and paper products, printing and reproduction of recorded media; 19 to coke and refined petroleum products; 20-21 to chemicals and chemical products; 22-23 to rubber and plastics products, and other non-metallic mineral products; 24-25 to basic metals and fabricated metal products, except machinery and equipment; 26-27 to computer, electronic and optical products, and electrical equipment; 28 to machinery and equipment n.e.c.; 29-30 to transport equipment; 31-33 to other manufacturing; repair and installation of machinery and equipment; F to construction; G to wholesale and retail trade; repair of motor vehicles and motorcycles; H to transportation and storage; I to accommodation and food service activities; 58-60 to publishing, audio-visual and broadcasting activities; 61 to telecommunications; 62-63 to IT and other information services; K to financial and insurance activities; L to real estate activities; and M-N to professional, scientific and technical activities, administrative and support service activities.
Sources: National EU-SILC; own calculations.

Figure 2. Total offshoring by industry in 2009 (rhs) and the average offshoring growth rate between 2009 and 2018 (rhs)



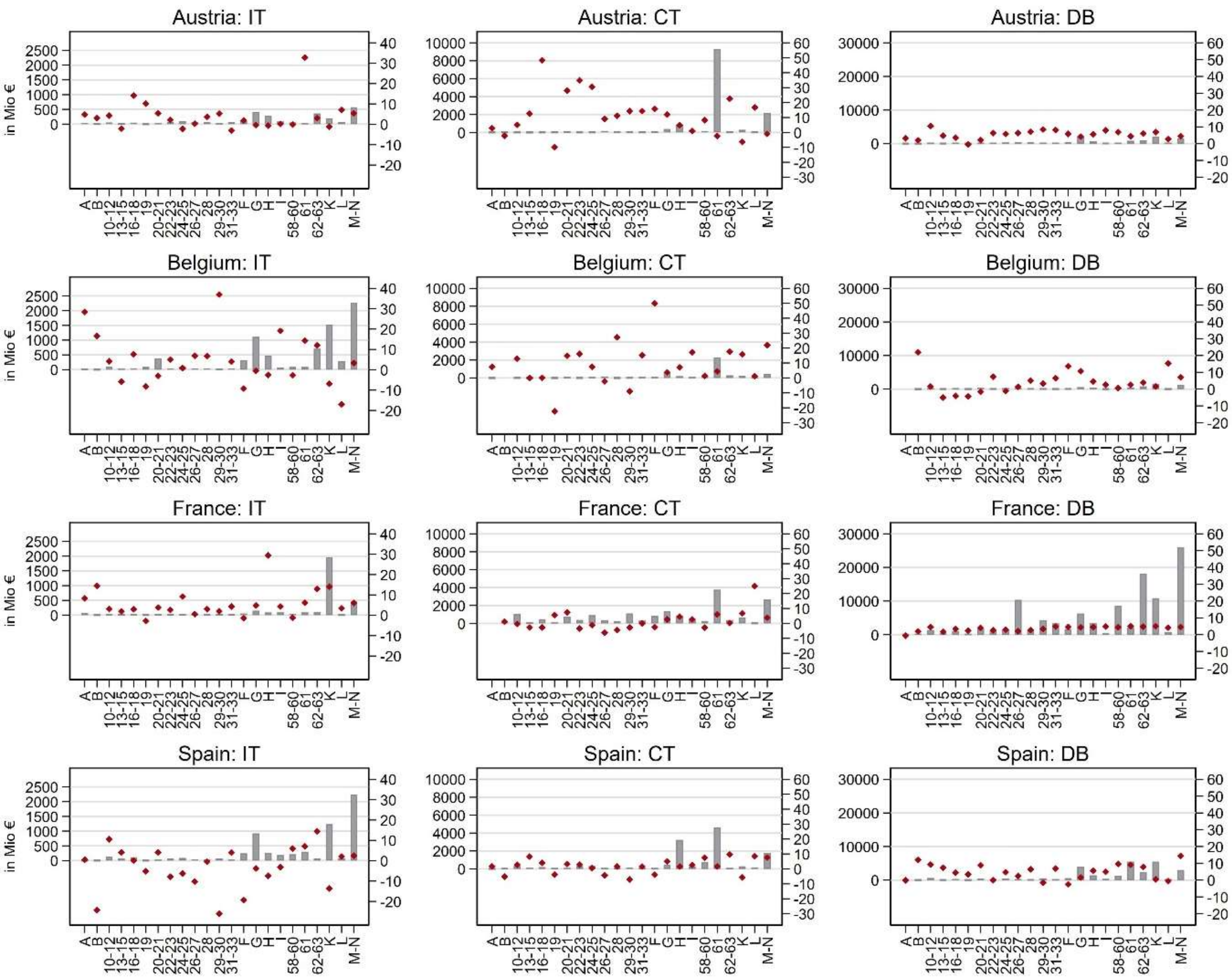
Note: The grey bar refers to total offshoring (as % of gross output) in 2009; the red diamonds to the growth rate (in %) between 2009 and 2018. A refers to agriculture, forestry and fishing; B to mining and quarrying; 10-12 to food products, beverages and tobacco; 13-15 to textiles, wearing apparel, leather and related products; 16-18 to wood and paper products, printing and reproduction of recorded media; 19 to coke and refined petroleum products; 20-21 to chemicals and chemical products; 22-23 to rubber and plastics products, and other non-metallic mineral products; 24-25 to basic metals and fabricated metal products, except machinery and equipment; 26-27 to computer, electronic and optical products, and electrical equipment; 28 to machinery and equipment n.e.c.; 29-30 to transport equipment; 31-33 to other manufacturing; repair and installation of machinery and equipment; F to construction; G to wholesale and retail trade; repair of motor vehicles and motorcycles; H to transportation and storage; I to accommodation and food service activities; 58-60 to publishing, audio-visual and broadcasting activities; 61 to telecommunications; 62-63 to IT and other information services; K to financial and insurance activities; L to real estate activities; and M-N to professional, scientific and technical activities, administrative and support service activities.
Sources: WIOD 2022 release; own calculations.

Figure 3. Average robot density in 2009 (rhs) and the average growth rate between 2009 and 2018 (rhs)



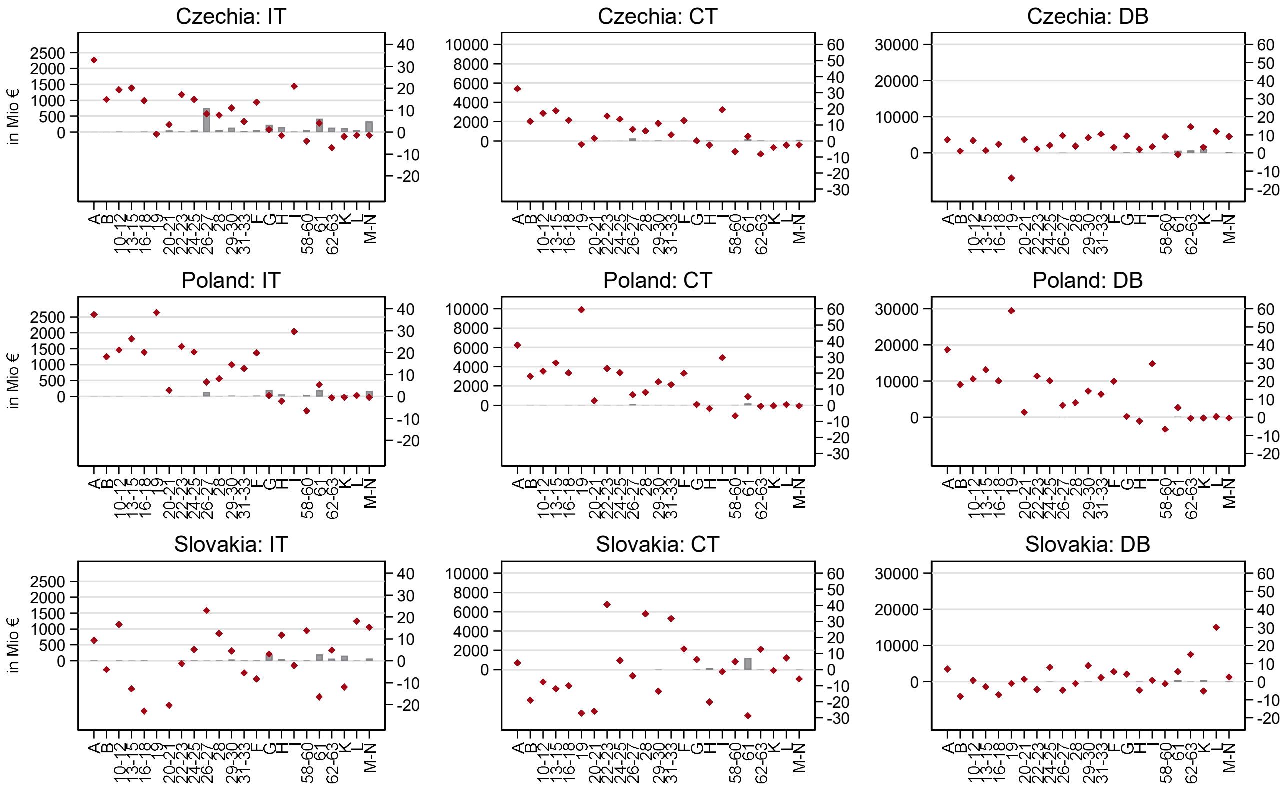
Note: Robot density is defined as the number of robots per 1,000 employees. The grey bar refers to the average of the first three years (2009-2011); the red diamonds to the average growth rate. A refers to agriculture, forestry and fishing; B to mining and quarrying; 10-12 to food products, beverages and tobacco; 13-15 to textiles, wearing apparel, leather and related products; 16-18 to wood and paper products, printing and reproduction of recorded media; 19 to coke and refined petroleum products; 20-21 to chemicals and chemical products; 22-23 to rubber and plastics products, and other non-metallic mineral products; 24-25 to basic metals and fabricated metal products, except machinery and equipment; 26-27 to computer, electronic and optical products, and electrical equipment; 28 to machinery and equipment n.e.c.; 29-30 to transport equipment.
Sources: World Robotics Industrial Robots statistics; national EU-SILC; own calculations.

Figure 4. Information technology (IT), communications technology (CT) and database (DB) in 2009 (rhs) and the average growth rate between 2009 and 2018 (rhs)



Contd.

Figure 4. Continued



Note: The grey bar refers to the real stock of capital (in € m) in 2009; the red diamonds to the average growth rate (in %). A refers to agriculture, forestry and fishing; B to mining and quarrying; 10-12 to food products, beverages and tobacco; 13-15 to textiles, wearing apparel, leather and related products; 16-18 to wood and paper products, printing and reproduction of recorded media; 19 to coke and refined petroleum products; 20-21 to chemicals and chemical products; 22-23 to rubber and plastics products, and other non-metallic mineral products; 24-25 to basic metals and fabricated metal products, except machinery and equipment; 26-27 to computer, electronic and optical products, and electrical equipment; 28 to machinery and equipment n.e.c.; 29-30 to transport equipment; 31-33 to other manufacturing; repair and installation of machinery and equipment; F to construction; G to wholesale and retail trade; repair of motor vehicles and motorcycles; H to transportation and storage; I to accommodation and food service activities; 58-60 to publishing, audio-visual and broadcasting activities; 61 to telecommunications; 62-63 to IT and other information services; K to financial and insurance activities; L to real estate activities; and M-N to professional, scientific and technical activities, administrative and support service activities.
Sources: WIOD 2022 release; own calculations.

2.5. Results

In what follows, we discuss the results of our estimations, first without taking endogeneity issues into account. Specifically, Section 2.5.1 reports the results on the impact of total offshoring and technological change on labour demand, in *total* and further differentiated by type of employment in terms of *typical* and *atypical* employment. In Section 2.5.2, we further differentiate between various offshoring measures, namely narrow (N) and broad (B) offshoring, manufacturing (M) and services (S) offshoring, and offshoring to different regions – developing countries (Devg), developed countries (Devd), and the 'new' EU13 member states (EU13). In both sections, we also discuss potential differences between country samples – 'old' EU member states (EU15) plus Switzerland versus the 'new' EU13 member states (EU13) – of the impact of total offshoring and technological change on labour demand. In Section 2.5.3, we address the role of employment protection legislation (EPL) in potentially moderating the effect of offshoring and technological change on labour demand (total and by type). In Section 2.6, we report the results of IV estimations that attempt to address various endogeneity issues.

In general, for reasons discussed in the Data sources section (2.3), we present two sets of results: one including the total set of industries covered in the analysis, which include both manufacturing and service industries (excluding the public service industries), and another that focuses only on manufacturing industries. As discussed above, we use the technology variables differently in the two samples: for the total sample, we included the three ICT variables but excluded the robot density variable; for the manufacturing sample, we included the robot density variable but excluded the three ICT variables. In discussing our results, we focus on three-, five- and nine-year differences, which allows us to compare the effects of medium- to longer-term effects of offshoring and technological change, as opposed to the more volatile and erratic short-term effects.[16]

2.5.1. Total offshoring, technological change and labour demand – in total and by type

As concerns the impact of total offshoring and technological change on employment, our results are quite different between the two samples analysed (see Table 1 and Table 2). Specifically, in the total sample, an increase in total offshoring increases the demand for total employment and atypical employment – but only in the short run – while in the manufacturing sample, the opposite is true, as it reduces the demand for typical employment – in the short run and also in the long run. This finding points to important

[16] For the sake of brevity, the results for the short term (one- and two- year differences) are not presented here, but are available from the authors upon request.

differences between manufacturing and service industries (which make up the bulk of non-manufacturing industries in the total sample), suggesting that offshoring has important differentiated compositional effects: more offshoring leads to a reduction of typical employment in manufacturing industries, with unchanged demand for atypical employment, but to an expansion of atypical employment in services industries, with unchanged demand for typical employment.

With regard to technological change, with only one exception, we find little evidence that IT, CT or DB have an impact on labour demand in the total sample. The exception relates to CT: in the long run, an increase in CT increases the demand for total employment, mainly as a result of an increase in the demand for atypical employment.

This is in contrast to what is observed for robot density, the expansion of which leads to a decrease in total employment, in the short, medium and long run, which is mainly due to a decrease in typical employment in all three of these timeframes. However, the coefficients point to a decline in the effect over time. The negative effect on typical employment can be explained by the different educational and skill endowments of typical and atypical workers and the polarisation effect of robotisation. In particular, as low-skilled workers are overrepresented in atypical employment (Leitner et al., forthcoming; Schmid, 2011), they are less vulnerable to technology-induced displacement effects which mainly affect medium-skilled workers (Autor et al., 2003), who predominantly hold typical jobs. By contrast, atypical employment falls only in the long run. Because the coefficient for total employment is larger (in absolute terms) than that for atypical employment, our results for robot density suggest that the share of atypical employment in total employment is increasing as a result of robotisation. This is in line with the results presented in Section 3 below.

Overall, our results are only partly in line with what is found in the related literature, which shows that both more offshoring (or GVC integration) as well as increased ICT/robotisation are associated with increased atypical employment (Machikita and Sato, 2011; Nikulin and Szymczak, 2020; Rutledge et al., 2019; Kiyota and Maruyama, 2017).

Moreover, the results in Table 3 and Table 4 indicate that the impact of technological change (but not of offshoring) also differs between the groups of countries in our sample, namely the ‘old’ member states (EU15) and the ‘new’ member states (EU13). Specifically, in the total sample, an increase in IT leads to a decline in atypical employment in the EU13 member states – but only in the long run – but to an increase in atypical employment in the EU15 member states; an increase in CT leads to a decrease in typical employment in the EU13 member states, but to an increase in typical employment in the EU15 member states, while the employment-enhancing effects on atypical employment are similar across the EU15 and the EU13 member states; an increase in DB leads to an increase in atypical employment in the EU15 member states in the short run but an increase in typical employment in the long run.

In the manufacturing sample, an increase in robot density leads to a decrease in total employment in both the EU15 and the EU13 member states, but significantly more so in the EU15 member states. This can also be observed for the two types of employment: an increase in robot density leads to a much stronger decline in employment of both typical and atypical employment in the EU15 member states – although the coefficients suggest that atypical employment appears to decline more than typical employment – while in the EU13 member states, the decline in typical employment is less pronounced, with demand for atypical employment remaining unchanged.

For the remaining control variables, our results show that employment – in total and by type – reacts very little to changes in input prices, that is, neither to wages nor to the price of materials. The only exception is atypical employment in the manufacturing sample in the longer run (i.e. for nine-year differences), which has the expected negative sign. This suggests that, unlike typical employment, atypical employment in manufacturing is sensitive to changes in wages in the longer run. Specifically, the estimated coefficient suggests that the demand for atypical employment falls by 0.63% in response to an increase in wages by 1% over a nine-year period. Moreover, employment responds positively to changes in output. This refers to total employment (in the total sample) and typical employment (in both samples), suggesting that only the demand for typical employment increases during economic upturns, while the demand for atypical employment does not. Finally, we find little evidence that employment reacts to trade openness, except for atypical employment in the total sample, where greater trade openness of an industry leads to a lower demand for atypical employment in the short run.

Table 1. Employment effect (total economy): total offshoring

	3-year differences (D3)			5-year differences (D5)			9-year differences (D9)		
	total	typical	atypical	total	typical	atypical	total	typical	atypical
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
w	-0.0918	-0.0553	0.0832	0.201	0.330	-0.0636	0.0921	0.319	-0.217
	(0.124)	(0.142)	(0.0688)	(0.177)	(0.210)	(0.0825)	(0.278)	(0.295)	(0.176)
p	-0.243	-0.282	0.191	-0.296	-0.0688	0.0974	-0.181	-0.0300	-0.0759
	(0.192)	(0.260)	(0.188)	(0.219)	(0.158)	(0.167)	(0.284)	(0.265)	(0.356)
GO	0.565***	0.837***	0.0972	0.495***	0.658***	0.175	0.441	0.845***	0.353
	(0.148)	(0.214)	(0.238)	(0.150)	(0.179)	(0.180)	(0.303)	(0.275)	(0.382)
IP	-0.616*	-0.277	-1.577**	-0.581	-0.346	-0.129	-0.346	-0.0514	-1.914
	(0.332)	(0.448)	(0.624)	(0.512)	(0.443)	(0.522)	(0.603)	(0.448)	(1.333)
IIM^T	0.628**	0.316	1.416***	0.479	0.286	0.267	0.290	0.123	1.513
	(0.305)	(0.392)	(0.506)	(0.481)	(0.400)	(0.481)	(0.587)	(0.410)	(1.259)
IT	0.0336	0.0185	-0.0187	0.0297	0.0202	0.0145	-0.0932*	-0.103*	-0.0861
	(0.0270)	(0.0303)	(0.0537)	(0.0313)	(0.0353)	(0.0480)	(0.0535)	(0.0553)	(0.0598)
CT	0.0135	0.0120	0.0319	0.0294	0.00592	0.0194	0.105**	0.0677	0.140**
	(0.0266)	(0.0276)	(0.0457)	(0.0295)	(0.0297)	(0.0410)	(0.0478)	(0.0453)	(0.0709)
DB	-0.0349	-0.0197	0.0808	-0.0315	-0.0132	0.0780	-0.00441	0.0583	-0.0568
	(0.0456)	(0.0455)	(0.0841)	(0.0562)	(0.0525)	(0.0655)	(0.0743)	(0.0631)	(0.0957)
Constant	0.0243	0.0152	0.0354	-0.00418	-0.0409	0.0424	0.0826	-0.0915	0.328**
	(0.0296)	(0.0265)	(0.0410)	(0.0593)	(0.0471)	(0.0679)	(0.125)	(0.113)	(0.147)
Obs.	1,083	1,050	1,050	772	749	749	152	150	150
R^2	0.069	0.097	0.032	0.111	0.190	0.037	0.147	0.269	0.185

Note: All variables are in logs. Standard errors clustered at the country-industry level. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. w refers to average gross annual wages, p to the price of materials, GO to gross output, IP to import penetration, IIM^T to total offshoring, IT to information technology, CT to communications technology, and DB to software and databases.

Table 2. Employment effect (manufacturing): total offshoring

	3-year differences (D3)			5-year differences (D5)			9-year differences (D9)		
	total	typical	atypical	total	typical	atypical	total	typical	atypical
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
w	0.0183	-0.125	0.0462	0.208	0.570*	-0.0537	0.0681	0.373	-0.630**
	(0.128)	(0.180)	(0.0958)	(0.235)	(0.297)	(0.128)	(0.397)	(0.403)	(0.278)
p	-0.122	-0.384	0.0202	-0.296	-0.256*	0.134	-0.0569	0.399	0.877*
	(0.192)	(0.271)	(0.177)	(0.246)	(0.150)	(0.215)	(0.338)	(0.358)	(0.490)
GO	0.241	0.477***	0.216	0.223	0.307**	-0.0512	-0.0271	0.0359	-0.741*
	(0.151)	(0.139)	(0.233)	(0.162)	(0.120)	(0.228)	(0.314)	(0.328)	(0.422)
IP	0.422	0.600	-0.275	-0.252	-0.109	-0.559	-0.241	0.370	0.364
	(0.495)	(0.433)	(0.661)	(0.494)	(0.393)	(0.694)	(0.637)	(0.419)	(0.824)
IIM^T	-0.578	-0.793**	0.235	-0.0894	-0.254	0.261	-0.106	-0.807**	-0.464
	(0.451)	(0.392)	(0.595)	(0.443)	(0.324)	(0.617)	(0.627)	(0.385)	(0.879)
RD	-0.391***	-0.387***	-0.130*	-0.326***	-0.299***	-0.109	-0.253***	-0.273***	-0.240**
	(0.0769)	(0.0761)	(0.0683)	(0.0671)	(0.0521)	(0.0670)	(0.0676)	(0.0574)	(0.0979)
Constant	0.153***	0.187***	0.193***	0.166**	0.118**	0.236***	0.486***	0.338***	0.776***
	(0.0424)	(0.0401)	(0.0638)	(0.0785)	(0.0587)	(0.0885)	(0.156)	(0.124)	(0.233)
Obs.	576	547	547	405	384	384	75	71	71
R^2	0.471	0.462	0.069	0.506	0.620	0.088	0.563	0.692	0.409

Note: All variables are in logs. Standard errors clustered at the country-industry level. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. w refers to average gross annual wages, p to the price of materials, GO to gross output, IP to import penetration, IIM^T to total offshoring, and RD to robot density.

