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# 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 in a group of 'old' and 'new' EU member states between 2009 and 2018, and also examines the moderating role of labour market institutions and regulation in the EU, specifically employment protection legislation (EPL). The results show that offshoring had a negative effect on employment in the manufacturing sector, but a positive effect on employment in the service sector. The former was due to a reduction in typical employment and the latter to an increase in atypical employment, making offshoring an important driver of the expansion of atypical employment in the service sector. Information and communications technology, especially communications technology, has increased total employment, mainly through an increase in the demand for atypical employment, for which it is another important driver. Robotisation had a labour displacement effect, mainly at the expense of typical employment, which was more pronounced in the 'old' EU member states than in the less automated 'new' EU member states. EPL played an important mediating role: it dampened employment adjustments due to offshoring of the more protected type of employment and encouraged stronger adjustments of the less protected type of employment. Conversely, strict EPL acted as an amplifier of the negative effect of robotisation on employment.

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

JEL classification: F16, F22, F66

CONTENTS


Abstract ..... 5

1. Introduction ..... 9

2. Methodological approach and data ..... 13

2.1. The model ..... 13
2.2. Offshoring and technological change ..... 16
2.3. Data sources ..... 17

3. Descriptive analysis ..... 20

4. Results ..... 27

4.1. Total offshoring, technological change and labour demand – in total and by type ..... 27
4.2. Other offshoring measures and labour demand – in total and by type ..... 31
4.3. Employment protection, total offshoring, technological change, labour demand – in total and by type of employment ..... 36

5. Endogeneity ..... 41

5.1. Correlation of offshoring and technological change with exogenous shocks ..... 41
5.2. Interrelationship between offshoring and technological change ..... 43

6. Summary and conclusion ..... 44

References ..... 46

Annex ..... 51

## TABLES AND FIGURES


Table 1 / Employment effect (total economy): Total offshoring ........ 28
Table 2 / Employment effect (manufacturing): Total offshoring ........ 29
Table 3 / Employment effect (total economy): Total offshoring – EU15 vs. EU13 ........ 30
Table 4 / Employment effect (manufacturing): Total offshoring – EU15 vs. EU13 ........ 31
Table 5 / Employment effect (total economy): Other offshoring measures ........ 32
Table 6 / Employment effect (manufacturing): Other offshoring measures ........ 33
Table 7 / Employment effect (total economy): Other offshoring measures – EU15 vs. EU13 ........ 34
Table 8 / Employment effect (manufacturing): Other offshoring measures – EU15 vs. EU13 ........ 35
Table 9 / Employment effect (total economy): Total offshoring and employment protection – regular contracts ........ 37
Table 10 / Employment effect (manufacturing): Total offshoring and employment protection – regular contracts ........ 38
Table 11 / Employment effect (total economy): Total offshoring and employment protection – temporary contracts ........ 39
Table 12 / Employment effect (manufacturing): Total offshoring and employment protection – temporary contracts ........ 40
Table 13 / Instrumental variable results for endogenous offshoring: total economy and manufacturing . 42
Table 14 / Instrumental variable results for endogenous capital asset types (total economy) ........ 42
Table 15 / Instrumental variable results for endogenous robot density (manufacturing) ........ 43

Figure 1 / Atypical employment share in 2009 (lhs) and absolute change (in percentage points) between 2009 and 2018 (rhs) ........ 22
Figure 2 / Total offshoring by industry in 2009 (rhs) and the average offshoring growth rate between 2009 and 2018 (rhs) ........ 23
Figure 3 / Average robot density in 2009 (rhs) and the average growth rate between 2009 and 2018 (rhs) ........ 24
Figure 4 / Information technology (IT), communications technology (CT) and database (DB) in 2009 (rhs) and the average growth rate between 2009 and 2018 (rhs) ........ 25

Table A.1 / Industry classification – NACE Rev. 2 ........ 51
Table A.2 / Employment effect (total economy): other offshoring measures and employment protection – regular contracts ........ 52
Table A.3 / Employment effect (manufacturing): other offshoring measures and employment protection – regular contracts ........ 53
Table A.4 / Employment effect (total economy): other offshoring measures and employment protection – temporary contracts ........ 54
Table A.5 / Employment effect (manufacturing): other offshoring measures and employment protection – temporary contracts ........ 55
Table A.6 / Instrumental variable approach for endogenous offshoring: total economy ........ 56
Table A.7 / Instrumental variable approach for endogenous offshoring: manufacturing ........ 57
Table A.8 / Instrumental variable results for endogenous capital asset types: total economy ........ 58
Table A.9 / Instrumental variable results for endogenous robot density: manufacturing ........ 59

# 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.

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

[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.

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, 2019), while offshoring to high-income countries leads to employment gains (Ebenstein et al., 2014; 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 contributes to the literature in several important ways. First, it analyses the short-, medium- and long-term effects on employment of offshoring and technological change in the EU, in total as well as by type of employment in terms of typical and atypical employment. Although there is a large body of literature