Table 3. Employment effect (total economy): total offshoring – EU15 vs EU13

	3-year differences (D3)			5-year differences (D5)			9-year differences (D9)		
	total	Typical	atypical	total	typical	atypical	total	typical	atypical
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
w	-0.0698	-0.0348	0.0691	0.237	0.351*	-0.0716	0.204	0.331	-0.184
	(0.121)	(0.142)	(0.0676)	(0.171)	(0.207)	(0.0809)	(0.245)	(0.294)	(0.174)
p	-0.254	-0.288	0.207	-0.313	-0.0825	0.114	-0.0866	0.0245	-0.0104
	(0.193)	(0.258)	(0.197)	(0.220)	(0.156)	(0.167)	(0.271)	(0.255)	(0.335)
GO	0.565***	0.830***	0.0471	0.486***	0.635***	0.133	0.358	0.757***	0.214
	(0.154)	(0.214)	(0.248)	(0.161)	(0.179)	(0.185)	(0.291)	(0.261)	(0.353)
IP	-0.520	-0.244	-1.487***	-0.444	-0.279	-0.114	-0.218	0.0263	-1.707
	(0.342)	(0.451)	(0.567)	(0.521)	(0.444)	(0.527)	(0.633)	(0.468)	(1.277)
EU15	0.0358	0.0433	0.0816	-0.00942	0.113**	0.0181	0.189	0.283**	0.304
	(0.0348)	(0.0356)	(0.0518)	(0.0680)	(0.0574)	(0.0905)	(0.126)	(0.127)	(0.197)
IIM^T	0.453	0.236	1.097*	0.209	0.119	0.344	0.0976	-0.0267	1.172
	(0.322)	(0.418)	(0.571)	(0.505)	(0.425)	(0.488)	(0.629)	(0.460)	(1.309)
EU15*IIM^T	0.214	0.105	0.539	0.311*	0.193	-0.136	0.207	0.217	0.280
	(0.130)	(0.144)	(0.352)	(0.185)	(0.186)	(0.190)	(0.241)	(0.216)	(0.487)
IT	0.0701*	0.0770*	-0.109	0.0408	0.0419	-0.123	-0.0836**	-0.0438	-0.297**
	(0.0368)	(0.0421)	(0.104)	(0.0486)	(0.0509)	(0.0881)	(0.0420)	(0.0460)	(0.119)
EU15*IT	-0.0397	-0.0719	0.145	0.0190	0.00123	0.221**	0.0195	-0.0612	0.324**
	(0.0532)	(0.0580)	(0.113)	(0.0663)	(0.0715)	(0.100)	(0.0951)	(0.0955)	(0.137)
CT	-0.0522*	-0.0892***	0.134**	-0.0451	-0.0878**	0.124**	0.0550	0.0121	0.205*
	(0.0273)	(0.0287)	(0.0659)	(0.0367)	(0.0369)	(0.0555)	(0.0460)	(0.0458)	(0.119)
EU15*CT	0.113**	0.176***	-0.152*	0.127**	0.165***	-0.138*	0.0796	0.0788	-0.0311
	(0.0497)	(0.0505)	(0.0889)	(0.0558)	(0.0575)	(0.0775)	(0.0774)	(0.0774)	(0.145)
DB	-0.0491	-0.00712	-0.000875	-0.0329	0.0201	0.0406	-0.0825	-0.0300	-0.00733
	(0.0630)	(0.0519)	(0.113)	(0.0681)	(0.0525)	(0.0824)	(0.0707)	(0.0462)	(0.134)
EU15*DB	0.0841	0.0143	0.310**	0.118	-0.00909	0.193	0.460**	0.417***	0.148
	(0.100)	(0.0978)	(0.152)	(0.132)	(0.130)	(0.133)	(0.185)	(0.162)	(0.224)
Constant	0.00972	-0.0292	0.0514	0.0230	-0.157**	0.0819	-0.138	-0.396**	0.273
	(0.0413)	(0.0437)	(0.0520)	(0.0855)	(0.0759)	(0.0919)	(0.176)	(0.171)	(0.342)
Obs.	1,083	1,050	1,050	772	749	749	152	150	150
R^2	0.079	0.107	0.048	0.136	0.206	0.057	0.209	0.304	0.228

Note: All variables are in logs. Standard errors clustered at the country-industry level. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. w refers to average gross annual wages, p to the price of materials, GO to gross output, IP to import penetration, EU15 to 'old' EU member states, IIM^T to total offshoring, IT to information technology, CT to communications technology, and DB to software and databases.

Table 4. Employment effect (manufacturing): total offshoring – EU15 vs EU13

	3-year differences (D3)			5-year differences (D5)			9-year differences (D9)		
	total	typical	atypical	total	typical	atypical	total	typical	atypical
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
w	-0.0455	-0.187	0.0116	0.0957	0.390	-0.0809	0.136	0.517	-0.641***
	(0.117)	(0.151)	(0.0845)	(0.195)	(0.264)	(0.121)	(0.361)	(0.383)	(0.249)
p	-0.0709	-0.360	0.0209	-0.232	-0.160	0.202	-0.402	0.00699	0.455
	(0.200)	(0.283)	(0.160)	(0.257)	(0.154)	(0.193)	(0.271)	(0.275)	(0.491)
GO	0.206*	0.457***	0.193	0.187	0.356***	-0.000678	0.366	0.411	-0.357
	(0.115)	(0.154)	(0.207)	(0.128)	(0.123)	(0.213)	(0.256)	(0.295)	(0.440)
IP	0.689	0.731*	-0.234	-0.00486	0.164	-0.416	-0.0948	0.460	0.376
	(0.525)	(0.435)	(0.625)	(0.493)	(0.456)	(0.599)	(0.532)	(0.327)	(0.796)
EU15	-0.105	-0.0773*	0.0450	-0.209	-0.111	-0.0917	-0.165	0.0331	0.0528
	(0.0695)	(0.0432)	(0.0811)	(0.159)	(0.0787)	(0.146)	(0.192)	(0.120)	(0.299)
IIM^T	-1.113**	-1.191**	0.210	-0.254	-0.499	0.643	0.295	-0.674*	0.626
	(0.515)	(0.520)	(0.671)	(0.514)	(0.477)	(0.627)	(0.798)	(0.374)	(1.304)
EU15*IIM^T	0.327	0.316	-0.0832	-0.251	-0.174	-0.813**	-0.829	-0.413	-1.563
	(0.230)	(0.271)	(0.389)	(0.359)	(0.241)	(0.393)	(0.602)	(0.323)	(1.187)
RD	-0.235**	-0.205***	0.0548	-0.173***	-0.143***	0.0560	-0.0533	-0.102***	-0.00344
	(0.0917)	(0.0742)	(0.0445)	(0.0548)	(0.0428)	(0.0357)	(0.0575)	(0.0365)	(0.106)
EU15*RD	-0.343***	-0.391***	-0.394***	-0.382***	-0.384***	-0.405***	-0.478***	-0.410***	-0.556***
	(0.126)	(0.124)	(0.111)	(0.102)	(0.0967)	(0.111)	(0.0929)	(0.0898)	(0.158)
Constant	0.0225	0.0126	0.0647	0.0810	-0.0724	0.183	0.147	-0.338**	0.182
	(0.0889)	(0.0391)	(0.0586)	(0.171)	(0.0855)	(0.131)	(0.175)	(0.139)	(0.245)
Obs.	576	547	547	405	384	384	75	71	71
R^2	0.539	0.532	0.113	0.577	0.680	0.142	0.699	0.767	0.495

Note: All variables are in logs. Standard errors clustered at the country-industry level. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. w refers to average gross annual wages, p to the price of materials, GO to gross output, IP to import penetration, EU15 to the EU15 member states, IIM^T to total offshoring, and RD to robot density.

2.5.2. Other offshoring measures and labour demand – in total and by type

Table 5 and Table 6 below report the results when total offshoring is further split into (i) narrow (N) and broad (B) offshoring, (ii) manufacturing (M) and services (S) offshoring, and (iii) offshoring by source country in terms of developing countries (Devg), developed countries (Devd), and the 'new' member states (EU13) (as defined in Section 2.2 above). Because the coefficients for the other control variables are similar to those already observed (see Table 1 and Table 2 above), we concentrate on the different offshoring indicators.[17]

The results show that the different offshoring indicators play different roles in the two samples, again highlighting that workers in manufacturing and service industries are affected differently. For instance, in the total sample, an increase in narrow offshoring increases the demand for both typical and atypical employment, but only in the short to medium run (Table 5). By contrast, an increase in broad offshoring or services offshoring reduces the demand for typical employment, while the demand for atypical employment remains unchanged. There are also interesting results by sourcing country: offshoring to either developed or developing countries increases the demand for atypical employment, but it does so only in the long run in the case of the former and in the short run in the case of the latter. Offshoring to the EU13 has no significant employment effect on either typical or atypical employment. Hence, together with the results on total offshoring above, this shows that the offshoring-induced increase in the demand for atypical employment is mainly due to an increase in narrow (intra-industry) offshoring and in offshoring to either developed or developing countries.

In manufacturing, both services offshoring – but only in the short run – and offshoring to developing countries – in the short, medium and longer run – decrease the demand for typical employment, while the demand for atypical employment remains unchanged (Table 6). Conversely, broad offshoring increases the demand for atypical employment (in the long run), while the demand for typical employment remains unchanged. Hence, the decrease in the demand for typical employment from total offshoring (see above) is mainly due to more services offshoring – which, starting from a low level, has increased markedly in the last two decades – and offshoring to developing countries.

Moreover, Table 7 and Table 8 below again point to differences between the group of EU15 and EU13 countries in our sample. Although there are no differences in the effect of narrow and broad offshoring between EU15 and EU13 countries in the total sample, in manufacturing the demand for typical

[17] The full results tables are available from the authors upon request.

employment increases in the EU15 but decreases in the EU13 with an increase in broad offshoring – but only in the shorter run. Conversely, the demand for both typical and atypical employment decreases in the EU15, while it remains unchanged in the EU13 (at least in the short to medium run), with an increase in narrow offshoring.

Moreover, in the EU15, an increase in manufacturing offshoring increases the demand for both typical employment (only in the total sample) and atypical employment (in both samples), while it remains unchanged in the EU13.

The employment effect also differs according to the country of origin of the intermediate inputs: in the EU15, an increase in offshoring to developed countries increases the demand for atypical employment, while it remains unchanged in the EU13 (in both samples). Conversely, while an increase in offshoring to developing countries reduces the demand for atypical employment in the EU15, it increases the demand for atypical employment in the EU13 (albeit only in the manufacturing sample).

Table 5. Employment effect (total economy): other offshoring measures

	3-year differences (D3)			5-year differences (D5)			9-year differences (D9)		
	total	typical	atypical	total	typical	atypical	total	typical	atypical
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Narrow and broad offshoring									
IIM^N	0.0884***	0.0708**	0.110**	0.0970***	0.0660**	0.0274	0.0593	0.0390	0.138
	(0.0222)	(0.0300)	(0.0493)	(0.0290)	(0.0330)	(0.0535)	(0.0388)	(0.0444)	(0.0966)
IIM^B	0.0409	-0.0203	0.212	-0.141	-0.218**	0.127	-0.116	-0.0678	0.166
	(0.0711)	(0.0775)	(0.175)	(0.0979)	(0.103)	(0.125)	(0.178)	(0.160)	(0.272)
Obs.	1,083	1,050	1,050	772	749	749	152	150	150
R^2	0.075	0.101	0.029	0.129	0.203	0.038	0.154	0.271	0.180
Manufacturing and services offshoring									
IIM^M	0.0316	0.0609	-0.0475	0.0234	-0.0551	0.0863	0.0537	-0.0135	-0.0887
	(0.0615)	(0.0906)	(0.143)	(0.0903)	(0.0897)	(0.0962)	(0.110)	(0.113)	(0.168)
IIM^S	-0.0613	-0.0977**	0.119*	-0.0877	-0.0720	0.0515	-0.0833	-0.00880	0.137
	(0.0411)	(0.0458)	(0.0639)	(0.0534)	(0.0626)	(0.0614)	(0.0885)	(0.0813)	(0.132)
Obs.	1,083	1,050	1,050	772	749	749	152	150	150
R^2	0.067	0.102	0.028	0.113	0.193	0.038	0.150	0.268	0.172
Offshoring to developed countries, developing countries and the EU13									
IIM^{Devd}	0.258**	0.670*	0.0885	0.159*	0.0741	0.368*	-0.239	0.271	1.175**
	(0.121)	(0.355)	(0.332)	(0.0888)	(0.169)	(0.206)	(0.266)	(0.299)	(0.479)
IIM^{Devg}	-0.0524	-0.0197	0.201**	-0.00100	-0.0792	0.128	-0.140	-0.157	0.120
	(0.0449)	(0.0600)	(0.0891)	(0.0731)	(0.0727)	(0.0782)	(0.115)	(0.147)	(0.268)
IIM^{EU13}	0.150**	0.0612	0.222	0.264**	0.149	0.0519	0.619***	0.290	0.0604
	(0.0653)	(0.0794)	(0.140)	(0.114)	(0.107)	(0.118)	(0.215)	(0.227)	(0.281)
Obs.	1,083	1,050	1,050	772	749	749	152	150	150
R^2	0.083	0.139	0.034	0.130	0.196	0.046	0.201	0.292	0.216

Note: All variables are in logs. Standard errors clustered at the country-industry level. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. All regressions also include the usual controls (i.e. the wage rate, the price of materials, real gross output, import penetration, IT, CT and DB). IIM^N and IIM^B refer to narrow and broad offshoring, respectively; IIM^M and IIM^S to manufacturing and services offshoring, respectively; and IIM^{Devd} to offshoring to developed countries, IIM^{Devg} to offshoring to developing countries and IIM^{EU13} to offshoring to the EU13 member states.

Table 6. Employment effect (manufacturing): other offshoring measures

	3-year differences (D3)			5-year differences (D5)			9-year differences (D9)		
	total	typical	atypical	total	typical	atypical	total	typical	atypical
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Narrow and broad offshoring									
IIM^{N}	0.0450	-0.0265	-0.124	0.0756	-0.0450	-0.0280	0.0305	-0.254*	0.448
	(0.120)	(0.100)	(0.129)	(0.196)	(0.0887)	(0.188)	(0.200)	(0.153)	(0.284)
IIM^{B}	-0.139	-0.175	-0.187	0.0919	-0.0688	-0.0288	0.453	-0.0794	1.611**
	(0.187)	(0.179)	(0.279)	(0.237)	(0.191)	(0.311)	(0.333)	(0.311)	(0.641)
Obs.	576	547	547	405	384	384	75	71	71
R^2	0.469	0.459	0.070	0.507	0.620	0.088	0.572	0.697	0.480
Manufacturing and services offshoring									
II^{M}	-0.201	0.322	0.0932	-0.186	0.0778	0.241	-0.360	-0.304	0.697
	(0.264)	(0.273)	(0.223)	(0.377)	(0.146)	(0.286)	(0.450)	(0.377)	(0.756)
IIM^{S}	-0.150**	-0.221**	-0.0455	-0.0420	-0.0078	-0.0344	0.253	0.134	0.295
	(0.0754)	(0.101)	(0.0965)	(0.0998)	(0.0802)	(0.124)	(0.167)	(0.198)	(0.296)
Obs.	576	547	547	405	384	384	75	71	71
R^2	0.480	0.473	0.069	0.510	0.620	0.090	0.580	0.687	0.432
Offshoring to developed countries, developing countries and the EU13									
IIM^{Devd}	0.106	0.513*	-0.359	-0.0706	-0.261	0.616**	-0.0512	-0.713*	0.333
	(0.0801)	(0.304)	(0.306)	(0.113)	(0.169)	(0.259)	(0.278)	(0.432)	(0.624)
IIM^{Devg}	-0.175***	-0.289***	0.210	-0.0667	-0.246***	0.292*	-0.0540	-0.505**	-0.0491
	(0.0633)	(0.0825)	(0.141)	(0.112)	(0.0861)	(0.161)	(0.233)	(0.218)	(0.432)
IIM^{EU13}	0.127**	-0.0287	0.328*	0.347**	0.158	-0.108	0.476**	0.264	-0.0564
	(0.0607)	(0.107)	(0.193)	(0.135)	(0.0965)	(0.145)	(0.197)	(0.280)	(0.557)
Obs.	576	547	547	405	384	384	75	71	71
R^2	0.481	0.498	0.088	0.526	0.635	0.115	0.607	0.725	0.413

Note: All variables are in logs. Standard errors clustered at the country-industry level. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. All regressions also include the usual controls (i.e. the wage rate, the price of materials, real gross output, import penetration, and robot density). IIM^{N} and IIM^{B} refer to narrow and broad offshoring, respectively; IIM^{M} and IIM^{S} to manufacturing and services offshoring, respectively, and IIM^{Devd} to offshoring to developed countries, IIM^{Devg} to offshoring to developing countries and IIM^{EU13} to offshoring to the EU13 member states.

Table 7. Employment effect (total economy): other offshoring measures – EU15 vs EU13

	3-year differences (D3)			5-year differences (D5)			9-year differences (D9)		
	total	typical	atypical	total	atypical	atypical	total	typical	atypical
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Narrow and broad offshoring									
EU15	0.0311	0.0605**	0.0860	-0.0281	0.110*	0.187**	0.156	0.258**	0.321
	(0.0344)	(0.0299)	(0.0527)	(0.0651)	(0.0580)	(0.0729)	(0.123)	(0.125)	(0.199)
IIM^N	0.0756***	0.0577**	0.0884*	0.0786***	0.0496*	-0.000782	0.0217	0.0130	0.104
	(0.0178)	(0.0240)	(0.0530)	(0.0221)	(0.0278)	(0.0481)	(0.0357)	(0.0350)	(0.0913)
$EU15*IIM^N$	0.116*	0.113*	0.194*	0.160	0.185*	0.167	0.0226	-0.00102	0.157
	(0.0598)	(0.0675)	(0.110)	(0.0991)	(0.0946)	(0.124)	(0.149)	(0.134)	(0.209)
IIM^B	-0.0423	-0.0951	0.126	-0.220*	-0.260*	0.368**	-0.237	-0.180	0.0720
	(0.0880)	(0.0994)	(0.223)	(0.132)	(0.146)	(0.178)	(0.210)	(0.176)	(0.330)
$EU15*IIM^B$	0.326**	0.277*	0.370	0.396**	0.321*	-0.334	0.466*	0.401*	0.490
	(0.140)	(0.160)	(0.333)	(0.173)	(0.184)	(0.230)	(0.264)	(0.228)	(0.394)
Obs.	1,083	1,050	1,050	772	749	749	152	150	150
R^2	0.093	0.117	0.046	0.164	0.229	0.065	0.221	0.310	0.232
Manufacturing and services offshoring									
EU15	0.0427	0.0804**	0.0801	-0.0137	0.0307	0.171**	0.199	0.280**	0.435**
	(0.0346)	(0.0321)	(0.0530)	(0.0637)	(0.0646)	(0.0752)	(0.140)	(0.140)	(0.204)
IIM^M	-0.0203	0.0636	-0.205	-0.0170	-0.226*	0.250	0.00691	-0.136	-0.421**
	(0.0959)	(0.173)	(0.250)	(0.158)	(0.130)	(0.179)	(0.121)	(0.0918)	(0.198)
$EU15*IIM^M$	0.0955	-0.0358	0.299	0.151	0.352**	-0.269	0.286	0.385***	0.844**
	(0.126)	(0.185)	(0.284)	(0.172)	(0.153)	(0.205)	(0.184)	(0.143)	(0.361)
IIM^S	-0.0410	-0.0607	0.104	-0.100	-0.0680	0.0824	-0.0971	0.00562	0.260*
	(0.0475)	(0.0546)	(0.0759)	(0.0756)	(0.0767)	(0.0755)	(0.116)	(0.0855)	(0.145)
$EU15*IIM^S$	-0.0232	-0.0915	0.0858	0.104	0.0573	-0.0360	0.144	0.0578	-0.174
	(0.0777)	(0.0881)	(0.147)	(0.105)	(0.117)	(0.127)	(0.192)	(0.160)	(0.221)
Obs.	1,083	1,050	1,050	772	749	749	152	150	150
R^2	0.075	0.112	0.041	0.135	0.214	0.062	0.220	0.313	0.244
Offshoring to developed countries, developing countries and the EU13									
EU15	0.0565*	0.107**	0.0834	0.00407	0.0581	0.101	0.00638	0.258**	0.553*
	(0.0338)	(0.0473)	(0.0602)	(0.0646)	(0.0676)	(0.0856)	(0.140)	(0.105)	(0.286)
IIM^{Devd}	0.257*	0.725**	-0.121	0.0429	0.102	0.0626	-0.471	0.361	0.876
	(0.137)	(0.350)	(0.280)	(0.0816)	(0.176)	(0.202)	(0.291)	(0.344)	(0.536)
$EU15*IIM^{Devd}$	0.0371	-0.192	1.126***	0.275	0.0149	0.462	0.770*	-0.0735	0.365
	(0.159)	(0.248)	(0.413)	(0.205)	(0.273)	(0.283)	(0.414)	(0.364)	(0.619)
IIM^{Devg}	0.00932	0.0256	0.227**	-7.03e-05	0.0108	0.146	-0.173	-0.0756	-0.0526
	(0.0492)	(0.0616)	(0.104)	(0.0762)	(0.0766)	(0.0926)	(0.165)	(0.120)	(0.354)
$EU15*IIM^{Devg}$	-0.103	-0.0178	-0.126	0.0260	-0.0906	-0.116	0.0328	-0.173	0.343
	(0.0872)	(0.122)	(0.163)	(0.125)	(0.128)	(0.149)	(0.197)	(0.208)	(0.427)
IIM^{EU13}	0.0368	-0.0605	0.418*	0.345*	0.000312	0.342*	0.786***	0.0243	0.379
	(0.0937)	(0.107)	(0.227)	(0.191)	(0.146)	(0.191)	(0.179)	(0.191)	(0.477)
$EU15*IIM^{EU13}$	0.220*	0.257*	-0.343	-0.0706	0.288	-0.395	-0.442	0.401	-0.333
	(0.128)	(0.151)	(0.278)	(0.197)	(0.201)	(0.246)	(0.348)	(0.339)	(0.611)
Obs.	1,083	1,050	1,050	772	749	749	152	150	150
R^2	0.096	0.153	0.059	0.156	0.215	0.067	0.280	0.334	0.263

Note: All variables are in logs. Standard errors clustered at the country-industry level. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. All regressions also include the usual controls (i.e. the wage rate, the price of materials, real gross output, import penetration, IT, CT and DB). EU15 refers to 'old' EU15 member states; IIM^N and IIM^B to narrow and broad offshoring, respectively; IIM^M and IIM^S to manufacturing and services offshoring, respectively; and IIM^{Devd} to offshoring to developed countries, IIM^{Devg} to offshoring to developing countries and IIM^{EU13} to offshoring to the EU13 member states.

Table 8. Employment effect (manufacturing): other offshoring measures – EU15 vs EU13

	3-year differences (D3)			5-year differences (D5)			9-year differences (D9)		
	total	typical	atypical	total	typical	atypical	total	typical	atypical
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Narrow and broad offshoring									
EU15	-0.106 (0.0644)	-0.158*** (0.0535)	0.0201 (0.0948)	-0.216 (0.148)	-0.166** (0.0764)	0.170 (0.120)	-0.179 (0.179)	-0.0345 (0.127)	0.0814 (0.299)
IIM^N	0.196 (0.150)	0.0799 (0.0655)	-0.146 (0.125)	0.346 (0.233)	0.109 (0.0991)	0.146 (0.104)	0.118 (0.161)	-0.153*** (0.0564)	0.652*** (0.110)
$EU15{*}IIM^N$	-0.454** (0.184)	-0.331*** (0.0967)	0.0325 (0.183)	-0.712*** (0.234)	-0.436*** (0.134)	-0.434** (0.189)	-0.599*** (0.190)	-0.426** (0.204)	-0.712*** (0.269)
IIM^B	-0.753*** (0.273)	-0.636*** (0.223)	-0.00224 (0.303)	-0.613** (0.293)	-0.367 (0.280)	0.189 (0.351)	-0.0997 (0.406)	-0.154 (0.346)	1.458* (0.872)
$EU15{*}IIM^B$	0.937*** (0.324)	0.894** (0.360)	-0.0765 (0.480)	1.189*** (0.422)	0.700* (0.383)	-0.168 (0.544)	1.301** (0.503)	0.538 (0.456)	0.875 (1.047)
Obs.	576	547	547	405	384	384	75	71	71
R^2	0.560	0.540	0.115	0.628	0.693	0.148	0.764	0.786	0.595
Manufacturing and services offshoring									
EU15	-0.0934 (0.0573)	-0.115* (0.0589)	0.0454 (0.0987)	-0.229** (0.108)	-0.122* (0.0702)	-0.0723 (0.151)	-0.198 (0.178)	-0.0880 (0.186)	-0.0711 (0.347)
IIM^M	-0.470 (0.318)	0.401 (0.414)	0.0766 (0.195)	-0.521 (0.444)	-0.204 (0.191)	0.0867 (0.246)	-0.670** (0.280)	0.0144 (0.444)	-1.373 (0.875)
$EU15{*}IIM^M$	0.665* (0.339)	-0.116 (0.420)	0.0877 (0.420)	0.841* (0.472)	0.399 (0.264)	0.197 (0.470)	1.369** (0.553)	-0.175 (0.575)	3.107*** (1.040)
IIM^S	-0.0627 (0.0715)	-0.104 (0.101)	0.0573 (0.108)	-0.0235 (0.117)	-0.0615 (0.100)	-0.0361 (0.143)	0.287 (0.184)	0.0278 (0.139)	0.569 (0.347)
$EU15{*}IIM^S$	-0.143 (0.128)	-0.173 (0.182)	-0.138 (0.209)	0.0122 (0.139)	0.208 (0.136)	0.0826 (0.240)	-0.252 (0.265)	0.265 (0.327)	0.107 (0.642)
Obs.	576	547	547	405	384	384	75	71	71
R^2	0.559	0.540	0.114	0.599	0.681	0.138	0.730	0.755	0.548
Offshoring to developed countries, developing countries and the EU13									
EU15	-0.0970 (0.0636)	-0.0776 (0.0635)	0.0336 (0.0803)	-0.173 (0.136)	-0.300*** (0.0809)	0.0148 (0.131)	-0.0847 (0.151)	-0.0674 (0.132)	0.125 (0.324)
IIM^{Devd}	0.190 (0.144)	0.825** (0.345)	-0.468*** (0.181)	0.0580 (0.132)	-0.0193 (0.223)	0.138 (0.228)	-0.122 (0.207)	-0.406 (0.336)	-1.218 (0.831)
$EU15{*}IIM^{Devd}$	-0.0972 (0.206)	-0.758* (0.424)	1.223** (0.513)	-0.126 (0.246)	-0.434 (0.396)	1.126** (0.445)	0.119 (0.450)	-0.600 (0.693)	2.351** (1.046)
IIM^{Devg}	-0.256** (0.118)	-0.436** (0.187)	0.577*** (0.165)	-0.253 (0.206)	-0.134 (0.148)	0.698*** (0.192)	-0.166 (0.277)	-0.211 (0.223)	1.293** (0.542)
$EU15{*}IIM^{Devg}$	0.105 (0.130)	0.238 (0.208)	-0.463** (0.224)	0.211 (0.224)	-0.142 (0.161)	-0.556** (0.245)	0.252 (0.353)	-0.218 (0.288)	-1.914*** (0.621)
IIM^{EU13}	0.129 (0.0994)	-0.0655 (0.138)	0.569* (0.328)	0.884** (0.398)	-0.0163 (0.226)	0.273 (0.298)	0.889*** (0.182)	0.340 (0.270)	0.265 (0.738)
$EU15{*}IIM^{EU13}$	0.0104 (0.122)	0.262 (0.166)	-0.524 (0.395)	-0.701* (0.409)	0.293 (0.252)	-0.527 (0.342)	-0.725*** (0.264)	0.116 (0.504)	-0.986 (0.890)
Obs.	576	547	547	405	384	384	75	71	71
R^2	0.548	0.591	0.156	0.616	0.694	0.191	0.748	0.789	0.552

Note: All variables are in logs. Standard errors clustered at the country-industry level. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. All regressions also include the usual controls (i.e. the wage rate, the price of materials, real gross output, import penetration, and robot density). EU15 refers to the 'old' EU15 member states, IIM^N and IIM^B to narrow and broad offshoring, respectively; IIM^M and IIM^S to manufacturing and services offshoring, respectively; and IIM^{Devd} to offshoring to developed countries, IIM^{Devg} to offshoring to developing countries and IIM^{EU13} to offshoring to the 'new' EU13 member states.

2.5.3. Employment protection, total offshoring, technological change, labour demand – in total and by type of employment

Table 9 to Table 12 below report the results when the role of employment protection legislation (EPL) – the rules that govern the dismissal and hiring of workers – is also taken into consideration. While Table 9 and Table 10 refer to the results for EPL for regular workers (on regular contracts), Table 11 and Table 12 refer to those for temporary workers (on temporary contracts). All tables refer to the results with total offshoring as the main offshoring indicator. The results for the other offshoring measures (for both samples) can be found in the Annex (see Table A.2 to Table A.5).

As highlighted above, EPL changes very little across time, which makes it difficult to use in a dynamic analysis such as ours. Hence, we classified the countries in our sample according to the strictness of their EPLs into countries with 'strict' EPL – in the case of above-mean EPL – and 'weak' EPL – in the case of average or below-mean EPL. The latter group serves as the reference group.

Our results show that the strictness of EPL matters for labour demand in general and the type of labour in particular. Specifically, as concerns offshoring, the results seem to indicate that the 'other' type of employment appears to be affected more strongly by the two different EPL indicators analysed: specifically, atypical employment increases more strongly in countries with stricter EPL for regular contracts while, conversely, typical employment increases more strongly in countries with stricter EPL for temporary contracts. This not only holds for total offshoring (see Table 9 to Table 12) but is also observed for the other offshoring measures (see Table A.2 to Table A.5 in the Annex), suggesting that regulations tend to dampen employment adjustments of more protected types of employment and to encourage stronger adjustments of less protected types of employment.

For technological change, our results show that an increase in CT increases the demand for atypical employment, but only in countries with stricter EPL both for regular and temporary contracts. However, the effect is observed only in the short to medium term; in the long term, an increase in typical employment can be observed as well, especially in countries with stricter EPL for temporary contracts. By contrast, there are no differences with respect to either IT or DB. Moreover, the effect of an increase in robot density differs by EPL indicator: countries with stricter EPL for regular contracts experience a stronger decline in the demand for both typical and atypical employment than those with weaker EPL for regular contracts. But there are no differences with respect to the strictness of EPL for temporary contracts.

Table 9. Employment effect (total economy): total offshoring and employment protection – regular contracts

	3-year differences (D3)			5-year differences (D5)			9-year differences (D9)		
	total	typical	atypical	total	typical	atypical	total	typical	atypical
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
w	-0.091	-0.069	0.080	0.193	0.313	-0.066	0.105	0.366	-0.208
	(0.122)	(0.139)	(0.068)	(0.177)	(0.214)	(0.081)	(0.298)	(0.304)	(0.172)
p	-0.244	-0.312	0.194	-0.289	-0.099	-0.004	-0.257	-0.111	-0.197
	(0.190)	(0.258)	(0.190)	(0.216)	(0.155)	(0.167)	(0.294)	(0.274)	(0.351)
GO	0.569***	0.850***	0.074	0.488***	0.652***	0.142	0.451	0.846***	0.368
	(0.149)	(0.209)	(0.233)	(0.152)	(0.174)	(0.176)	(0.298)	(0.271)	(0.362)
IP	-0.605*	-0.261	-1.772***	-0.439	-0.266	-0.530	-0.469	-0.235	-1.816
	(0.329)	(0.463)	(0.603)	(0.516)	(0.432)	(0.537)	(0.646)	(0.513)	(1.313)
EPL	-0.042	-0.032	-0.076	-0.008	-0.042	-0.099	-0.185	-0.304**	-0.394**
	(0.035)	(0.036)	(0.053)	(0.070)	(0.072)	(0.116)	(0.145)	(0.145)	(0.193)
IIM^T	0.563*	0.240	1.523***	0.316	0.125	0.305	0.238	0.143	1.375
	(0.293)	(0.383)	(0.534)	(0.468)	(0.384)	(0.468)	(0.579)	(0.425)	(1.111)
EPL*IIM^T	0.087	0.125	0.118	0.059	0.184	0.642***	0.290	0.254	0.082
	(0.104)	(0.134)	(0.342)	(0.156)	(0.171)	(0.200)	(0.287)	(0.293)	(0.528)
IT	0.071	0.045	-0.043	0.110	0.103	0.104	0.039	0.007	0.133
	(0.087)	(0.103)	(0.080)	(0.071)	(0.073)	(0.081)	(0.082)	(0.057)	(0.117)
EPL*IT	-0.052	-0.025	0.031	-0.105	-0.096	-0.092	-0.167	-0.127	-0.248*
	(0.091)	(0.107)	(0.097)	(0.079)	(0.084)	(0.100)	(0.112)	(0.101)	(0.140)
CT	0.069	0.094	-0.121*	0.065	0.052	-0.098	0.074	-0.005	0.093
	(0.049)	(0.064)	(0.064)	(0.047)	(0.042)	(0.064)	(0.091)	(0.074)	(0.097)
EPL*CT	-0.068	-0.095	0.187**	-0.045	-0.056	0.157**	0.056	0.110	0.079
	(0.057)	(0.070)	(0.082)	(0.057)	(0.056)	(0.078)	(0.105)	(0.091)	(0.125)
DB	-0.106	-0.150	0.222*	-0.141*	-0.158**	0.021	-0.134	-0.038	-0.334*
	(0.086)	(0.115)	(0.118)	(0.080)	(0.079)	(0.111)	(0.125)	(0.091)	(0.175)
EPL*DB	0.067	0.200	-0.141	0.118	0.210*	0.220	0.208	0.212	0.490*
	(0.105)	(0.125)	(0.164)	(0.116)	(0.125)	(0.157)	(0.183)	(0.158)	(0.261)
Constant	0.054*	0.024	0.174***	0.035	-0.015	0.196**	0.236	0.069	0.737**
	(0.032)	(0.028)	(0.055)	(0.066)	(0.066)	(0.081)	(0.184)	(0.160)	(0.345)
Obs.	1,083	1,050	1,050	772	749	749	152	150	150
R^2	0.072	0.101	0.036	0.117	0.198	0.061	0.166	0.288	0.214

Note: All variables are in logs. Standard errors clustered at the country-industry level. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. w refers to average gross annual wages, p to the price of materials, GO to gross output, IP to import penetration, EPL to 'strict' employment protection legislation, IIM^T to total offshoring, IT to information technology, CT to communications technology, and DB to software and databases.

Table 10. Employment effect (manufacturing): total offshoring and employment protection – regular contracts

	3-year differences (D3)			5-year differences (D5)			9-year differences (D9)		
	total	typical	atypical	total	typical	atypical	total	typical	atypical
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
w	-0.050	-0.190	0.042	0.091	0.462*	-0.063	0.106	0.397	-0.621**
	(0.101)	(0.166)	(0.099)	(0.216)	(0.262)	(0.129)	(0.416)	(0.378)	(0.262)
p	-0.190	-0.433**	-0.055	-0.306	-0.280**	0.041	-0.239	0.184	0.765
	(0.174)	(0.220)	(0.181)	(0.213)	(0.128)	(0.209)	(0.320)	(0.330)	(0.529)
GO	0.289	0.500***	0.222	0.245	0.312***	-0.026	0.093	0.181	-0.712*
	(0.176)	(0.142)	(0.230)	(0.162)	(0.109)	(0.212)	(0.275)	(0.308)	(0.424)
IP	-0.022	0.245	-0.542	-0.580	-0.378	-0.944	-0.370	0.299	0.093
	(0.400)	(0.450)	(0.617)	(0.520)	(0.480)	(0.592)	(0.737)	(0.444)	(0.719)
EPL	0.094	0.134**	-0.055	0.215	0.307***	-0.170	0.146	-0.571***	-0.377
	(0.077)	(0.060)	(0.079)	(0.146)	(0.095)	(0.131)	(0.223)	(0.164)	(0.278)
IIM^T	-0.132	-0.367	0.263	0.232	0.026	0.438	0.041	-0.600	-0.530
	(0.386)	(0.393)	(0.625)	(0.456)	(0.400)	(0.621)	(0.640)	(0.396)	(0.743)
$EPL*IIM^T$	0.066	-0.197	1.031**	0.423	0.257	1.313***	0.332	-0.085	1.540
	(0.253)	(0.284)	(0.447)	(0.400)	(0.303)	(0.484)	(0.773)	(0.610)	(1.132)
RD	-0.224***	-0.212***	-0.086	-0.209***	-0.211***	-0.037	-0.198***	-0.197***	-0.229***
	(0.070)	(0.059)	(0.085)	(0.060)	(0.048)	(0.070)	(0.052)	(0.056)	(0.073)
EPL*RD	-0.367***	-0.416***	-0.108	-0.330***	-0.274***	-0.263**	-0.120	-0.160	-0.055
	(0.112)	(0.129)	(0.132)	(0.109)	(0.102)	(0.129)	(0.116)	(0.105)	(0.198)
Constant	0.018	0.041	0.179**	0.021	-0.039	0.246**	0.247	-0.058	0.469*
	(0.042)	(0.038)	(0.076)	(0.071)	(0.077)	(0.111)	(0.180)	(0.154)	(0.264)
Obs.	576	547	547	405	384	384	75	71	71
R^2	0.543	0.534	0.081	0.557	0.649	0.127	0.574	0.704	0.431

Note: All variables are in logs. Standard errors clustered at the country-industry level. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. w refers to average gross annual wages, p to the price of materials, GO to gross output, IP to import penetration, EPL to 'strict' employment protection legislation, IIM^T to total offshoring and RD to robot density.

Table 11. Employment effect (total economy): total offshoring and employment protection – temporary contracts

	3-year differences (D3)			5-year differences (D5)			9-year differences (D9)		
	total	typical	atypical	total	typical	atypical	total	typical	atypical
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
w	-0.100	-0.059	0.083	0.163	0.310	-0.072	0.019	0.238	-0.205
	(0.125)	(0.141)	(0.069)	(0.177)	(0.206)	(0.084)	(0.284)	(0.282)	(0.178)
p	-0.246	-0.286	0.198	-0.311	-0.087	0.077	-0.250	-0.078	-0.114
	(0.196)	(0.262)	(0.189)	(0.229)	(0.155)	(0.169)	(0.283)	(0.262)	(0.353)
GO	0.564***	0.836***	0.103	0.497***	0.660***	0.171	0.493*	0.869***	0.376
	(0.150)	(0.211)	(0.230)	(0.155)	(0.171)	(0.174)	(0.291)	(0.267)	(0.369)
IP	-0.640**	-0.246	-1.726***	-0.589	-0.202	-0.122	-0.175	0.203	-1.636
	(0.315)	(0.410)	(0.627)	(0.526)	(0.435)	(0.538)	(0.628)	(0.515)	(1.295)
EPL	-0.041	-0.059*	0.006	0.040	-0.043	0.063	-0.153	-0.370***	-0.208
	(0.037)	(0.033)	(0.067)	(0.085)	(0.068)	(0.107)	(0.145)	(0.143)	(0.208)
IIM^T	0.584*	0.215	1.651***	0.375	-0.059	0.161	-0.113	-0.368	1.274
	(0.307)	(0.393)	(0.593)	(0.530)	(0.419)	(0.517)	(0.625)	(0.488)	(1.284)
EPL*IIM^T	0.102	0.123	-0.171	0.205	0.420**	0.184	0.491*	0.512**	0.094
	(0.107)	(0.135)	(0.319)	(0.162)	(0.172)	(0.201)	(0.288)	(0.254)	(0.472)
IT	0.037	0.003	0.079	0.033	0.028	0.040	-0.092	-0.060	-0.129*
	(0.041)	(0.042)	(0.049)	(0.035)	(0.034)	(0.044)	(0.058)	(0.047)	(0.076)
EPL*IT	-0.001	0.036	-0.184*	0.004	0.011	-0.033	0.015	-0.054	0.087
	(0.056)	(0.059)	(0.104)	(0.069)	(0.072)	(0.095)	(0.108)	(0.100)	(0.113)
CT	-0.003	0.005	-0.016	0.006	-0.017	-0.027	0.075	0.018	0.124
	(0.033)	(0.032)	(0.054)	(0.033)	(0.031)	(0.050)	(0.059)	(0.053)	(0.080)
EPL*CT	0.047	0.025	0.103	0.102	0.092	0.165**	0.142	0.187**	0.094
	(0.057)	(0.070)	(0.087)	(0.073)	(0.084)	(0.083)	(0.096)	(0.094)	(0.159)
DB	-0.014	0.015	0.003	-0.029	-0.000	0.082	0.004	0.076	-0.008
	(0.053)	(0.052)	(0.089)	(0.064)	(0.053)	(0.065)	(0.076)	(0.061)	(0.104)
EPL*DB	-0.055	-0.103	0.243	0.003	-0.064	0.006	-0.068	-0.167	-0.221
	(0.098)	(0.099)	(0.179)	(0.135)	(0.122)	(0.174)	(0.200)	(0.186)	(0.303)
Constant	0.067**	0.034	0.155***	0.062	-0.009	0.113	0.168	-0.033	0.616*
	(0.032)	(0.029)	(0.053)	(0.066)	(0.063)	(0.082)	(0.175)	(0.150)	(0.324)
Obs.	1,083	1,050	1,050	772	749	749	152	150	150
R^2	0.071	0.099	0.041	0.119	0.202	0.045	0.174	0.292	0.193

Note: All variables are in logs. Standard errors clustered at the country-industry level. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. w refers to average gross annual wages, p to the price of materials, GO to gross output, IP to import penetration, EPL to 'strict' employment protection legislation, IIM^T to total offshoring, IT to information technology, CT to communications technology, and DB to software and databases.

Table 12. Employment effect (manufacturing): total offshoring and employment protection – temporary contracts

	3-year differences (D3)			5-year differences (D5)			9-year differences (D9)		
	total	typical	atypical	total	typical	atypical	total	typical	atypical
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
w	-0.020	-0.147	0.025	0.205	0.553*	-0.063	0.142	0.388	-0.593**
	(0.117)	(0.174)	(0.091)	(0.213)	(0.296)	(0.124)	(0.382)	(0.403)	(0.297)
p	-0.119	-0.360	0.040	-0.268	-0.222	0.157	-0.014	0.364	1.061**
	(0.176)	(0.278)	(0.166)	(0.242)	(0.148)	(0.225)	(0.368)	(0.384)	(0.521)
GO	0.241**	0.490***	0.229	0.191	0.316***	-0.007	-0.076	0.068	-0.914**
	(0.118)	(0.144)	(0.223)	(0.139)	(0.118)	(0.227)	(0.335)	(0.344)	(0.454)
IP	0.332	0.687	-0.200	-0.306	-0.131	-0.366	-0.264	0.351	0.351
	(0.435)	(0.458)	(0.710)	(0.502)	(0.402)	(0.722)	(0.673)	(0.427)	(0.792)
EPL	0.103	-0.248***	-0.052	0.209	-0.225**	0.063	0.117	0.152	-0.421
	(0.075)	(0.071)	(0.094)	(0.154)	(0.097)	(0.147)	(0.242)	(0.148)	(0.414)
IIM^T	-0.650	-1.149**	-0.091	0.114	-0.154	-0.310	0.305	-0.760	0.206
	(0.516)	(0.523)	(0.822)	(0.681)	(0.443)	(0.810)	(0.789)	(0.499)	(1.030)
EPL*IIM^T	0.168	0.375	0.338	-0.393	-0.239	0.552	-0.573	-0.055	-0.895
	(0.251)	(0.268)	(0.386)	(0.404)	(0.263)	(0.417)	(0.504)	(0.428)	(0.968)
RD	-0.301***	-0.326***	-0.072	-0.267***	-0.252***	-0.091	-0.243***	-0.259***	-0.267***
	(0.076)	(0.084)	(0.077)	(0.068)	(0.051)	(0.070)	(0.089)	(0.077)	(0.082)
EPL*RD	-0.215	-0.152	-0.144	-0.200	-0.152	-0.051	-0.021	-0.035	0.071
	(0.142)	(0.153)	(0.124)	(0.145)	(0.125)	(0.142)	(0.134)	(0.116)	(0.232)
Constant	-0.022	-0.014	0.159**	-0.035	-0.092	0.169	0.170	-0.143	0.363
	(0.041)	(0.034)	(0.078)	(0.066)	(0.076)	(0.120)	(0.177)	(0.162)	(0.266)
Obs.	576	547	547	405	384	384	75	71	71
R^2	0.497	0.475	0.076	0.524	0.629	0.093	0.569	0.693	0.422

Note: All variables are in logs. Standard errors clustered at the country-industry level. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. w refers to average gross annual wages, p to the price of materials, GO to gross output, IP to import penetration, EPL to 'strict' employment protection legislation, IIM^T to total offshoring and RD to robot density.

2.6. Endogeneity

We discussed in Section 2.1 several endogeneity issues – either related to the correlation of our key variables of interest (offshoring, technological change) with exogenous industry-level demand (and/or productivity) shocks or to their potential interrelation. We addressed these by separate IV estimations. We use a standard IV approach for total employment and a multi-equations GMM approach for typical and atypical employment, and assess the relevance of the instruments, using the results from the first-stage IV regression.[18] Because our IV models are just-identified, the instruments' exogeneity cannot be identified.

2.6.1. Correlation of offshoring and technological change with exogenous shocks

Regarding offshoring (see Table 13), which utilises a shift-share instrument based on the augmented composition of intermediate imports from various developing countries three years before the estimation period, we found for the total sample highly relevant instruments ($p<0.05$) across all differencing periods, which are also quite strong, but only in the short term. For manufacturing, the instruments are relevant ($p<0.05$) although not particularly strong in the short run, but irrelevant and weak in the longer run. By and large, this also holds for both types of employment. Moreover, the Wu-Hausman tests for endogeneity are all significant, indicating that offshoring is endogenous. However, in the case of invalid/weak instruments, this test needs to be interpreted with caution. We find that addressing the endogeneity of offshoring leaves our results for total employment qualitatively unchanged: in the case of relevant and strong instruments (only for the total sample and the short run, i.e. D3), offshoring increases the demand for total employment. The coefficients for typical and atypical employment are insignificant.

Concerning technological change (see Table 14 and Table 15), which we instrumented by averaging the respective variable in other advanced countries in the sample (excluding the reporting country), our results were again mixed. In general, we do not find valid instruments for either of the three ICT asset types, either for total employment or by type of employment. Conversely, our instrument for robot density performs slightly better: it is relevant ($p<0.05$) in the short to medium run, but rather weak.

[18] We only report the most relevant information here. The full results are reported in Table A.6 to Table A.9 in the Annex.

Table 13. Instrumental variable results for endogenous offshoring: total economy and manufacturing

	3-year differences (D3)			5-year differences (D5)			9-year differences (D9)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	total	typical	atypical	total	typical	atypical	total	typical	atypical
Total economy									
IIM^T	9.526**	8.272*	14.909	8.763*	6.357	8.021	11.732	2.448	0.777
	(4.185)	(4.759)	(9.959)	(4.785)	(3.934)	(5.964)	(8.188)	(2.428)	(9.114)
Obs.	1,083	1,050	1,050	772	749	749	152	150	150
R^2	-0.820			-0.754			-1.531		
Underid.	11.38***			9.165***			4.461**		
K-P	18.480			12.970			4.455		
W-H	6.125**			4.368**			4.833**		
I-IIM^T		0.117***	0.106***		0.132***	0.150***		0.154	0.138
Manufacturing									
IIM^T	7.158*	11.076	15.628	13.150	17.728	8.220	-4.696*	-6.616*	14.338
	(4.184)	(9.725)	17.739	(9.979)	(17.296)	(10.609)	(2.786)	(3.575)	(27.422)
Obs.	576	547	547	405	384	384	75	71	71
R^2	-0.107			-1.232			0.229		
Underid.	5.042**			2.180			2.922*		
K-P	8.123			2.751			2.858		
W-H	7.012***			5.242**			9.790***		
I-IIM^T		0.137***	0.083		-0.010	-0.010		0.514*	0.432

Note: All variables are in logs. Standard errors clustered at the country-industry level. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. All regressions also include the usual controls (i.e. the wage rate, the price of materials, real gross output, import penetration, IT, CT and DB for the total economy sample, robot density for the manufacturing sample). IIM^T refers to total offshoring. Underid. refers to the underidentification test, K-P to the Kleinbergen-Paap rk Wald F statistic and W-H to the Wu-Hausman test. In the first-stage regression, a shift-share instrument based on the augmented composition of intermediate imports from different developing countries three years prior to the estimation period was used (see Section 2.1 for details). I-IIM^T refers to this instrument.

Table 14. Instrumental variable results for endogenous capital asset types: total economy

	3-year differences (D3)			5-year differences (D5)			9-year differences (D9)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	total	typical	atypical	total	typical	atypical	total	typical	atypical
IT	0.264	-0.320	-0.209	-0.045	-0.345	0.169	-0.578	-0.470	-0.481
	(0.358)	(2.230)	(1.595)	(0.479)	(0.881)	(0.779)	(1.153)	(0.946)	(0.714)
CT	0.147	0.721	-0.062	0.667	0.377	-0.851	0.319	-0.577	-0.384
	(0.443)	(2.229)	(1.658)	(0.761)	(1.244)	(1.992)	(1.300)	(1.080)	(0.686)
DB	-0.173	0.624	0.378	0.208	1.274	1.081	3.234	2.582	1.453
	(0.505)	(1.778)	(1.637)	(0.665)	(1.079)	(1.165)	(3.590)	(2.913)	(1.461)
Obs.	1,083	1,050	1,050	772	749	749	152	150	150
R^2	-0.107			-1.180			-10.706		
Underid.	1.361			1.359			0.746		
K-P	0.458			0.451			0.223		
W-H	3.097			5.326			10.39**		
I-IT		-0.260	-0.249		-0.323	-0.286		-0.327	-0.323
I-CT		-0.305**	-0.386***		-0.327*	-0.381**		-0.229	-0.262
I-DB		0.273	0.239		0.344	0.295		0.218	0.162

Note: All variables are in logs. Standard errors clustered at the country-industry level. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. All regressions also include the usual controls (i.e. the wage rate, the price of materials, real gross output, import penetration, and total offshoring) as well as a constant. IT refers to information technology, CT to communications technology, DB to software and database. Underid. refers to the underidentification test, K-P to the Kleinbergen-Paap rk Wald F statistic and W-H to the Wu-Hausman test. In the first-stage regression, the average of all available more advanced economies in Europe is used for each of the three instruments: IT, CT and DB (see Section 2.1 for details). I-IT, I-CT and I-DB refer to these instruments.

Table 15. Instrumental variable results for endogenous robot density: manufacturing

	3-year differences (D3)			5-year differences (D5)			9-year differences (D9)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	total	typical	atypical	total	typical	atypical	total	typical	atypical
RD	-0.092	-0.063	-0.132	-0.095	0.014	-0.217	7.051	0.906	-0.660
	(0.154)	(0.127)	(0.233)	(0.139)	(0.110)	(0.216)	(79.270)	(1.091)	(0.449)
Obs.	520	491	491	365	344	344	67	63	63
R^2	0.274			0.376			-106.843		
Underid.	5.636**			6.229**			0.008		
K-P	9.094			11.67			0.007		
W-H	3.630*			2.589			2.242		
I-RD		0.738***	0.867***		0.766***	0.818***		-0.021	0.352

Note: All variables are in logs. Standard errors clustered at the country-industry level. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. All regressions also include the usual controls (i.e. the wage rate, the price of materials, real gross output, import penetration, and total offshoring) as well as a constant. RD refers to robot density (i.e. the stock of robots per 1,000 employees). Underid. refers to the underidentification test, K-P to the Kleinbergen-Paap rk Wald F statistic and W-H to the Wu-Hausman test. In the first-stage regression, the average robot density in all other advanced countries in the sample (excluding the one for which the instrument is calculated) is used as instrument (see Section 2.1 for details). I-RD refers to this instrument.

2.6.2. Interrelationship between offshoring and technological change

Regarding the possible interactions of the variables of interest, we use the results from the first-stage IV regressions for offshoring and technological change (IT, CT, DB and robot density) to draw our inferences. These results are particularly suitable as they show the relationship (respective coefficient and its level of significance) between the two key variables (when an endogenous variable is regressed on its instrument(s) plus all the other variables), in addition to testing the relevance of the instruments.[19]

As for technological change, the results depend on the measure of technological change used. In the case of the three ICT asset types (IT, CT and DB) that we used for the total sample, we did not find any significant relationships with offshoring for total employment and by type of employment. In the case of robot density, which we used for the manufacturing sample, we find that robot density and offshoring are negatively related, suggesting that, possibly in response to rising labour costs in offshoring destination countries or the need for shorter/more flexible supply chains, firms find it cheaper to automate certain production processes rather than to move and operate part of their production abroad (Carbonero et al., 2018).

[19] For the sake of brevity, results are not reported here but are available from the authors upon request.

3. Technology adoption and involuntary atypical employment in the EU

3.1. Atypical employment definition

The primary source of information on atypical employment comes from the data provided in large-scale representative surveys. Several recent studies use country-specific sources of information to study a distinct relationship, which is rarely found in most countries - e.g. zero-hour contracts in the UK (Eichhorst and Marx, 2015; Farina et al., 2021). However, using these data allows us to draw limited conclusions on specific forms of atypical employment and its consequences. On the contrary, in this study, we aim to provide general findings for the European Countries. We use the EU Labour Force Survey (EU-LFS) to define involuntary forms of atypical employment. The EU-LFS is the main cross-country survey in the EU that provides data on employment outcomes, covering all workers. It allows us to explore the cross-country differences in the change of involuntary atypical employment. Yet, this limits the scope of the analysis due to a lack of information about all forms of non-standard employment in EU-LFS (see detail in Figure 5).

Figure 5. Atypical Employment definitions and data availability

Atypical Employment		
Involuntary	**Preference-based**	**Not avaliable in the data**
• Involuntary-part-time employment • Fixed-term contract • Underemployment	• Temporary agency work • Part-time employment • Marginal part-time employment • Self-employment	• Bogus self-employment/ Freelancing • Zero heour contract

Note: We outline our set of atypical employment definitions based on the European Parliament's Committee on Employment and Social Affairs policy report, which addresses work precariousness and highlights several definitions of atypical employment (Broughton et al., 2016).
Source: Own elaboration.

We define *involuntary* part-time employment as a contract involving individuals to work less than 30 hours[20] per week, assuming one wanted to work full-time but could not find such a job. For fixed-term

[20] The LFS distinguishes between usual and actual hours worked. To define part-time workers, we refer to the usual hours as the standard schedule of individuals' working hours. However, we use actual hours for individuals whose working hours vary, as no information on usual hours is available.

employment, we use the definition of all employees on fixed-term contracts who want a contract not constrained by time. Finally, we refer to underemployment if an employee wishes to work more than currently. To define the outcome, we used the usual hours from the survey rather than the actual hours. We focus on usual hours because many employees stated zero working hours, which can be correlated with holidays and paid leaves. For the analysis, we use a pooled definition of involuntary atypical employment. In other words, we look at whether an individual worked in any of the atypical forms of employment forms illustrated in the left panel of figure 5. The drawback of the EU-LFS data is its cross-sectional character, which limits the possibility of a direct study of shifts from typical to atypical employment of individual respondents. To tackle this issue, we use the 'demographic group' framework – we aggregate data by education (Higher, Middle, Low), age group (20-29, 30-39, 40-49, 50-59, 60+) and gender (M, F) (Acemoglu and Restrepo, 2022; Doorley et al., 2023). We use long differences of the employment rates between 2006 and 2018, which may better reflect the complexity of the relationship between technology adoption and involuntary atypical employment.

Our analysis covers the following thirteen countries: Belgium, Czechia, Germany, Estonia, France, Greece, Hungary, Italy, Lithuania, the Netherlands, Romania, Spain, Sweden. We combine two editions of the EU-LFS for the years 2006 and 2018. Our outcome is defined as the percentage point difference in the share of workers in involuntary non-standard employment.

3.2. Measure of technological displacement

We first identify the adoption of technologies that can substitute for human's work to study the impact of technology on atypical employment. We use two sources of technology, namely industrial robots used in many studies, especially on routine-manual occupations (Acemoglu and Restrepo, 2020; Albinowski and Lewandowski, 2024; Antón et al., 2020), as well as Software & Databases, which among the ICT technologies were found to shift workers from abstract to more routine tasks (Almeida et al., 2020).

We combine the data from International Federation of Robotics (IFR) on operational stock of robots as well as EU KLEMS data on net capital stock in Software & Databases technology. Because technology usually can substitute for routine tasks, we use the survey-based classification developed by Lewandowski et al. (2022) including harmonised task measures of non-routine and routine tasks. We use the measures of occupational routine task specialisation to reweight the demographic group exposure to technological adoption. However, standard EU-LFS does not cover detailed information on occupations. Thus, we use EU Structure of Earnings Survey (EU-SES) to properly calculate the exposure to technology adoption.

We start constructing the measure of technology adoption on country-industry level. Following the methodology provided by Acemoglu & Restrepo (2020), for each industry sector i in country c we define the adjusted penetration of robots[21] as:

$$\mathrm{AP\_Tech}_{\mathrm{i,c}} = \frac{\mathrm{M_{i,c,2018}} - \mathrm{M_{i,c,2006}}}{\mathrm{L_{i,c,2006}}} - \frac{\mathrm{Y_{i,c,2018}} - \mathrm{Y_{i,c,2006}}}{\mathrm{Y_{i,c,2006}}} * \frac{\mathrm{M_{i,c,2006}}}{\mathrm{L_{i,c,2006}}}, \quad (7)$$

where:

- $\mathrm{M_{i,c,t}}$ – stands for the industrial robots operational stock in industry i in country c in $t - th$ year;
- $\mathrm{L_{i,c,t}}$ – stands for the number of employees in the industry i in country c in $t - th$ year;
- $\mathrm{Y_{i,c,t}}$ – stands for the total output of industry i in country c in $t - th$ year.

In contrast to standard measures assessing technological penetration, such as the quantity change in the robots per worker, our analysis also incorporates changes in the sectors' gross output. By accounting for changes in gross output, we measure the increase in technological adoption within the specified sector, compared to the increase in technology adoption caused by increased output and employment. The positive values of adjusted technology penetration show a larger increase in the technology stock than in the industry's size.

We further aggregate the adjusted technology penetration to transform the variable from industry- to demographic group level. We refer to the treatment variable as the total displacement adjusted (TDA) of technology, as it sums up the reweighted exposure of the demographic group to a given technology. We calculate the TDA of the demographic group g in country c resulting from the automation as:

$$\mathrm{TDA}_{\mathrm{g,c}} = \sum_{i \in I} \omega_{g,c}^{i} * \frac{\omega_{g,i,c}^{R}}{\omega_{i,c}^{R}} \, \mathrm{IHS}(\mathrm{AP}_{\mathrm{Tech}})^{22}{}_{\mathrm{i,c}}, \quad (8)$$

[21] To ease the reading, we describe the construction of the measure only for Industrial Robots. However, it can be done similarly for software and database net capital stock.

[22] Because of the negative values of the technological treatment, we apply inverse hyperbolic sine transformation (IHS). When the transformed variable is relatively large, the IHS transformation can be interpreted in the same manner as the logarithm.

where:

- $\omega_{g,c}^{i}$ – refer to the share of demographic group g employed in industry i in country c;
- $\frac{\omega_{g,i,c}^{R}}{\omega_{i,c}^{R}}$ – represents the relative share of routine workers of demographic group g in industry i in relation to all routine workers in industry i in country c.

Thus, the variation of the obtained variable comes from demographic groups' differences in technology adoption and employment structure. Similarly, we construct the total displacement for other sources of capital (Information and Communication Technology), which we further use as controls during analysis.

3.3. Measure of labour protection

Institutional factors can sometimes offset the negative influence of the changes in the labour market. As mentioned in the introduction, there is evidence showing that trade unions can effectively reduce the negative effect of the technology. However, neither EU-LFS nor EU-SES includes information on the individual membership to a trade union. Thus, we aggregate the 2006, 2008 and 2010[23] releases of the European Social Survey (ESS) to the demographic group level. In the analytical part, we interact the membership of a demographic group in a trade union with its exposure to technology to assess the possible mitigating effect. Since ESS has small sample size, we use the data on union density from OECD/AIS[24] database as a robustness check.

3.4. Effect of Software and Industrial Robots on atypical employment

We estimate the following equation to disentangle the impact of technology adoption on the change in atypical employment:

$$\Delta \mathrm{AE}_{\mathrm{g,c}} = \beta_{\mathrm{Soft}} \mathrm{TDA}_{\mathrm{Soft}_{\mathrm{g,c}}} + \beta_{\mathrm{Robots}} \mathrm{TDA}_{\mathrm{Robots}_{\mathrm{g,c}}} + \beta_{\mathrm{SoftTrade}} \mathrm{TDA}_{\mathrm{Soft}_{\mathrm{g,c}}} * \mathrm{TradeUnion} + \beta_{\mathrm{Robots}_{\mathrm{Trade}}} \mathrm{TDA}_{\mathrm{Robots}_{\mathrm{g,c}}} * \mathrm{TradeUnion} + \delta \mathrm{X}_{\mathrm{g,c}} + \alpha_{age_{g,c}} + \alpha_{gender_{g,c}} + \alpha_{country_{g,c}} + \varepsilon_{\mathrm{g,c}} \tag{9}$$

[23] In ESS not all countries from the sample were found in 2006 release. As can be seen in the OECD data, trade union density does not change significantly in short term, which allows us to extend the analysis period. Thus, we use the three releases of the data to end with indicator of the demographic group membership to the trade union.

[24] Not shown here but available from the authors upon request.

where $\Delta AE_{g,c}$ stands for the change in the share of employees in (any) involuntary atypical employment of a demographic group g in the country c between 2006 and 2018. $X_{g,c}$[25] is a matrix of controls, which includes the share of employees working in manufacturing (on the demographic group level), industry shifters (change in real value added of industries weighted by demographic groups employment) and trade union density. The alphas stand for the fixed effects of age-groups, gender and country, which account for demographic group-specific for non-standard employment demand factors.

Technology adoption is complex and may be endogenous in the equation listed above. In particular, the change in Industrial Robots and Software & Databases adoption may come from unobserved factors that also affected the change in involuntary atypical employment (e.g. financial crisis). To account for the endogeneity bias, we employ GMM-IV estimation. In each case, we generalise the "technology frontier" instrument previously applied in several works in labour economics (Acemoglu and Restrepo, 2020; Albinowski and Lewandowski, 2024; Dauth et al., 2021). However, instead of choosing a fixed rate of countries, for each sector we look for country with the highest penetration of industrial robots and/or Software & Databases. We refer to the applied instrument as the envelope instrument, in relation to the envelope theorem. In other words, our instrument mimics the behaviour of firms who adjust the technology adoption based on the technological leaders (Table A.11 in the Appendix depicts the industries used for the instrument).

$$\mathrm{AP\_Tech}_i^{IV} = \max_{c \in C} \mathrm{AP\_Tech}_{i,c} \tag{10}$$

Among the group of countries used for the 'envelope' instrument, only 6 out of 21 countries were out-of-the-sample in terms of Software & Database. It means that in majority the technological leaders in terms of software were usually countries studied in the analysis. In the highest majority, 10 out of 21 sectoral information on Software & Databases (those with highest exposure in the industry) was from the Netherlands. For industrial robots, 9 out of 16 sectoral information was out-of-sample, while 4 was from the Netherlands. Since the results can be contaminated by the overrepresentation of the Netherlands in

[25] We have used LASSO regression as a variable-selection model. The final results do not include change in gross output between 2008 and 2009 (Financial Crisis proxy) and the exposure to net capital stock in research & development. We have set country, gender and age fixed effects, robots and software & databases displacement, trade union density and industry shifters as variables that cannot be excluded.

the instrument, we also estimate 2SLS model with a fixed out-of-sample European countries (Austria, Denmark, Finland, Slovenia).

We use the results from 2SLS estimation to assess the relative importance of Software & Databases, Industrial Robots and total effect in predicting the differences in demographic groups' change in involuntary atypical employment change. For that purpose, we calculate the linear prediction of the atypical employment change at a demographic group level. In a further step, we decompose the linear prediction using the approach proposed by Morduch and Sicular (2002). The share of variance explained by a variable $\boldsymbol{k}$ can be written as follows:

$$\sigma_k = \frac{cov(\beta_k x_{i,c}^k, \Delta \mathrm{AE}_{\mathrm{g,c}})}{var(\Delta \mathrm{AE}_{\mathrm{g,c}})}. \tag{11}$$

In the last part, we use k-means to cluster the effects of Industrial Robots and Software & Databases. We use clustering to see if there is any dimension in similarity between demographic groups regarding the exposure to technology. To evaluate the number of clusters, we use silhouette metrics.

3.5. Descriptive Evidence

Table 16 presents descriptive statistics of the variables used in the regression. On average, the share of employees in atypical employment has increased by 1.45 percentage points (around a 13% increase). Fixed-term contracts have increased most significantly among the chosen definitions of atypical employment (1.25 p.p), while involuntary part-time has even decreased. The sample is balanced in terms of gender. Most workers are between 40 and 59 years old and have a middle education. In Eastern–Central European countries and Italy, the share of employees with atypical employment decreased over the years (Figure 6). On the contrary, in Western Countries and Greece, the share of employees in involuntary atypical employment increased. We find the most significant change in Greece, where in 2006 the share of employees in non-standard work was one of the lowest among the countries in the sample.

Table 16. Descriptive Statistics

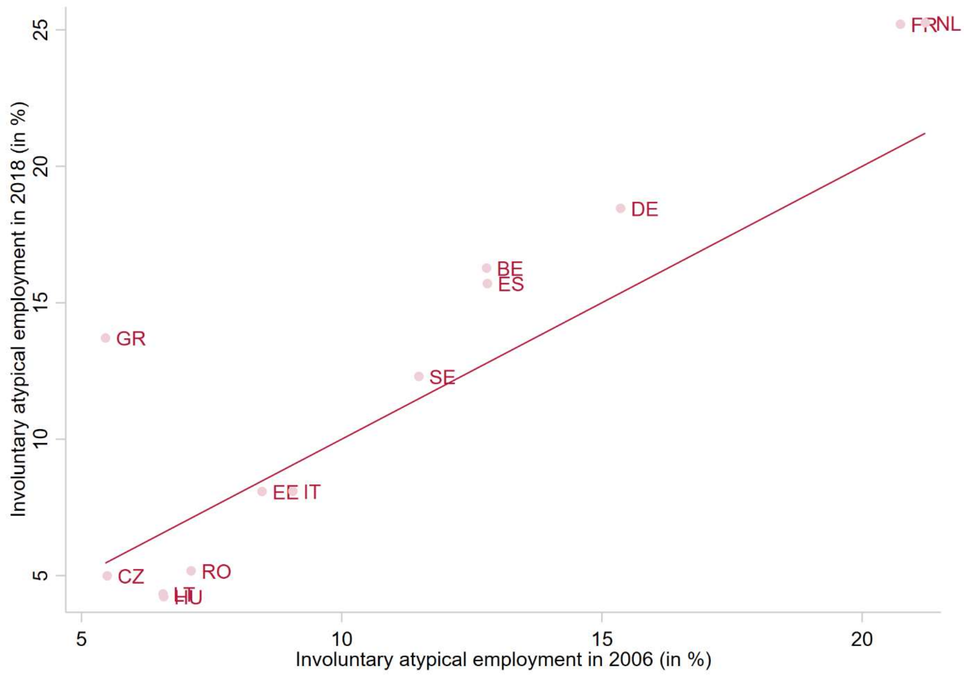
	Mean	Standard deviation	Observations
Dependent Variable			
Change in involuntary atypical employment	1.45	5.15	390
Change in involuntary part-time employment	-0.14	2.93	390
Change in involuntary fixed-time employment	1.25	2.98	390
Change in underemployment	0.60	3.77	390
Task Displacement[26]			
Penetration of Industrial Robots	0.11	0.13	390
Penetration of Software & Databases	0.08	0.12	390
Control Variables			
Gender: woman	0.50	0.50	390
Basic education	0.15	0.36	390
Secondary education	0.50	0.50	390
Tertiary education	0.35	0.48	390
Age: 20-29	0.15	0.36	390
Age: 30-39	0.22	0.41	390
Age: 40-49	0.28	0.45	390
Age: 50-59	0.26	0.44	390
Age: 60+	0.09	0.29	390
Initial atypical employment	11.01	9.31	390
Manufacture share	24.64	13.4	390
Trade Union density[27]	2.10	17.75	390
Share of natives	-2.71	6.07	390

Note: This table presents weighted means, standard deviations and the number of observations for selected variables. We weigh observations by their within-country employment shares (each country has equal weight in the analysis). Source: Own elaboration based on EU-SES, EU-LFS, ESS, EU-KLEMS and IFR.

[26] The technological displacement adjustments are presented after IHS transformation. While interpreting the results of the regression we refer to standard deviations of the variables before transformation, which is a standard mechanism when using logarithmic transformation.

[27] After subtracting mean.

Figure 6. Change in involuntary atypical employment by country

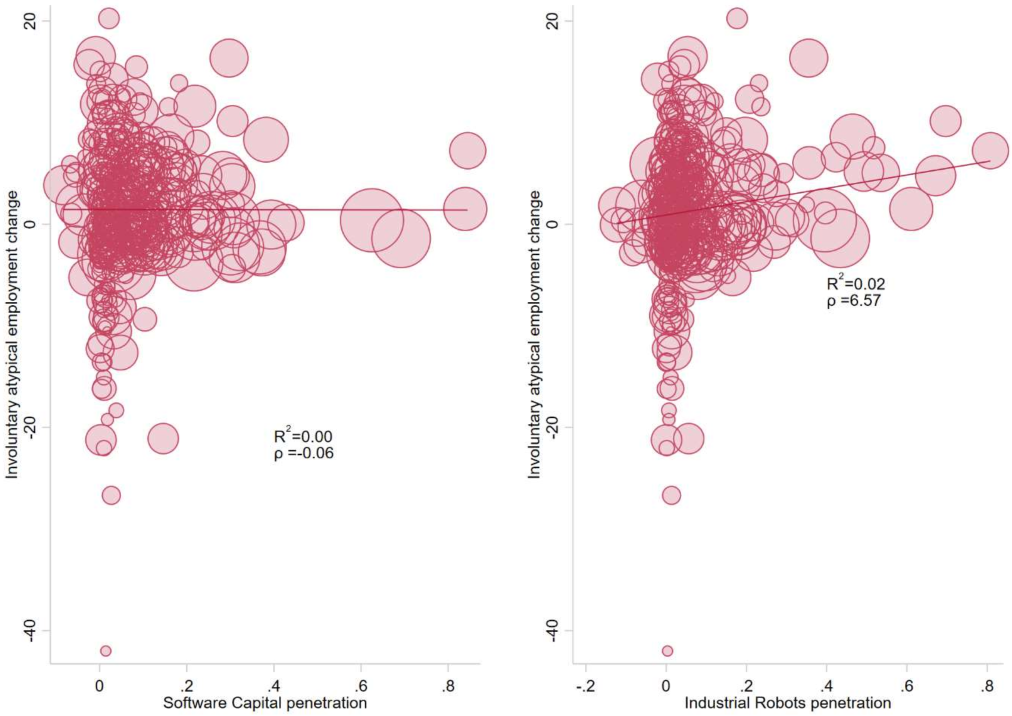


Source: Own elaboration based on EU-LFS data.

The majority of the demographic groups experienced little change in atypical employment between 2006 and 2018. Mostly, groups above 60 have seen a large decrease in atypical jobs – on average, the share of employees decreased by 3.2 percentage points. The share of employees increased more among women than men.

We plot the relationship between the penetration of software, databases, and industrial robots against the change in involuntary atypical employment (Figure 7). We find no relationship between Software & Database penetration and change in involuntary atypical employment. In contrast, a positive correlation exists between the change in employees' share in atypical employment and Industrial Robot penetration.

Figure 7. Technology penetration and change in atypical employment



Source: Own elaboration based on EU-LFS data.

3.6. Results

3.6.1. The effects of industrial robots and software & databases on involuntary atypical employment

Table 17 presents the empirical results from OLS and 2SLS estimation. We find a significant and positive association between Industrial Robots and the change in involuntary atypical employment. The results for Software & Databases are not statistically significant at the 5% level when using OLS. However, in the 5th column in the bottom panel, we find a significant impact of Software and databases when interacting the industrial robot displacement with trade union density. Nevertheless, this result is marginally statistically significant and should be interpreted with caution.

Quantitatively, one standard deviation is associated with an increase in involuntary atypical employment by 3.7 percentage points. However, strong trade unions mitigate the negative effect of industrial robots. Among the demographic groups with trade union density above 48%, an increase in industrial robot penetration does not increase atypical employment. In our sample, only 29 demographic groups reached that share: 16 groups in Sweden, 10 groups in Belgium, two groups in Romania, and 1 group in Italy.

Table 17. Technology exposure and the incidence of atypical jobs, 2006-2018

	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	OLS
Software and Databases Displacement	1.96 (2.82)	2.18 (2.83)	-1.90 (2.42)	-2.28 (2.42)	-5.19 (2.76)
Industrial Robots Displacement	8.90** (2.68)	10.19*** (2.80)	9.18*** (2.40)	7.23** (2.40)	9.77*** (2.79)
Industrial Robots Displacement x Trade Unions					-0.24** (0.08)
	2SLS	2SLS	2SLS	2SLS	2SLS
Software and Databases Displacement	6.31 (4.00)	6.38 (3.96)	-3.49 (3.34)	-6.22 (3.43)	-8.41* (4.01)
Industrial Robots Displacement	4.53 (3.43)	6.17 (3.43)	9.10** (3.00)	8.08** (3.05)	10.17** (3.62)
Industrial Robots Displacement x Trade Union					-0.29** (0.11)
Country FE	Yes	Yes	Yes	Yes	Yes
Gender FE	No	Yes	Yes	Yes	Yes
Age group FE	No	No	Yes	Yes	Yes
Industry shifters	No	No	Yes	Yes	Yes
Trade Union	No	No	Yes	Yes	Yes
Manufacture Share	No	No	No	Yes	Yes
First Stage Kleibergen-Paap F-Statistic	77.63	77.49	65.64	68.55	40.08
Mean of outcome	1.45	1.45	1.45	1.45	1.45
Mean of Software and Databases	0.11	0.11	0.11	0.11	0.11
Mean of Industrial Robots	0.08	0.08	0.08	0.08	0.08
Obs.	390	390	390	390	390

Note: *** p<0.001, ** p<0.01, * p<0.05. Standard errors in parentheses. We use standardized weights, based on EU-LFS employment structure in 2018, that give each country equal weight.
Source: own estimations based on EU-LFS, EU-SES, EU-KLEMS, ESS and IFR data.

3.6.2. The effects of industrial robots and software & databases on fixed-term employment, part-time employment and underemployment

We also run our model for detailed definitions of involuntary atypical employment - involuntary part-time, fixed-term, and underemployment. We find no statistically significant relationship between any form of technology adoption and the change in employees' share when using 2SLS. Table 18 accounts for the interaction between industrial robot displacement and trade union density. We find a marginally significant association between underemployment and displacement of industrial robots. We find that a one standard deviation increase in industrial robot displacement is associated with an increase in underemployment by 2.57 percentage points. Similarly to involuntary atypical employment, the effect of industrial robots can be mitigated by high trade union density.

Table 18. Technology exposure and involuntary part-time, fixed-term employment and underemployment, 2006-2018 – Trade Union Interactions

	Involuntary part-time	Involuntary fixed-term	Under-employment
	OLS	OLS	OLS
Software and Databases Displacement	-1.76	1.40	-5.60**
	(1.69)	(1.74)	(2.05)
Industrial Robots Displacement	4.84*	2.44	5.42*
	(2.04)	(1.83)	(2.47)
Industrial Robots Displacement x Trade Union	0.09	-0.12	-0.20*
	(0.06)	(0.06)	(0.08)
	2SLS	2SLS	2SLS
Software and Databases Displacement	-3.38	-2.15	-5.05
	(3.04)	(2.16)	(3.29)
Industrial Robots Displacement	3.44	3.09	7.02*
	(3.00)	(2.31)	(3.51)
Industrial Robots Displacement x Trade Union	0.10	-0.14	-0.26**
	(0.08)	(0.07)	(0.10)
Country FE	Yes	Yes	Yes
Other Capital Penetration	Yes	Yes	Yes
Trade Union	Yes	Yes	Yes
Manufacture Share	Yes	Yes	Yes
Gender FE	Yes	Yes	Yes
Age group FE	Yes	Yes	Yes
First Stage Kleibergen-Paap F-Statistic	40.08	40.08	40.08
Mean of outcome	-0.14	1.25	0.60
Mean of Software and Databases	0.11	0.11	0.11
Mean of Industrial Robots	0.08	0.08	0.08
Obs.	390	390	390

Note: *** p<0.001, ** p<0.01, * p<0.05. Standard errors in parentheses. We use standardized weights, based on EU-LFS employment structure in 2018, that give each country equal weight.
Source: own estimations based on EU-LFS, EU-SES, EU-KLEMS, ESS and IFR data.

3.6.3. The contribution of technology to atypical employment change

We decompose the difference between demographic groups in terms of gender and age. The share of variance explained is the highest for the younger groups, while it diminishes with age. Among women, Industrial Robots contribute more to the total effect of technology. In general, as mentioned in the previous parts, Table 19 aligns with the hypothesis that technological change influences mainly already marginalised groups—women and young workers.

Table 19. Decomposition of the cross-demographic group variance by technological displacement (% of total variance), by age group and gender

	Software & Databases	Industrial Robots & Trade Unions	Total Effect of Technology
		Females	
20-29	1.1	17.1	18.2
30-39	0.3	14.3	14.5
40-49	4.2	11.5	15.7
50-59	8.6	4.1	12.7
60+	2.9	0.3	3.2
		Males	
20-29	11.7	-0.8	10.9
30-39	8.1	-1.2	6.9
40-49	6.2	-2.4	3.8
50-59	9.1	-5.2	3.9
60+	1.3	-0.6	0.6

Note: the contributions of particular factors to involuntary atypical employment change variance, calculated in line with equation (11) using the model presented in Table 17.
Source: own estimations based on EU-LFS, EU-SES, EU-KLEMS, ESS and IFR data.

We also decompose the share of variance explained by country (Table 20). We find large differences between the countries, which do not align with Eastern-Western Europe differentiation. The highest share of variance explained by technology and trade unions covers the Netherlands (43.5%), Czechia (21.1%) and Greece (21.1%). On the contrary, in Hungary, only 1.5% of the total variance can be attributed to the total effect of the technology. Interestingly, only in Sweden the sign of the effect attributed to Software & Databases is positive.

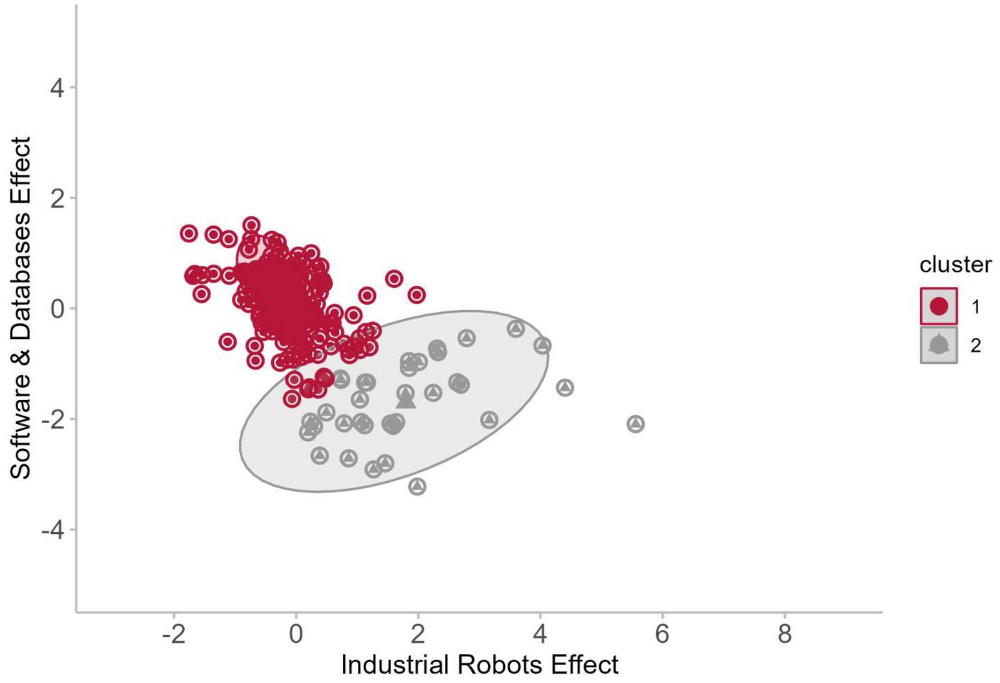
Table 20. Decomposition of the cross-demographic group variance by technological displacement (% of total variance), by country

	Software & Databases	Industrial Robots & Trade Unions	Total Effect of Technology
Belgium	-4.6	10.9	6.3
Czechia	-37.5	58.6	21.1
Estonia	-9.5	17.0	7.5
France	-1.5	8.0	6.5
Germany	-10.0	15.3	5.3
Greece	-0.8	21.9	21.1
Hungary	-16.8	18.3	1.5
Italy	-15.0	26.8	11.8
Lithuania	-21.1	13.1	-7.9
Netherlands	-19.8	63.3	43.5
Sweden	13.4	7.3	20.8

Note: the contributions of particular factors to involuntary atypical employment change variance, calculated in line with equation (11) using the model presented in Table 17.
Source: own estimations based on EU-LFS, EU-SES, EU-KLEMS, ESS and IFR data.

We cluster the effects attributed to Software & Databases and Industrial Robots. Based on silhouette metrics, we find two clusters. Figure 8 presents the clusters, where each point corresponds to one demographic group. In the first cluster, we find 351 observations – 90% of the sample. The second cluster consists of only 10% of all observations. The average effect for the first cluster is negative – on average industrial robots and software & databases reduced the share of employees in atypical employment by 0.23 percentage points. However, in the second clusters, the difference between Industrial Robots and Software & Databases effects is negative – on average, the share of employees in non-standard work increased by 0.07 percentage points. Hence, the results are generally small. In cluster 2, the effect of industrial robots is significantly higher, while the opposite happens for software & databases. Interestingly, Czechia and Hungary stood for around 60% of the second cluster.

Figure 8. Clustering of Software & Databases and Industrial Robots effects



Source: own estimations based on EU-LFS, EU-SES, EU-KLEMS, ESS and IFR data.

3.7. Robustness Check

3.7.1. Placebo regression

The result derived from the estimation above may be biased. One could argue that at the same time, as involuntary atypical employment increased, technology could have expanded in firms due to the popularisation of modern managerial techniques. In this sense, both outcome and treatment are associated with time (an increase over time), indicating a possible spurious correlation. We test this hypothesis by regressing the change in involuntary atypical employment against two unrelated variables – exposure to net capital stock in brand intellectual property and net capital stock in training. However, due to the construction of the instruments, we only compare the placebo results to OLS results. However, it should not be a problem since the OLS and 2SLS results were highly similar. Obtaining similar results, as in Table 17, would suggest our results are biased.

We only find a marginally statistically significant result in the first model, including only country-fixed effects for the Training parameter. However, after adding additional controls, the parameter loses its statistical significance.

Table 21. Robustness check – placebo regression

	(1)	(2)	(3)	(4)
	OLS	OLS	OLS	OLS
	Atypical Employment Share			
Training	-7.00*	-5.07	-4.59	0.00
	(3.31)	(2.89)	(2.91)	(2.99)
Brand Intellectual Property	-1.06	-2.84	-2.88	-2.99
	(2.19)	(1.95)	(1.96)	(1.90)
Country FE	Yes	Yes	Yes	Yes
Gender FE	No	Yes	Yes	Yes
Age group FE	No	No	Yes	Yes
Industry shifters	No	No	Yes	Yes
Trade Union	No	No	Yes	Yes
Manufacture Share	No	No	No	Yes
Mean of outcome	1.45	1.45	1.45	1.45
Mean of Training	0.00	0.00	0.00	0.00
Mean of Brand Intellectual Property	0.01	0.01	0.01	0.01
Obs.	360	360	360	360

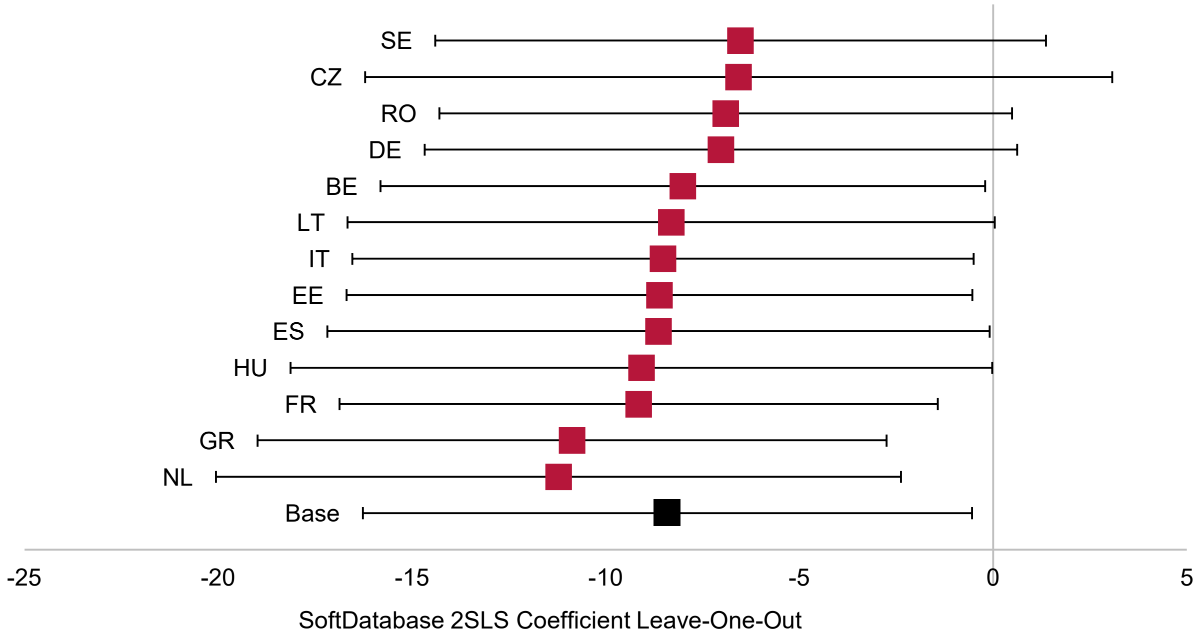
Note: *** p<0.001, ** p<0.01, * p<0.05. Standard errors in parentheses. We use standardized weights, based on EU-LFS employment structure in 2018, that give each country equal weight.
Source: own estimations based on EU-LFS, EU-SES, EU-KLEMS, ESS and IFR data.

3.7.2. Country leave-one-out

We validate the results by running 13 regressions, excluding each country from the sample to estimate the possible confounding impact of particular countries on the estimated parameters. We focus on the parameters estimated for Software & Databases and Industrial Robots' impacts on atypical employment and for trade union mitigating effect.

Figure 9 presents the parameters for Software & Databases derived from the 2SLS estimation. We find that there are no significant differences between parameters. However, when individually excluding Sweden, Belgium, Czechia, Romania, or Germany, the parameter loses its statistical significance. Nevertheless, there are no significant differences between the estimated results.

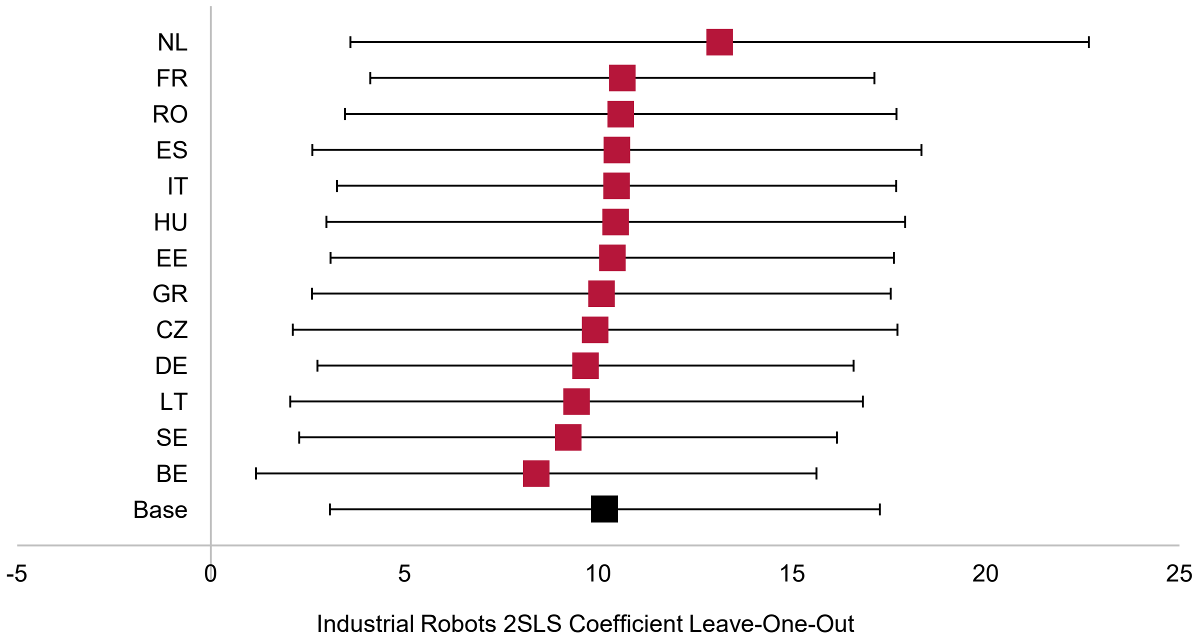
Figure 9. Country Leave-One-Out - Software & Databases



Source: own estimations based on EU-LFS, EU-SES, EU-KLEMS, ESS and IFR data.

Figure 10 presents the leave-one-out estimated parameters for Industrial Robots. In all studied countries, there are no statistical differences. On average, in the Netherlands, the estimated parameter was slightly above that of others.

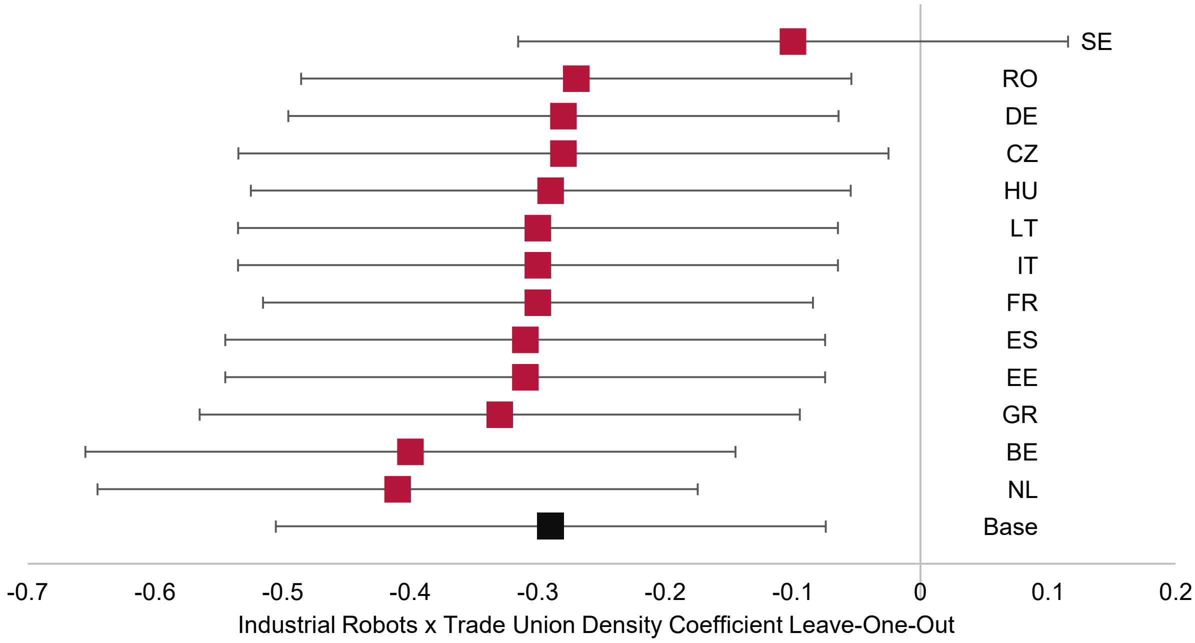
Figure 10. Country Leave-One-Out - Industrial Robots



Source: own estimations based on EU-LFS, EU-SES, EU-KLEMS, ESS and IFR data.

Finally, we determine if country exclusion would significantly change the Industrial Robots x Trade Union interaction (Figure 11). We find that Belgium and the Netherlands are fairly different from all countries except Sweden. In Sweden, the mitigating effect is not statistically significant, but it is still comparable to the parameter estimated in the base model.

Figure 11. Country Leave-One-Out - Industrial Robots x Trade Union



Source: own estimations based on EU-LFS, EU-SES, EU-KLEMS, ESS and IFR data.

3.7.3. Out-of-sample European Instrument

Our instrument was constructed based on the maximum technological penetration at the sector level. The problem in using such an instrument comes from the overrepresentation of the Netherlands in the final choice of country sectors. Thus, we use the out-of-sample instrument, which averages the technological displacement in Austria, Denmark, Finland and Slovenia – a set of countries not found in the final sample.

Table 22 presents the 2SLS results when using an out-of-sample European instrument. We find that the results are comparable to those using the envelope instrument. We find lower first-stage F-statistics for the models estimated using out-of-sample European instruments. Thus, we prefer the envelope instrument when interpreting the results, as larger first-stage f-statistic is associated with more minor standard errors of the endogenous variables' parameters. Based on the table below, we reject the hypothesis that the choice of envelope instrument contaminates the interpretation of the results.

Table 22. Robustness check – out-of-sample European instrument

	(1)	(2)	(3)	(4)	(5)
	2SLS	2SLS	2SLS	2SLS	2SLS
Software and Databases Displacement	10.53*	-0.59	-2.31	-5.91	-6.65
	(4.58)	(3.78)	(3.81)	(3.91)	(4.21)
Industrial Robots Displacement	0.92	8.54*	8.25*	8.02*	8.53*
	(3.84)	(3.36)	(3.29)	(3.37)	(3.65)
Industrial Robots Displacement x Trade Union					-0.33*
					(0.14)
Country FE	Yes	Yes	Yes	Yes	Yes
Gender FE	No	Yes	Yes	Yes	Yes
Age group FE	No	No	Yes	Yes	Yes
Industry shifters	No	No	Yes	Yes	Yes
Trade Union	No	No	Yes	Yes	Yes
Manufacture Share	No	No	No	Yes	Yes
First Stage Kleibergen-Paap F-Statistic	45.79	39.32	39.72	44.15	26.28
Mean of outcome	1.45	1.45	1.45	1.45	1.45
Mean of Software and Databases	0.11	0.11	0.11	0.11	0.11
Mean of Industrial Robots	0.08	0.08	0.08	0.08	0.08
Obs.	390	390	390	390	390

Note: *** p<0.001, ** p<0.01, * p<0.05. Standard errors in parentheses. We use standardized weights, based on EU-LFS employment structure in 2018, that give each country equal weight.
Source: own estimations based on EU-LFS, EU-SES, EU-KLEMS, ESS and IFR data.

4. Summary and conclusion

This paper has analysed the effect of offshoring and technological change on employment, in general and by type of employment, and the role of different labour market institutions in the EU. The novelty of this report lies in its focus on atypical employment and how it is affected by two key megatrends: the expansion of global supply chains – i.e. the international outsourcing, or offshoring, of production stages; and the diffusion of new technologies (robots, IT, CT and DB), which has progressed in tandem with atypical forms of employment. It also sheds light on the moderating role of the moderating role of employment protection legislation and labour market institutions such as trade unions, which has so far received little attention in this line of literature.

The paper is structured in two parts. In the first part, we have analysed the short-, medium- and longer-term employment effects of different types of offshoring and technological change in the EU, both in total as well as by type of employment in terms of typical and atypical employment. The latter was captured in terms of part-time work and temporary work (as available in the data). We have analysed two different data samples – a total economy sample (but excluding all public industries) and a smaller manufacturing sample – to identify differences between sectors. We have used the strictness of EPL and identified its moderating role in this context. In the second part, we have focused on *involuntary* atypical employment, in total and by type in terms of involuntary part-time work, involuntary fixed-term work, and underemployment (as available in the data) and have analysed the long-term effect of two specific types of technological change –automation, and software and databases – on the change in the share of involuntary atypical employment (in total and by type). Importantly, we have also identified the specific demographic groups most affected by both types of technological change, differentiated by gender and age, and have analysed the moderating effect of trade unions in this context.

The first part of our analysis shows that both offshoring and technological change had an impact on European labour markets, but their effect differed depending on the sample analysed. In the total sample, offshoring – in total, but also narrow offshoring and offshoring to developing and developed countries – has increased the demand for total employment, mainly as the result of an increase in demand for atypical employment. However, this effect was short-lived. By contrast, in the manufacturing sample, offshoring – in total and by type – had little effect on total employment, and when it did, it was negative and the result of lower demand for typical employment. This effect was also felt in the medium to long run. Hence, in line with the literature on the effects of offshoring on total employment, we find important differences between manufacturing and service industries (Landesmann and Leitner, 2023b): negative (or insignificant) employment effects in manufacturing, but positive employment effects in services. However, our analysis also shows that these changes were the result of a reduction of typical employment in manufacturing and an expansion of atypical employment in services. From a policy perspective, therefore, particular attention needs to be paid to the service sector, where atypical employment was more prevalent to begin with and has expanded more, on average, because of offshoring.

Moreover, technological change also affected labour demand. For the three ICT components, only CT capital – i.e. communications equipment – mattered in this context as an increase in CT capital increased the demand for total employment, mainly through an increase in the demand for atypical employment, making CT an important driver of atypical employment in Europe.

By contrast, robotisation has had an important labour displacement effect, mainly at the expense of typical employment. This finding is robust in the short, medium and long run. By contrast, atypical employment fell only in the long run, but then to a similar extent as typical employment. A negative overall employment effect of robotisation is also found in other studies (e.g. Acemoglu and Restrepo, 2020; Acemoglu et al., 2020; Anton et al., 2020; Chiacchio et al., 2018; Jestl, 2024) and calls for policy intervention along three lines: compensation policies that aim to financially provide for workers displaced by technology through the public provision of social protection; investment policies that aim to prepare new or retrain displaced workers (mainly medium-skilled workers) with the relevant skills needed in the labour market; and steering policies, such as taxation or labour market policies, which aim to influence the pace and direction of technological change (Bürgisser, 2023).

There are also differences between groups of countries: robotisation has reduced total employment as well as typical and atypical employment much more in the 'old' EU15 than in the 'new' EU13 member states, highlighting a greater need for policy intervention in the EU15, for both types of workers.

We also find that the strictness of EPL is important for labour demand, in general and by type of employment, but differs by the 'force' considered. Specifically, as concerns offshoring, our results show that regulation tends to dampen employment adjustments of the more protected type of employment and to encourage stronger adjustments of the less protected type of employment. Hence, the 'gap' in the strictness of employment regulations becomes important for the relative employment effect of typical and atypical workers (Centeno and Novo, 2012; Hijzen et al., 2017), calling for a balanced policy approach with similarly strict EPL for both types of workers. As regards technological change, the impact on labour demand was more nuanced and unexpected: the increase in the demand for atypical employment in response to an increase in CT capital was observed only in countries with stricter EPL. Conversely, the demand for both typical and atypical employment has fallen much more in response to increased robotisation in countries with stricter EPL than in those with weaker EPL. This only holds for EPL for temporary contracts. Hence, our results suggest that the effect of EPL depends on the 'force/megatrend' studied and is as expected in the case of offshoring but unexpected in the case of technological change, where EPL has amplified, rather than dampened, employment adjustments.

We have also attempted to deal with a number of endogeneity issues related to offshoring and technological change through the use of IV/GMM estimation techniques. Our successful IV results (i.e. when the instruments were relevant and strong) confirm our OLS-based results. Finally, we found few interrelationships between offshoring and technological change. The only exception is offshoring and robot density (in the manufacturing sample), which are substitutes, suggesting that firms may choose to automate certain production processes, rather than move and operate part of their production abroad.

The second part of the analysis shows that technology adoption can play a major role in predicting changes in the share of *involuntary* atypical employment. Women and the youngest age cohorts are particularly vulnerable to an increase in the involuntary forms of atypical employment as a result of technological change. We have also found that strong trade unions can mitigate the negative impact of industrial robots. However, in this context it is difficult to assess if sudden changes in labour protection would not end up in decreasing employment rather than shifting workers from non-standard to standard contracts. Indeed, as shown by Kostøl and Svarstad (2023), labour protection of routine workers, although beneficial for workers in routine occupations, speeds up routine-biased technological change, as the relative demand for routine work decreases as a consequence of compressing wages between routine and non-routine employment. Policy makers should therefore focus on policies that would simultaneously increase employment and reduce the share of non-standard employment – providing flexible learning opportunities, targeting middle-skilled workers.

Adult Education can increase individual's bargaining power and consequently lower the incidence of atypical employment. Doorn and Vliet (2022) shows that the change in atypical employment is moderated by participation in training or education since workers who participate in adult education, increase their bargaining power, and are therefore less likely to accept the offer (or be offered) of atypical employment. Training itself is more effective than employment opportunities, as these encourage workers to accept any employment opportunity, including part-time jobs.

As the labour market evolves, we observe increase in demand for new skills and reduction of the importance of the obsolete, automated competencies (Autor et al., 2022). In contrast to the previous period of automation, the current situation associated with the development of Artificial Intelligence may take place faster. Thus, it is important to take actions before the situation gets out of control. Autor (2024) argues that the 'AI revolution' will mainly benefit workers with sufficient skills, complementary to the use of AI tools. Hence, educational policy should focus on increasing individuals' digital skills to adapt to new technologies. However, differently than in the cases of previous technological transformations, the application of AI goes beyond the scope of industrial robots and software, as the functionalities can also influence more non-routine tasks (e.g. medical diagnosis). Thus, although policy makers should target middle-skilled employees, the education offer should include also opportunities for high-skilled workers, as these will also be exposed to artificial intelligence.

Yet, in Europe, active labour market policies fail to target the low- and middle-educated workers, as usually the highly-educated participate in training most often. As of 2022, only 25% of low- and 41.5% of middle-skilled population participated at least once in training, compared to 65.7% among high-skilled individuals. What is more, workers exposed to automation not only learn less, but also train themselves in skills that are not important from the perspective of job transition (Heß et al., 2023). The problem is especially evident in Eastern Europe[28], where the share of highly-skilled individuals participating in training is, on average, almost 3.8 times larger than those with low education. In comparison the ratio is 3.5 in Southern Europe[29], 2.7 in Western Europe[30], and 1.8 in Northern Europe[31]. Thus, Eastern European countries should prioritise their investment in training to converge towards Western Europe without precarisation of the labour market.

Despite the strand of literature on the importance of training low-skilled employees, there is scarce evidence explaining why workers with little competencies invest less in training and what can be done about it. Lower willingness to participate in training is often associated with higher school anxiety, locus of control, which could be targeted at primary educational levels (Caliendo et al., 2022; Fouarge et al., 2013; Innocenti and Golin, 2022). Besides factors on individual levels, such as financial satisfaction, it is the learning culture of the firm that can significantly influence the decision of individuals (Kyndt et al., 2013). Similarly, trade unions can positively contribute to increasing low-skilled training. Thus, building a positive learning culture in the workplace is crucial to increase the middle-skilled training rates. In response to the problem, trade unions and workers' representatives could take more active role in building the strategy of the companies, as higher representation of workers in HR bodies in the firm can increase the training in the workplace, especially among the low-skilled employees (Wotschack, 2020).

[28] Estonia, Bulgaria, Czechia, Slovakia, Latvia, Slovenia, Lithuania, Hungary, Poland, Croatia and Romania.

[29] Spain, Malta, Portugal, Cyprus, Italy and Greece.

[30] The Netherlands, France, Germany, Belgium, Austria.

[31] Sweden, Finland, Denmark and Norway.

5. References

Acemoglu, D., and Restrepo, P. (2022). Tasks, Automation, and the Rise in U.S. Wage Inequality. *Econometrica,* 90, 1973–2016.

Acemoglu, D., and Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. *Journal of Political Economy*, 128(6), 2188-2244.

Acemoglu, D., Lelarge, C., and Restrepo, P. (2020). Competing with robots: Firm-level evidence from france. *AEA Papers and Proceedings*, 110, 383-388, https://doi.org/10.1257/pandp.20201003.

Albinowski, M., and Lewandowski, P. (2024). The impact of ICT and robots on labour market outcomes of demographic groups in Europe. *Labour Economics*, 87, 102481.

Almeida, R.K., Fernandes, A.M., and Viollaz, M. (2020). Software Adoption, Employment Composition, and the Skill Content of Occupations in Chilean Firms. *The Journal of Development Studies*, 56, 169–185.

Amiti and Ekholm (2006). The effect of offshoring on employment in rigid labor markets: Evidence from EU countries. Mimeo.

Amiti, M., and Wei, S. J. (2009). Service offshoring and productivity: Evidence from the US. *The World Economy*, 32(2), 203-220, https://doi.org/10.1111/j.1467-9701.2008.01149.x.

Amiti, M. and Wei, S. J. (2006). Service offshoring, productivity and employment: Evidence from the US, CEPR Discussion Paper No. 5475 (London, Centre for Economic Policy Research).

Amiti, M., and Wei, S. J. (2005). Fear of service outsourcing: Is it justified?. *Economic Policy*, 20(42), 308-347, https://doi.org/10.1111/j.1468-0327.2005.00140.x.

Anton, J.-I., Klenert, D., Fernandez-Macias, E., Brancati, M. C. U., Alaveras, G. (2020). The labour market impact of robotisation in Europe (JRC Working Paper Series No. 2020/06). Joint Research Centre (Seville site).

Antón, J.-I., Fernández-Macías, E., and Winter-Ebmer, R. (2020). Does Robotization Affect Job Quality? Evidence from European Regional Labour Markets. SSRN Journal.

Autor, D.H., 2024. Applying AI to Rebuild Middle Class Jobs. SSRN Journal.

Autor, D., Donohue, J., and Schwab, S. (2006). The costs of wrongful-discharge laws. *Review of Economics and Statistics*, 88(2), 211-231, http://www.jstor.org/stable/40042991.

Autor, D. H., and Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the US labor market. *American Economic Review*, 103(5), 1553-1597, https://doi.org/10.1257/aer.103.5.1553.

Autor, D. H., Dorn, D., and Hanson, G. H. (2015). Untangling trade and technology: Evidence from local labour markets. *The Economic Journal*, 125(584), 621-646, https://doi.org/10.1111/ecoj.12245.

Autor, D. H., Levy, F., and Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *Quarterly Journal of Economics*, 118(4), 1279-1334, https://doi.org/10.1162/003355303322552801.

Becker, S. O., Ekholm, K., and Muendler, M-A. (2013). Offshoring and the onshore composition of tasks and skills. *Journal of International Economics*, 90(1), 91-106, https://doi.org/10.1016/j.jinteco.2012.10.005.

Blásquez Cuesta, M., and Moral Carcedo, J. (2014). Women's part-time jobs: 'Flexirisky' employment in five European countries. *International Labour Review*, 153(2), 269-292, https://doi.org/10.1111/j.1564-913X.2014.00204.x

Boeri, T., and Jimeno, J. (2005). The effects of employment protection: Learning from variable enforcement. *European Economic Review*, 49(8),2057-2077,https://doi.org/10.1016/j.euroecorev.2004.09.013.

Broughton, A., Green, M., Rickard, C., Swift, S., Eichhorst, W., Tobsch, V., Magda, I., Lewandowski, P., Keister, R., Jonaviciene, D., Ramos Martín, N.E., Valsamis, D., and Tros, F. (2016). Precarious employment in Europe: Patterns, trends and policy strategies: study.

Buddelmeyer, H., G., Mourre, and Ward-Wermedinger, M.E. (2004). Recent developments in part-time work in EU-15 countries: Trends and policy. IZA Discussion Paper No. 1415.

Bürgisser, R. (2023). Policy responses to technological change in the workplace. European Commission, Seville, JRC130830.

Cadarso, M. Á., Gómez, N., López, L. A., and Tobarra, M. Á. (2008). The EU enlargement and the impact of outsourcing on industrial employment in Spain, 1993-2003. *Structural Change and Economic Dynamics*, 19, 95-108, https://doi.org/10.1016/j.strueco.2007.11.008.

Caliendo, M., Cobb-Clark, D.A., Obst, C., Seitz, H., and Uhlendorff, A. (2022). Locus of control and investment in training. *Journal of Human Resources*, 57, 1311–1349.

Carbonero, F., Ernst, E., and Weber, E. (2018). Robots worldwide: The impact of automation on employment and trade (Working Paper No. 36). ILO.

Centeno, M., and Novo, Á. (2012). Excess worker turnover and fixed-term contracts: Causal evidence in a two-tier system. *Labour Economics*, 19(3), 320-328, https://doi.org/10.1016/j.labeco.2012.02.006.

Chiacchio, F., Petropoulos, G., Pichler D. (2018). The impact of industrial robots on EU employment and wages: A local labour market approach, Bruegel Working Paper Issue 02.

Crinò, R. (2012). Service offshoring and the skill composition of labour demand. *Oxford Bulletin of Economics and Statistics*, *74*(1), 20-57.

Crinò, R. (2010a). Service offshoring and white-collar employment. *Review of Economic Studies*, *77*, 595-632, https://doi.org/10.1111/j.1468-0084.2010.00634.x.

Crinò, R. (2010b). Employment effects of service offshoring: Evidence from matched firms. *Economics Letters*, 107(2), 253-256, https://doi.org/10.1016/j.econlet.2010.01.039.

Darvas, Z., and G. B. Wolff (2016). An anatomy of inclusive growth in Europe. Bruegel Blueprint Series, available at http://bruegel.org/2016/10/an-anatomy-of-inclusive-growth-in-europe/.

Dauth, W., Findeisen, S., Suedekum, J., and Woessner, N. (2019). The adjustment of labor markets to robots. *Journal of the European Economic Association*, 19(6), 3104-3153.

de Vries, G. J., Gentile, E., Miroudot, S., and Wacker, K. M. (2020). The rise of robots and the fall of routine jobs. *Labour Economics*, 66, 101885, https://doi.org/10.1016/j.labeco.2020.101885.

Doorley, K., Gromadzki, J., Lewandowski, P., Tuda, D., and Van Kerm, P. (2023). Automation and income inequality in Europe. IZA Discussion Paper No. 16499.

Doorn, L.V., and Vliet, O.V. (2022). Wishing for more: Technological change, the rise of involuntary part-time employment and the role of active labour market policies. *Journal of Social Policy* 1–21.

Dottori, D. (2021). Robots and employment: evidence from Italy. *Economia Politica*, 1-57, https://doi.org/10.1007/s40888-021-00223-x.

Ebenstein, A., Harrison, A., McMillan, M., Phillips, S. (2009). Estimating the impact of trade and offshoring on American workers using the current population surveys. NBER Working Paper No. 15107 (Cambridge, MA, National Bureau of Economic Research).

Eurofound (2018). Non-standard forms of employment: Recent trends and future prospects. Eurofound, Dublin, https://data.europa.eu/doi/10.2806/882537.

Feenstra, R.C., and Hanson, G. H. (1999). The impact of outsourcing and high-technology capital on wages: Estimates for the United States, 1979-1990. *Quarterly Journal of Economics*, 114(3), 907-940, https://doi.org/10.1162/003355399556179.

Foster-McGregor, N., Stehrer, R., & de Vries, G. J. (2013). Offshoring and the skill structure of labour demand, *Review of World Economics*,*149*, 631-662, https://doi.org/10.1007/s10290-013-0163-4.

Fouarge, D., Schils, T., and de Grip, A. (2013). Why do low-educated workers invest less in further training? *Applied Economics*, 45, 2587–2601.

Gaggl, P., and Wright, G. C. (2017). A short-run view of what computers do: Evidence from a UK tax incentive. *American Economic Journal: Applied Economics*, 9(3), 262-294, https://doi.org/10.1257/app.20150411.

Ghodsi, M., Reiter, O., Stehrer, R., and Stöllinger, R. (2020). Robotisation, employment and industrial growth intertwined across global value chains. wiiw Working Paper No. 177.

Goos, M., and A. Manning (2007). Lousy and lovely jobs: The rising polarization of work in Britain. *The Review of Economics and Statistics*, 89(1), 118-133, https://www.jstor.org/stable/40043079.

Goos, M., Manning, A., and Salomons, A. (2014). Explaining job polarization: routine-biased technological change and offshoring. *American Economic Review*, 104(8), 2509-2526, https://doi.org/10.1257/aer.104.8.2509.

Goos, M., Manning, A., and Salomons, A. (2009). Job polarization in Europe. *American Economic Review Papers and Proceedings*, 99(2), 58-63, https://doi.org/10.1257/aer.99.2.58.

Görg, H., and Görlich, D. (2015) Offshoring, wages and job security of temporary workers. *Review of World Economics*, 151, 533-554, https://doi.org/10.1007/s10290-015-0220-2.

Görg, H., and Hanley, A. (2005). International outsourcing and productivity: evidence from the Irish electronics industry. *The North American Journal of Economics and Finance*, *16*(2), 255-269, https://doi.org/10.1016/j.najef.2004.11.006.

Graetz, G., and Michaels, G. (2018). Robots at work. *Review of Economics and Statistics*, 100(5), 753-768, https://doi.org/10.1162/rest_a_00754.

Groshen, E.L., Hobijn, B., and McConnell, M.M. (2005). U.S. jobs gained and lost through trade: A net measure. Federal Reserve Bank of New York, Current Issues in Economics and Finance, 11(8), 1-7.

Gregory, T., Salomons, A., and Zierahn, U. (2022). Racing with or against the machine? Evidence on the role of trade in Europe. *Journal of the European Economic Association*, 20(2), 869-906, https://doi.org/10.1093/jeea/jvab040.

Haltiwanger, J., Scarpetta, S., and Schweiger, H. (2014). Cross country differences in job reallocation: The role of industry, firm size and regulations. *Labour Economics*, 26(C),11-25, https://doi.org/10.1016/j.labeco.2013.10.001.

Hamermesh, D. (1993). *Labour Demand*. Princeton. NJ: Princeton University Press.

Heß, P., Janssen, S., and Leber, U. (2023). The effect of automation technology on workers' training participation. *Economics of Education Review*, 96, 102438.

Hijzen, A., Görg, H., and Hine, R. C. (2005). International outsourcing and the skill structure of labour demand in the United Kingdom. *Economic Journal*, 115(506), 860-878, https://doi.org/10.1111/j.1468-0297.2005.01022.x.

Hijzen, A., Mondauto, L., and Scarpetta, S. (2017). The impact of employment protection on temporary employment: Evidence from a regression discontinuity design. *Labour Economics*, 46, 64-76, https://doi.org/10.1016/j.labeco.2017.01.002.

Hijzen, A., Pisu, M. Upward, R., and Wright, P.W. (2011). Employment, job turnover, and trade in producer services: UK firm-level evidence. *Canadian Journal of Economics/Revue canadienne d'conomique*, 44(3), 1020-1043, https://doi.org/10.1111/j.1540-5982.2011.01664.x.

Hijzen, A., and Swaim, P. (2010). Offshoring, labour market institutions and the elasticity of labour demand. *European Economic Review*, 54, 1016-1034, https://doi.org/10.1016/j.euroecorev.2010.04.001.

Hirsch, B. T. (2005). Why do part-time workers earn less? The role of worker and job skills. *Industrial and Labor Relations Review*, 58(4), 525-551, https://doi.org/10.1177/00197939050580.

ILO (2016). Non-standard employment around the world: Understanding challenges, shaping prospects, Geneva.

Innocenti, S., and Golin, M. (2022). Human capital investment and perceived automation risks: Evidence from 16 countries. Jo*urnal of Economic Behavior & Organization*, 195, 27–41.

Jensen, B., and Kletzer, L. G. (2005). Tradable services: Understanding the scope and impact of services offshoring. Brookings Trade Forum, Brookings Institution Press.

Jestl, S. (2024). Industrial robots, and information and communication technology: the employment effects in EU labour markets. *Regional Studies*, 1-18, https://doi.org/10.1080/00343404.2023.2292259.

Kalleberg, A. L. (2001). Organizing Flexibility: The Flexible Firm in a New Century*. British Journal of Industrial Relations*, 39(4), 479-504, https://doi.org/10.1111/1467-8543.00211.

Kiyota, K., and Maruyama, S. (2017). ICT, offshoring, and the demand for part-time workers: The case of Japanese manufacturing. *Journal of Asian Economics*, 48, 75-86, https://doi.org/10.1016/j.asieco.2016.10.007.

Koch, M., Manuylov, I., and Smolka, M. (2021). Robots and firms. *The Economic Journal*, 131(638), 2553-2584, https://doi.org/10.1093/ej/ueab009.

Kostøl, F.B., and Svarstad, E. (2023). Trade unions and the process of technological change. *Labour Economics*, 84, 102386.

Kyndt, E., Dochy, F., Onghena, P., and Baert, H. (2013). The learning intentions of low-qualified employees: A multilevel approach. *Adult Education Quarterly*, 63, 165–189.

Lakhani, T., Kuruvilla, S., and Avgar, A. (2013). From the firm to the network: global value chains and employment relations theory. *British Journal of Industrial Relations*, 51(3), 440-472.

Landesmann, M., and Leitner, S.M. (2023a) Immigration and offshoring: two forces of globalisation and their impact on employment and the bargaining power of occupational groups. *Review of World Economics*, 159, 361-397, https://doi.org/10.1007/s10290-022-00470-5.

Landesmann, M., and Leitner, S.M. (2023b). Employment effects of offshoring, technological change and migration in a group of Western European economies: Impact on different occupations, wiiw Working Paper, No. 226.

Leitner, S., Hauret, L., Holtgrewe, U., and Martin, L. (forthcoming). Offshoring, technological change and the quality of work in the EU: On the mediating role of trade unions. WeLaR Working Paper.

Lewandowski, P., Park, A., Hardy, W., Du, Y., and Wu, S. (2022). Technology, skills, and globalization: Explaining international differences in routine and nonroutine work using survey data. *The World Bank Economic Review*, 36, 687–708.

Liu, R., and Trefler, D. (2011). *A shorted tale of globalization: White collar jobs and the rise of service offshoring.* NBER Working Paper No. 17559.

Lo Turco, A., and Maggioni, D. (2012). Offshoring to high and low income countries and the labour demand. Evidence from Italian firms. *Review of International Economics*, 20(3), 636-653, https://doi.org/10.1111/j.1467-9396.2012.01043.x.

Machikita, T., and Sato, H. (2011). Temporary Jobs and Globalization: Evidence from Japan. *RIETI Discussion Paper Series* 11-E-29.

Månsson, J., and Ottosson, J. (2011). Transitions from part-time unemployment: Is part-time work a dead end or a stepping stone to the labour market? *Economic and Industrial Democracy*, 32(4), 569-589, https://doi.or10.1177/0143831X10387836.

Mäkinen, N., Tanskanen, J., Ojala, S., and Pyöriä, P. (2023). Part-time workers' employment trajectories by length of hours and reason for working part-time: An 8-Year follow-up study. *SAGE Open*, 13(4), https://doi.org/10.1177/21582440231210690.

Micco, A., Pagés, C. (2006). The economic effects of employment protection: Evidence from international industry-level data. IZA Discussion Papers, No. 2433.

Michaels, G., Natraj, A., and van Reenen, J. (2014). Has ICT polarized skill demand? Evidence from eleven countries over 25 years. *Review of Economics and Statistics*, 96(1), 60-77, https://www.jstor.org/stable/43554913.

Milberg W., and Winkler, D. (2011). Actual and perceived effects of offshoring on economic insecurity: The role of labour market regimes, in (ed. Bacchetta, M. and Jansen, M.) Making Globalization Socially Sustainable, 147-198.

Mion, G., and Zhu, L. (2013). Import competition from and offshoring to China: A curse or blessing for firms?. *Journal of International Economics*, 89, 202-215, https://doi.org/10.1016/j.jinteco.2012.06.004.

Nadvi, K. (2004). Globalisation and poverty: How can Global Value Chain research inform the policy debate? *IDS Bulletin*, 35(1), 20-30.

Nikulin, D., and Szymczak, S. (2020). Effect of the integration of global value chains on the employment contract in Central and Eastern European countries. *Equilibrium: Quarterly Journal of Economics and Economic Policy*, 15(2), 275-293.

OECD (2020). OECD Employment Outlook 2020: Worker security and the COVID-19 crisis. OECD Publishing, Paris, https://doi.org/10.1787/1686c758-en.

OECD (2007). Offshoring and employment: Trends and impacts. Organisation for Economic Co-operation and Development, Paris.

Plank, L., Rossi, A., and Staritz, C. (2012). Workers and social upgrading in 'fast fashion': the case of the apparel industry in Morocco and Romania. Austrian Foundation for Development Research (ÖFSE), *ÖFSE Working Paper* No. 33, https://www.econstor.eu/handle/10419/98794.

Rutledge, M. S., Wettstein, G., and King, S. E. (2019). Will more workers have nontraditional jobs as globalization and automation spread?, Center for Retirement Research at Boston College, CRR WP 2019-10, https://ssrn.com/abstract=3448067.

Saad, A. F. (2017). Trade and technology adoption. *The Journal of International Trade & Economic Development*, 26(1), 1-24, https://doi.org/10.1080/09638199.2016.1197298.

Schmid, G. (2011). Non-standard employment in Europe: its development and consequences for the European Employment Strategy. *German Policy Studies*, 7(1), 171+.

Schmid, G., and Wagner, J. (2017). Managing social risks of non-standard employment in Europe. *Conditions of Work and Employment Series* No. 91, International Labour Organization (ILO), Geneva, https://www.ilo.org/wcmsp5/groups/public/---ed_protect/---protrav/---travail/documents/publication/wcms_584686.pdf.

Shire, K. A., Schönauer, A., Valverde, M., and Mottweiler, H. (2009). Temporary work in coordinated market economies: Evidence from front-line service workplaces. *Industrial & Labor Relations Review*, 62(4), 602-617.

Spattini, S. (2012). Agency work: A comparative analysis. *E-Journal of International and Comparative Labour Studies*, 1(3-4), 169-210, https://ejcls.adapt.it/index.php/ejcls_adapt/article/view/45.

Westhoff, L., (2022). Wage differences between atypical and standard workers in European Countries: Moving beyond average effects. *European Sociological Review*, 38(5), 770-784, https://doi.org/10.1093/esr/jcac015.

World Bank (2009). Reshaping Economic Geography, The World Bank.

Webb, M. (2020). The impact of artificial intelligence on the labour market. Mimeo Stanford University.

Wotschack, P. (2020). When do companies train low-skilled workers? The role of institutional arrangements at the company and sectoral Level. *British Journal of Industrial Relations*, 58, 587–616.

Wright, G. C. (2014). Revisiting the employment impact of offshoring. *European Economic Review*, 66, 63-83, https://doi.org/10.1016/j.euroecorev.2013.11.008.

Wright, G. C. (2010). Revisiting the employment impact of offshoring. Job Market Paper. University of California, Davis.

Zeytinoglu, I.U., and Cooke, G.B. (2005). Non-standard work and benefits: Has anything changed since the Wallace report? *Relations Industrielles/Industrial Relation*, 60(1), 29-63, https://www.jstor.org/stable/23077635.

6. Annex

Table A. 1. Industry classification – NACE Rev. 2

Code	Industry
A	Agriculture, forestry and fishing
B	Mining and quarrying
10-12	Food products, beverages and tobacco
13-15	Textiles, wearing apparel, leather and related products
16-18	Wood and paper products; printing and reproduction of recorded media
19	Coke and refined petroleum products
20-21	Chemicals and chemical products
22-23	Rubber and plastics products, and other non-metallic mineral products
24-25	Basic metals and fabricated metal products, except machinery and equipment
26-27	Computer, electronic and optical products; electrical equipment
28	Machinery and equipment n.e.c.
29-30	Transport equipment
31-33	Other manufacturing; repair and installation of machinery and equipment
D-E	Electricity, gas, steam and air conditioning supply; water supply, sewerage, waste management and remediation activities
F	Construction
G	Wholesale and retail trade; repair of motor vehicles and motorcycles
H	Transportation and storage
I	Accommodation and food service activities
58-60	Publishing, audio-visual and broadcasting activities
61	Telecommunications
62-63	IT and other information services
K	Financial and insurance activities
L	Real estate activities
M-N	Professional, scientific and technical activities; administrative and support service activities
O	Public administration and defence; compulsory social security
P	Education
Q	Human health and social work activities
R-S	Arts, entertainment and recreation; other service activities
T	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use

Table A. 2. Employment effect (total economy): other offshoring measures and employment protection – regular contracts

	3-year differences (D3)			5-year differences (D5)			9-year differences (D9)		
	total	typical	atypical	total	typical	atypical	total	typical	atypical
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Narrow and broad offshoring									
EPL	-0.039	-0.039	-0.071	0.005	-0.045	-0.109	-0.160	-0.293**	-0.388**
	(0.034)	(0.036)	(0.053)	(0.063)	(0.068)	(0.115)	(0.148)	(0.147)	(0.191)
IIM^N	0.068**	0.072*	0.080	0.029	0.004	0.005	-0.006	-0.049	0.053
	(0.031)	(0.042)	(0.072)	(0.037)	(0.035)	(0.062)	(0.071)	(0.071)	(0.108)
$EPL*IIM^N$	0.029	-0.005	0.063	0.107**	0.113**	0.070	0.128	0.179*	0.163
	(0.035)	(0.046)	(0.089)	(0.045)	(0.051)	(0.075)	(0.085)	(0.092)	(0.179)
IIM^B	0.025	-0.099	0.165	-0.071	-0.200*	-0.236	-0.153	-0.123	0.260
	(0.110)	(0.104)	(0.266)	(0.157)	(0.121)	(0.176)	(0.251)	(0.144)	(0.380)
$EPL*IIM^B$	0.031	0.135	0.070	-0.096	0.009	0.626***	0.105	0.123	-0.060
	(0.132)	(0.140)	(0.337)	(0.188)	(0.166)	(0.224)	(0.279)	(0.196)	(0.484)
Constant	0.025	0.013	0.100**	0.000	-0.038	0.158**	0.156	0.005	0.496***
	(0.031)	(0.028)	(0.045)	(0.062)	(0.052)	(0.068)	(0.141)	(0.124)	(0.166)
Obs.	1,083	1,050	1,050	772	749	749	152	150	150
R^2	0.078	0.105	0.033	0.138	0.212	0.064	0.177	0.300	0.219
Manufacturing and services offshoring									
EPL	-0.033	-0.021	-0.090	0.011	-0.012	-0.086	-0.188	-0.277*	-0.321
	(0.037)	(0.038)	(0.057)	(0.069)	(0.075)	(0.116)	(0.151)	(0.147)	(0.216)
IIM^M	-0.053	-0.178	0.019	-0.158	-0.266**	-0.181	-0.065	-0.057	0.197
	(0.125)	(0.142)	(0.201)	(0.145)	(0.125)	(0.167)	(0.252)	(0.158)	(0.393)
$EPL*IIM^M$	0.098	0.299*	-0.104	0.216	0.261*	0.375*	0.123	0.018	-0.425
	(0.134)	(0.164)	(0.286)	(0.174)	(0.140)	(0.199)	(0.281)	(0.182)	(0.433)
IIM^S	-0.009	-0.023	0.159**	-0.018	0.020	0.023	-0.043	0.024	0.269
	(0.061)	(0.069)	(0.078)	(0.077)	(0.081)	(0.073)	(0.126)	(0.101)	(0.164)
$EPL*IIM^S$	-0.080	-0.104	-0.079	-0.103	-0.135	0.129	-0.045	-0.026	-0.210
	(0.076)	(0.085)	(0.131)	(0.098)	(0.106)	(0.120)	(0.167)	(0.155)	(0.226)
Constant	0.013	-0.001	0.069	-0.017	-0.070	0.124*	0.136	-0.016	0.367**
	(0.035)	(0.032)	(0.046)	(0.066)	(0.054)	(0.070)	(0.150)	(0.135)	(0.186)
Obs.	1,083	1,050	1,050	772	749	749	152	150	150
R^2	0.073	0.111	0.031	0.124	0.204	0.059	0.166	0.286	0.220

Contd.

Table A. 2. Continued

	3-year differences (D3)			5-year differences (D5)			9-year differences (D9)		
	total	typical	atypical	total	typical	atypical	total	typical	atypical
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Offshoring to developing, developed countries and the EU13									
EPL	-0.069**	-0.004	-0.136**	-0.016	-0.024	-0.051	-0.059	-0.338*	-0.207
	(0.034)	(0.042)	(0.066)	(0.073)	(0.083)	(0.114)	(0.147)	(0.173)	(0.219)
IIM^{Devd}	0.040	0.263	0.029	0.154	0.057	0.187	0.097	0.080	0.887
	(0.116)	(0.212)	(0.349)	(0.123)	(0.186)	(0.202)	(0.283)	(0.332)	(0.555)
$EPL*IIM^{Devd}$	0.282**	0.525**	0.066	-0.036	-0.023	0.339	-0.495	0.285	0.585
	(0.132)	(0.246)	(0.415)	(0.159)	(0.258)	(0.259)	(0.364)	(0.388)	(0.552)
IIM^{Devg}	0.027	0.090	0.377**	0.118	-0.026	0.229	-0.133	-0.201	0.234
	(0.080)	(0.118)	(0.148)	(0.117)	(0.108)	(0.141)	(0.170)	(0.208)	(0.328)
$EPL*IIM^{Devg}$	-0.104	-0.129	-0.219	-0.199	-0.082	-0.009	0.037	0.149	-0.203
	(0.101)	(0.136)	(0.171)	(0.132)	(0.125)	(0.164)	(0.240)	(0.266)	(0.448)
IIM^{EU13}	0.191**	0.146	0.048	0.100	0.060	-0.164	0.397	0.405	0.284
	(0.094)	(0.125)	(0.169)	(0.103)	(0.129)	(0.162)	(0.257)	(0.262)	(0.401)
$EPL*IIM^{EU13}$	-0.074	-0.148	0.324	0.248	0.149	0.423*	0.446	-0.142	-0.557
	(0.128)	(0.166)	(0.278)	(0.160)	(0.220)	(0.241)	(0.462)	(0.495)	(0.555)
Constant	0.039	0.046	0.138**	0.053	-0.027	0.202**	0.151	0.087	0.709***
	(0.031)	(0.036)	(0.055)	(0.062)	(0.060)	(0.083)	(0.125)	(0.131)	(0.200)
Obs.	1,083	1,050	1,050	772	749	749	152	150	150
R^2	0.090	0.151	0.041	0.140	0.204	0.075	0.232	0.312	0.258

Note: All variables are in logs. Standard errors clustered at the country-industry level. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. w refers to average gross annual wages, p to the price of materials, GO to gross output, IP to import penetration, EPL to ‘strict’ employment protection legislation. IIM^N and IIM^B refer to narrow and broad offshoring, respectively; IIM^M and IIM^S to manufacturing and services offshoring, respectively; and IIM^{Devd} to offshoring to developed countries, IIM^{Devg} to offshoring to developing countries and IIM^{EU13} to offshoring to the EU13 member states.

Table A. 3. Employment effect (manufacturing): other offshoring measures and employment protection – regular contracts

	3-year differences (D3)			5-year differences (D5)			9-year differences (D9)		
	total	typical	atypical	total	typical	atypical	total	typical	atypical
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Narrow and broad offshoring									
EPL	0.093	-0.169***	-0.077	0.221	0.299***	-0.181	0.228	0.217	-0.337
	(0.070)	(0.051)	(0.083)	(0.139)	(0.095)	(0.134)	(0.190)	(0.159)	(0.250)
IIM^N	-0.042	0.010	-0.142	-0.062	-0.014	-0.116	-0.298*	-0.389**	0.153
	(0.084)	(0.093)	(0.168)	(0.109)	(0.089)	(0.233)	(0.151)	(0.152)	(0.285)
$EPL*IIM^N$	0.274*	0.117	0.154	0.304	0.106	0.373*	0.585**	0.328*	0.778**
	(0.153)	(0.127)	(0.171)	(0.202)	(0.126)	(0.214)	(0.244)	(0.199)	(0.329)
IIM^B	-0.145	-0.112	-0.787**	0.084	-0.148	-0.645**	0.678*	-0.059	1.027
	(0.225)	(0.202)	(0.368)	(0.310)	(0.188)	(0.324)	(0.386)	(0.225)	(0.679)
$EPL*IIM^B$	0.021	-0.053	1.296**	0.074	0.340	1.527***	-0.571	-0.035	1.555
	(0.405)	(0.419)	(0.549)	(0.487)	(0.427)	(0.567)	(0.750)	(0.701)	(1.156)
Constant	0.021	0.064*	0.142**	-0.010	-0.043	0.185*	0.192	-0.087	0.744***
	(0.043)	(0.039)	(0.071)	(0.078)	(0.072)	(0.106)	(0.148)	(0.148)	(0.219)
Obs.	576	547	547	405	384	384	75	71	71
R^2	0.554	0.535	0.087	0.565	0.651	0.136	0.618	0.712	0.538
Manufacturing and services offshoring									
EPL	0.086	0.126**	-0.098	0.188	-0.231***	-0.185	0.165	0.147	-0.632**
	(0.070)	(0.062)	(0.084)	(0.122)	(0.080)	(0.148)	(0.238)	(0.204)	(0.267)
IIM^M	0.011	-0.107	-0.285	0.189	-0.039	-0.050	0.806	-0.099	1.723*
	(0.222)	(0.197)	(0.422)	(0.297)	(0.208)	(0.497)	(0.531)	(0.389)	(1.046)
$EPL*IIM^M$	-0.310	0.347	0.518	-0.471	0.102	0.414	-1.590**	-0.464	-2.115
	(0.321)	(0.402)	(0.527)	(0.466)	(0.301)	(0.627)	(0.632)	(0.656)	(1.300)
IIM^S	-0.156	-0.079	-0.089	-0.189*	-0.137	-0.028	-0.122	-0.037	-0.133
	(0.105)	(0.094)	(0.156)	(0.096)	(0.094)	(0.141)	(0.259)	(0.204)	(0.310)
$EPL*IIM^S$	0.018	-0.172	0.127	0.127	0.194	-0.041	0.498*	0.320	1.303
	(0.133)	(0.161)	(0.197)	(0.169)	(0.132)	(0.222)	(0.288)	(0.481)	(0.877)
Constant	0.047	0.071*	0.155**	0.049	-0.020	0.192*	0.412**	0.069	0.699**
	(0.040)	(0.039)	(0.072)	(0.074)	(0.068)	(0.102)	(0.161)	(0.149)	(0.281)
Obs.	576	547	547	405	384	384	75	71	71
R^2	0.558	0.542	0.076	0.565	0.651	0.112	0.637	0.704	0.460

Contd.

Table A. 3. Continued

	3-year differences (D3)			5-year differences (D5)			9-year differences (D9)		
	total	typical	atypical	total	typical	atypical	total	typical	atypical
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Offshoring to developing, developed countries and the EU13									
EPL	0.093	0.075	-0.050	0.186	0.333***	-0.071	0.045	0.735***	-0.277
	(0.075)	(0.071)	(0.080)	(0.140)	(0.102)	(0.144)	(0.178)	(0.253)	(0.551)
IIM^{Devd}	-0.082	-0.046	-0.223	-0.072	-0.097	0.522*	0.771	-0.269	0.070
	(0.144)	(0.172)	(0.275)	(0.170)	(0.204)	(0.313)	(0.531)	(0.426)	(0.770)
$EPL*IIM^{Devd}$	0.142	0.677**	-0.285	-0.014	-0.139	0.446	-0.922	-1.585**	-0.598
	(0.169)	(0.306)	(0.508)	(0.251)	(0.395)	(0.496)	(0.595)	(0.687)	(1.236)
IIM^{Devg}	-0.058	-0.106	0.083	0.067	-0.143*	0.199	0.017	-0.484***	-0.473
	(0.077)	(0.080)	(0.174)	(0.129)	(0.074)	(0.208)	(0.214)	(0.178)	(0.385)
$EPL*IIM^{Devg}$	-0.175	-0.366**	0.513**	-0.142	-0.089	0.565**	0.132	0.457	1.634*
	(0.133)	(0.178)	(0.226)	(0.166)	(0.148)	(0.257)	(0.370)	(0.406)	(0.971)
IIM^{EU13}	0.157**	0.076	0.289	0.162**	0.014	-0.024	-0.292	0.020	0.433
	(0.077)	(0.119)	(0.199)	(0.080)	(0.156)	(0.210)	(0.437)	(0.329)	(0.613)
$EPL*IIM^{EU13}$	0.110	0.111	0.092	0.366	0.281	-0.089	0.992*	1.385**	-0.157
	(0.144)	(0.183)	(0.347)	(0.292)	(0.200)	(0.305)	(0.546)	(0.593)	(1.143)
Constant	0.022	0.043	0.178***	0.023	-0.069	0.284***	0.331**	-0.008	0.593**
	(0.040)	(0.035)	(0.068)	(0.065)	(0.073)	(0.087)	(0.149)	(0.147)	(0.245)
Obs.	576	547	547	405	384	384	75	71	71
R^2	0.555	0.570	0.108	0.582	0.660	0.171	0.656	0.753	0.447

Note: All variables are in logs. Standard errors clustered at the country-industry level. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. w refers to average gross annual wages, p to the price of materials, GO to gross output, IP to import penetration, EPL to 'strict' employment protection legislation. IIM^N and IIM^B refer to narrow and broad offshoring, respectively; IIM^M and IIM^S to manufacturing and services offshoring, respectively; and IIM^{Devd} to offshoring to developed countries, IIM^{Devg} to offshoring to developing countries and IIM^{EU13} to offshoring to the EU13 member states.

Table A. 4. Employment effect (total economy): other offshoring measures and employment protection – temporary contracts

	3-year differences (D3)			5-year differences (D5)			9-year differences (D9)		
	total	typical	atypical	total	typical	atypical	total	typical	atypical
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Narrow and broad offshoring									
EPL	-0.036	-0.068**	-0.080	0.047	-0.049	-0.048	-0.130	-0.332*	-0.235
	(0.036)	(0.033)	(0.057)	(0.077)	(0.065)	(0.118)	(0.146)	(0.194)	(0.207)
IIM^N	0.009	-0.001	0.068	0.028	-0.010	-0.012	-0.004	-0.059	0.062
	(0.023)	(0.033)	(0.064)	(0.027)	(0.028)	(0.053)	(0.060)	(0.063)	(0.117)
$EPL*IIM^N$	0.152***	0.170***	0.100	0.140***	0.174***	0.099	0.154*	0.198**	0.120
	(0.034)	(0.049)	(0.086)	(0.046)	(0.056)	(0.084)	(0.090)	(0.092)	(0.196)
IIM^B	0.167*	0.128	0.390*	-0.098	-0.193	0.070	-0.220	-0.082	0.109
	(0.096)	(0.111)	(0.230)	(0.143)	(0.136)	(0.194)	(0.226)	(0.171)	(0.377)
$EPL*IIM^B$	-0.127	-0.116	-0.237	0.024	0.079	0.188	0.310	0.134	0.192
	(0.126)	(0.150)	(0.363)	(0.171)	(0.175)	(0.236)	(0.275)	(0.228)	(0.453)
Constant	0.039	0.028	0.083**	0.023	-0.017	0.103	0.146	-0.020	0.403**
	(0.029)	(0.027)	(0.041)	(0.056)	(0.046)	(0.067)	(0.132)	(0.118)	(0.161)
Obs.	1,083	1,050	1,050	772	749	749	152	150	150
R^2	0.086	0.111	0.039	0.142	0.218	0.048	0.183	0.297	0.191
Manufacturing and services offshoring									
EPL	-0.025	-0.044	-0.003	0.078	0.003	0.049	-0.162	-0.297**	-0.152
	(0.038)	(0.035)	(0.067)	(0.081)	(0.071)	(0.112)	(0.148)	(0.131)	(0.216)
IIM^M	0.077	0.123	0.093	0.098	-0.007	0.014	0.158	0.142	0.054
	(0.071)	(0.117)	(0.134)	(0.101)	(0.097)	(0.093)	(0.131)	(0.121)	(0.228)
$EPL*IIM^M$	-0.067	-0.116	-0.355	-0.125	-0.084	0.159	-0.229	-0.331**	-0.272
	(0.090)	(0.138)	(0.310)	(0.123)	(0.152)	(0.236)	(0.204)	(0.167)	(0.337)
IIM^S	0.011	-0.014	0.136*	-0.031	-0.026	0.006	-0.086	-0.020	0.104
	(0.043)	(0.052)	(0.070)	(0.056)	(0.073)	(0.063)	(0.093)	(0.079)	(0.145)
$EPL*IIM^S$	-0.179**	-0.200**	-0.023	-0.197**	-0.182*	0.129	0.133	0.167	0.215
	(0.076)	(0.084)	(0.149)	(0.091)	(0.105)	(0.140)	(0.216)	(0.213)	(0.280)
Constant	0.028	0.022	0.052	0.013	-0.033	0.094	0.142	-0.029	0.299*
	(0.031)	(0.029)	(0.040)	(0.059)	(0.048)	(0.068)	(0.130)	(0.115)	(0.168)
Obs.	1,083	1,050	1,050	772	749	749	152	150	150
R^2	0.075	0.110	0.038	0.127	0.202	0.047	0.169	0.289	0.188

Contd.

Table A. 4. Continued

	3-year differences (D3)			5-year differences (D5)			9-year differences (D9)		
	total	typical	atypical	total	typical	atypical	total	typical	atypical
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Offshoring to developing, developed countries and the EU13									
EPL	-0.064*	-0.085**	-0.153**	-0.009	-0.074	-0.061	-0.390**	-0.354***	-0.154
	(0.037)	(0.039)	(0.065)	(0.088)	(0.084)	(0.118)	(0.165)	(0.137)	(0.223)
IIM^{Devd}	0.211	0.739*	-0.130	0.063	-0.167	0.330*	-0.567**	-0.241	0.551
	(0.156)	(0.383)	(0.303)	(0.076)	(0.199)	(0.195)	(0.233)	(0.371)	(0.601)
$EPL*IIM^{Devd}$	0.141	-0.265	0.744*	0.271	0.484*	0.175	1.223***	0.824**	0.917
	(0.154)	(0.278)	(0.386)	(0.200)	(0.258)	(0.272)	(0.371)	(0.415)	(0.597)
IIM^{Devg}	-0.006	0.002	0.312**	0.083	-0.017	0.214**	-0.042	-0.252	0.158
	(0.067)	(0.084)	(0.144)	(0.102)	(0.079)	(0.106)	(0.173)	(0.187)	(0.312)
$EPL*IIM^{Devg}$	-0.097	-0.058	-0.199	-0.152	-0.141	-0.174	-0.089	0.114	-0.168
	(0.102)	(0.126)	(0.173)	(0.136)	(0.124)	(0.155)	(0.258)	(0.247)	(0.428)
IIM^{EU13}	0.151*	-0.048	0.316	0.301**	0.177	-0.188	0.796***	0.502*	0.320
	(0.085)	(0.099)	(0.217)	(0.141)	(0.130)	(0.165)	(0.264)	(0.294)	(0.409)
$EPL*IIM^{EU13}$	-0.008	0.217	-0.190	-0.104	-0.029	0.490**	-0.758*	-0.336	-0.645
	(0.132)	(0.176)	(0.283)	(0.157)	(0.203)	(0.236)	(0.450)	(0.495)	(0.580)
Constant	0.050	0.044	0.129***	0.069	-0.008	0.144*	0.197	0.059	0.564***
	(0.031)	(0.033)	(0.048)	(0.059)	(0.056)	(0.074)	(0.126)	(0.126)	(0.195)
Obs.	1,083	1,050	1,050	772	749	749	152	150	150
R^2	0.086	0.143	0.050	0.139	0.208	0.064	0.268	0.323	0.232

Note: All variables are in logs. Standard errors clustered at the country-industry level. Robust standard ererors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. w refers to average gross annual wages, p to the price of materials, GO to gross output, IP to import penetration, EPL to 'strict' employment protection legislation. IIM^N and IIM^B refer to narrow and broad offshoring, respectively; IIM^M and IIM^S to manufacturing and services offshoring, respectively; and IIM^{Devd} to offshoring to developed countries, IIM^{Devg} to offshoring to developing countries and IIM^{EU13} to offshoring to the EU13 member states.

Table A. 5. Employment effect (manufacturing): other offshoring measures and employment protection – temporary contracts

	3-year differences (D3)			5-year differences (D5)			9-year differences (D9)		
	total	typical	atypical	total	typical	atypical	total	typical	atypical
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Narrow and broad offshoring									
EPL	0.107	0.139***	-0.092	0.211	0.294***	0.088	0.154	0.203	-0.553
	(0.071)	(0.053)	(0.099)	(0.157)	(0.094)	(0.146)	(0.234)	(0.148)	(0.372)
IIM^N	-0.202	-0.224	-0.503**	-0.036	-0.017	-0.294	-0.168	-0.493*	0.360
	(0.126)	(0.137)	(0.235)	(0.208)	(0.132)	(0.288)	(0.348)	(0.253)	(0.406)
$EPL*IIM^N$	0.359**	0.285**	0.506**	0.179	-0.005	0.320	0.282	0.246	0.188
	(0.161)	(0.142)	(0.222)	(0.247)	(0.149)	(0.269)	(0.339)	(0.260)	(0.390)
IIM^B	0.005	-0.193	-0.101	0.283	0.048	-0.293	0.700	-0.047	1.314
	(0.217)	(0.229)	(0.342)	(0.342)	(0.223)	(0.371)	(0.612)	(0.381)	(0.970)
$EPL*IIM^B$	-0.019	0.242	0.050	-0.149	-0.106	0.802	-0.365	-0.176	0.985
	(0.405)	(0.475)	(0.609)	(0.578)	(0.518)	(0.737)	(0.950)	(0.936)	(1.317)
Constant	-0.000	0.021	0.117*	-0.024	-0.074	0.137	0.216	-0.186	0.754***
	(0.041)	(0.034)	(0.070)	(0.071)	(0.071)	(0.108)	(0.192)	(0.180)	(0.280)
Obs.	576	547	547	405	384	384	75	71	71
R^2	0.505	0.473	0.085	0.526	0.627	0.098	0.580	0.702	0.489
Manufacturing and services offshoring									
EPL	0.105	0.122**	-0.114	0.275**	0.308***	0.031	0.289	0.248	-0.512
	(0.066)	(0.058)	(0.099)	(0.108)	(0.093)	(0.157)	(0.212)	(0.217)	(0.514)
IIM^M	0.420**	0.536	0.203	0.668***	0.151	0.037	0.952*	0.143	0.388
	(0.197)	(0.367)	(0.292)	(0.240)	(0.163)	(0.344)	(0.510)	(0.373)	(0.810)
$EPL*IIM^M$	-0.998***	-0.661	-0.359	-1.488***	-0.288	0.631	-2.023***	-0.850	1.537
	(0.268)	(0.471)	(0.533)	(0.332)	(0.338)	(0.747)	(0.521)	(1.118)	(1.886)
IIM^S	-0.085	-0.126	-0.028	-0.042	0.076	-0.055	0.132	0.345	0.363
	(0.061)	(0.107)	(0.125)	(0.079)	(0.088)	(0.140)	(0.141)	(0.216)	(0.291)
$EPL*IIM^S$	-0.166	-0.263	-0.033	0.006	-0.293*	0.107	-0.026	-0.733*	-0.823
	(0.136)	(0.181)	(0.202)	(0.168)	(0.161)	(0.318)	(0.241)	(0.375)	(0.935)
Constant	0.038	0.061	0.163**	0.014	-0.078	0.181*	0.220*	-0.055	0.374
	(0.040)	(0.039)	(0.066)	(0.073)	(0.070)	(0.099)	(0.112)	(0.135)	(0.249)
Obs.	576	547	547	405	384	384	75	71	71
R^2	0.538	0.491	0.076	0.591	0.632	0.096	0.663	0.713	0.444

Contd.

Table A. 5. Continued

	3-year differences (D3)			5-year differences (D5)			9-year differences (D9)		
	total	typical	atypical	total	typical	atypical	total	typical	atypical
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Offshoring to developed, developing countries and the EU13									
EPL	0.087	0.108*	-0.128	0.183	0.347***	-0.064	0.056	-0.439*	-0.474
	(0.071)	(0.059)	(0.103)	(0.157)	(0.103)	(0.163)	(0.219)	(0.259)	(0.491)
IIM^{Devd}	0.144	0.679**	-0.619***	-0.060	-0.167	0.417	-0.212	0.047	1.118
	(0.108)	(0.279)	(0.232)	(0.082)	(0.184)	(0.256)	(0.287)	(0.467)	(0.827)
$EPL*IIM^{Devd}$	0.138	-0.602	1.662***	0.133	-0.211	0.594	0.290	-1.600**	-1.375
	(0.210)	(0.414)	(0.475)	(0.423)	(0.493)	(0.510)	(0.600)	(0.691)	(1.461)
IIM^{Devg}	-0.117*	-0.264***	0.209	0.097	-0.180**	0.209	0.171	-0.567**	-0.104
	(0.069)	(0.081)	(0.178)	(0.127)	(0.076)	(0.212)	(0.269)	(0.226)	(0.388)
$EPL*IIM^{Devg}$	-0.178	-0.040	-0.053	-0.381*	-0.096	0.184	-0.584	0.395	0.219
	(0.133)	(0.172)	(0.232)	(0.208)	(0.174)	(0.280)	(0.430)	(0.354)	(0.774)
IIM^{EU13}	0.065	-0.240**	0.470**	0.288***	0.188*	-0.151	0.390*	-0.074	-0.620
	(0.076)	(0.099)	(0.221)	(0.095)	(0.103)	(0.195)	(0.227)	(0.418)	(0.703)
$EPL*IIM^{EU13}$	0.236	0.612***	-0.329	0.211	-0.004	0.224	0.138	0.690	0.790
	(0.149)	(0.195)	(0.309)	(0.274)	(0.294)	(0.341)	(0.525)	(0.626)	(1.063)
Constant	0.014	0.038	0.183***	0.002	-0.101	0.257***	0.151	-0.169	0.476**
	(0.041)	(0.037)	(0.071)	(0.070)	(0.074)	(0.090)	(0.172)	(0.146)	(0.236)
Obs.	576	547	547	405	384	384	75	71	71
R^2	0.513	0.524	0.127	0.554	0.643	0.133	0.626	0.744	0.425

Note: All variables are in logs. Standard errors clustered at the country-industry level. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. w refers to average gross annual wages, p to the price of materials, GO to gross output, IP to import penetration, EPL to 'strict' employment protection legislation. IIM^N and IIM^B refer to narrow and broad offshoring, respectively; IIM^M and IIM^S to manufacturing and services offshoring, respectively; and IIM^{Devd} to offshoring to developed countries, IIM^{Devg} to offshoring to developing countries and IIM^{EU13} to offshoring to the EU13 member states.

Table A. 6. Instrumental variable approach for endogenous offshoring: total economy

	3-year differences (D3)			5-year differences (D5)			9-year differences (D9)		
	total	typical	atypical	total	typical	atypical	total	typical	atypical
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
w	-0.083	-0.083	-0.501	0.280	0.294	-0.342	0.725	0.398	0.453
	(0.138)	(0.145)	(0.864)	(0.178)	(0.196)	(0.456)	(0.506)	(0.296)	(1.345)
p	-0.739**	-0.615	-0.435	-0.912**	-0.414	-0.397	-1.067	-0.204	-0.034
	(0.332)	(0.387)	(0.627)	(0.463)	(0.263)	(0.504)	(0.888)	(0.295)	(0.647)
GO	0.788***	0.874***	0.214	0.883***	0.848***	0.462	1.097*	1.002***	0.483
	(0.233)	(0.262)	(0.313)	(0.238)	(0.212)	(0.327)	(0.608)	(0.289)	(0.745)
IP	-9.934**	-8.654*	-15.892	-9.206*	-6.734	-8.314	-12.376	-2.482	-0.993
	(4.433)	(5.045)	(10.591)	(5.040)	(4.192)	(6.293)	(8.632)	(2.530)	(9.350)
IIM^T	9.526**	8.272*	14.909	8.763*	6.357	8.021	11.732	2.448	0.777
	(4.185)	(4.759)	(9.959)	(4.785)	(3.934)	(5.964)	(8.188)	(2.428)	(9.114)
IT	-0.014	-0.033	-0.116	-0.046	-0.045	-0.066	-0.211*	-0.127**	-0.119
	(0.048)	(0.047)	(0.117)	(0.057)	(0.051)	(0.087)	(0.128)	(0.063)	(0.218)
CT	0.010	0.022	0.031	0.006	0.001	0.017	0.032	0.055	0.151**
	(0.038)	(0.036)	(0.071)	(0.038)	(0.035)	(0.048)	(0.075)	(0.047)	(0.076)
DB	0.026	0.035	0.187	0.069	0.074	0.195	0.164	0.097	-0.060
	(0.092)	(0.084)	(0.209)	(0.105)	(0.091)	(0.154)	(0.187)	(0.081)	(0.213)
Constant	0.025	-0.003	0.042	-0.009	-0.064	0.032	0.073	-0.108	0.217
	(0.042)	(0.042)	(0.077)	(0.076)	(0.064)	(0.086)	(0.167)	(0.113)	(0.275)
Obs.	1,083	1,050	1,050	772	749	749	152	150	150
R^2	-0.820			-0.754			-1.531		
Underid.	11.38			9.165			4.461		
p-value	(0.001)			(0.002)			(0.035)		
K-P	18.48			12.97			4.455		
W-H	6.125			4.368			4.833		
p-value	(0.013)			(0.037)			(0.028)		

Note: All variables are in logs. Standard errors clustered at the country-industry level. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. w refers to average gross annual wages, p to the price of materials, GO to gross output, IP to import penetration, IIM^T to total offshoring, IT to information technology, CT to communications technology, and DB to software and database. Underid. refers to the underidentification test, K-P to the Kleinbergen-Paap rk Wald F statistic and W-H to the Wu-Hausman test. In the first-stage regression, a shift-share instrument based on the augmented composition of intermediate imports from different developing countries three years prior to the estimation period was used (see Section 2.1 for details).

Table A. 7. Instrumental variable approach for endogenous offshoring: manufacturing

	3-year differences (D3)			5-year differences (D5)			9-year differences (D9)		
	total	typical	atypical	total	typical	atypical	total	typical	atypical
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
w	0.093	-0.100	0.203	0.644	1.065*	0.472	-0.353	0.129	1.716
	(0.169)	(0.227)	(0.863)	(0.437)	(0.618)	(0.441)	(0.493)	(0.388)	(5.315)
p	-0.616	-1.049	-0.806	-1.728	-1.940	-0.363	0.431	1.008*	-0.688
	(0.411)	(0.760)	(1.247)	(1.416)	(2.021)	(1.090)	(0.396)	(0.515)	(2.834)
GO	0.493*	0.532**	0.264	1.162	1.200	0.205	-0.440	-0.543	1.486
	(0.266)	(0.262)	(0.429)	(1.055)	(1.412)	(0.726)	(0.377)	(0.478)	(4.171)
IP	-7.795*	-11.987	-16.562	-13.739	-18.424	-8.589	4.508	6.209	-13.819
	(4.264)	(9.944)	(18.601)	(9.448)	(16.591)	(10.570)	(3.165)	(4.101)	(27.142)
IIM^T	7.158*	11.076	15.628	13.150	17.728	8.220	-4.696*	-6.616*	14.338
	(4.184)	(9.725)	(17.739)	(9.979)	(17.296)	(10.609)	(2.786)	(3.575)	(27.422)
RD	-0.338***	-0.288**	-0.005	-0.119	-0.033	0.019	-0.353***	-0.420***	0.020
	(0.109)	(0.126)	(0.184)	(0.218)	(0.326)	(0.179)	(0.092)	(0.099)	(0.448)
Constant	0.102	0.057	0.022	-0.094	-0.362	-0.019	0.694***	0.656***	-0.234
	(0.062)	(0.139)	(0.213)	(0.297)	(0.586)	(0.279)	(0.206)	(0.238)	(1.878)
Obs.	576	547	547	405	384	384	75	71	71
R^2	-0.107			-1.232			0.229		
Underid.	5.042			2.180			2.922		
p-value	(0.025)			(0.140)			(0.087)		
K-P	8.123			2.751			2.858		
W-H	7.012			5.242			9.790		
p-value	(0.008)			(0.022)			(0.002)		

Note: All variables are in logs. Standard errors clustered at the country-industry level. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. w refers to average gross annual wages, p to the price of materials, GO to gross output, IP to import penetration, IIM^T to total offshoring, and RD to robot density (i.e. the stock of robots per 1,000 employees). Underid. refers to the underidentification test, K-P to the Kleinbergen-Paap rk Wald F statistic and W-H to the Wu-Hausman test. In the first-stage regression, a shift-share instrument based on the augmented composition of intermediate imports from different developing countries three years prior to the estimation period was used (see Section 2.1 for details).

Table A. 8. Instrumental variable results for endogenous capital asset types: total economy

	3-year differences (D3)			5-year differences (D5)			9-year differences (D9)		
	total	typical	atypical	total	typical	atypical	total	typical	atypical
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
w	-0.079	-0.145	-0.344	0.192	0.279	0.299	-0.299	-0.066	0.082
	(0.127)	(0.390)	(0.787)	(0.230)	(0.347)	(1.436)	(0.984)	(1.719)	(1.202)
p	-0.282	-0.468	0.158	-0.582*	-0.344	0.283	-1.528	0.033	0.249
	(0.218)	(0.519)	(0.407)	(0.329)	(0.469)	(0.799)	(2.491)	(1.604)	(1.143)
GO	0.588***	0.690	0.074	0.467*	0.281	-0.101	0.034	0.265	-0.038
	(0.170)	(0.510)	(0.438)	(0.249)	(0.433)	(0.477)	(1.224)	(0.850)	(0.705)
IP	-0.397	-0.670	-1.587	-0.290	-1.618	-1.003	-3.129	-4.044	-5.183
	(0.467)	(2.370)	(1.757)	(1.024)	(2.044)	(2.263)	(5.454)	(4.572)	(3.543)
IIM^T	0.386	0.840	1.410	0.225	1.504	1.121	2.049	3.313	4.400
	(0.524)	(2.683)	(1.988)	(1.006)	(1.945)	(2.235)	(4.727)	(3.800)	(3.513)
IT	0.264	-0.320	-0.209	-0.045	-0.345	0.169	-0.578	-0.470	-0.481
	(0.358)	(2.230)	(1.595)	(0.479)	(0.881)	(0.779)	(1.153)	(0.946)	(0.714)
CT	0.147	0.721	-0.062	0.667	0.377	-0.851	0.319	-0.577	-0.384
	(0.443)	(2.229)	(1.658)	(0.761)	(1.244)	(1.992)	(1.300)	(1.080)	(0.686)
DB	-0.173	0.624	0.378	0.208	1.274	1.081	3.234	2.582	1.453
	(0.505)	(1.778)	(1.637)	(0.665)	(1.079)	(1.165)	(3.590)	(2.913)	(1.461)
Constant	-0.005	-0.287	0.059	-0.345	-0.485	0.221	-0.730	-0.332	0.171
	(0.141)	(0.835)	(0.638)	(0.353)	(0.604)	(0.775)	(1.396)	(1.061)	(0.583)
Obs.	1,083	1,050	1,050	772	749	749	152	150	150
R^2	-0.107			-1.180			-10.706		
Underid.	1.361			1.359			0.746		
p-value	(0.243)			(0.244)			(0.388)		
K-P	0.458			0.451			0.223		
W-H	3.097			5.326			10.390		
p-value	(0.377)			(0.149)			(0.016)		

Note: All variables are in logs. Standard errors clustered at the country-industry level. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. w refers to average gross annual wages, p to the price of materials, GO to gross output, IP to import penetration, IIM^T to total offshoring, IT to information technology, CT to communications technology, DB to software and database. Underid. refers to the underidentification test, K-P to the Kleinbergen-Paap rk Wald F statistic and W-H to the Wu-Hausman test. In the first-stage regression, the average of all available more advanced economies in Europe is used for each of the three respective instruments: IT, CT and DB (see Section 2.1 for details).

Table A. 9. Instrumental variable results for endogenous robot density: manufacturing

	3-year differences (D3)			5-year differences (D5)			9-year differences (D9)		
	total	typical	atypical	total	typical	atypical	total	typical	atypical
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
w	-0.011	-0.239	0.155	0.292	0.566	0.181	4.259	1.708	-0.602
	(0.161)	(0.214)	(0.805)	(0.264)	(0.391)	(0.492)	(44.245)	(1.471)	(0.780)
p	-0.294	-0.597*	0.056	-0.469	-0.342	0.334	-11.743	-1.307	1.481*
	(0.289)	(0.345)	(0.300)	(0.364)	(0.210)	(0.321)	(123.464)	(1.606)	(0.828)
GO	0.521**	0.869***	0.211	0.466**	0.677***	-0.224	15.351	2.837	-1.501*
	(0.211)	(0.221)	(0.396)	(0.218)	(0.240)	(0.388)	(163.810)	(2.435)	(0.824)
IP	0.196	0.206	-0.180	-0.669	-0.590	-0.277	-6.374	-0.603	0.859
	(0.699)	(0.514)	(0.766)	(0.642)	(0.524)	(0.835)	(65.289)	(1.666)	(1.224)
IIM^T	-0.182	-0.259	0.127	0.594	0.572	-0.097	23.123	3.140	-1.954
	(0.653)	(0.492)	(0.705)	(0.712)	(0.546)	(0.858)	(248.805)	(3.495)	(1.662)
RD	-0.092	-0.063	-0.132	-0.095	0.014	-0.217	7.051	0.906	-0.660
	(0.154)	(0.127)	(0.233)	(0.139)	(0.110)	(0.216)	(79.270)	(1.091)	(0.449)
Constant	0.073	0.118**	0.184**	0.026	-0.055	0.245	-7.032	-1.216	1.166**
	(0.058)	(0.056)	(0.089)	(0.116)	(0.118)	(0.184)	(81.607)	(1.520)	(0.575)
Obs.	520	491	491	365	344	344	67	63	63
R^2	0.274			0.376			-106.843		
Underid.	5.636			6.229			0.008		
p-value	(0.018)			(0.013)			(0.927)		
K-P	9.094			11.670			0.007		
W-H	3.630			2.589			2.242		
p-value	(0.057)			(0.108)			(0.134)		

Note: All variables are in logs. Standard errors clustered at the country-industry level. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. w refers to average gross annual wages, p to the price of materials, GO to gross output, IP to import penetration, IIM^T to total offshoring, and RD to robot density (i.e. the stock of robots per 1,000 employees). Underid. refers to the underidentification test, K-P to the Kleinbergen-Paap rk Wald F statistic and W-H to the Wu-Hausman test. In the first-stage regression, the average robot density in all other advanced countries in the sample (excluding the one for which the instrument is calculated) is used as instrument (see Section 2.1 for details).

Table A. 10. The selection of countries to Software & Databases envelope instrument

Country	Industry	Gross Output growth	Software & Databases growth	Employment growth
DK	A	4.7%	142.3%	16.7%
NL	B	-39.7%	-9.0%	0.0%
DK	C	9.8%	116.5%	-16.6%
NL	C10-C15	20.9%	95.3%	1.4%
FR	C16-C18	-15.5%	40.3%	-33.2%
DK	C19-C23	64.5%	227.8%	9.1%
NL	C24-C28	25.3%	118.0%	-0.4%
FR	C29-C32	7.9%	60.3%	-15.9%
ES	D	22.4%	225.0%	-8.8%
ES	D-E	17.2%	159.6%	26.6%
NL	E	41.9%	211.1%	9.7%
NL	F	14.9%	99.3%	-19.1%
AT	G	16.1%	74.7%	9.6%
SE	H-J	44.6%	236.1%	16.6%
NL	I	16.1%	67.2%	43.1%
DK	K	4.4%	114.1%	-2.5%
NL	L-N	34.9%	198.9%	22.9%
NL	O	14.9%	79.8%	7.6%
NL	P	11.8%	91.9%	6.8%
NL	Q	31.5%	176.2%	15.0%
DK	R-S	3.7%	113.0%	11.4%

Note: The countries outlined in red indicate the out-of-sample countries.
Source: Own elaboration based on EU-KLEMS data.

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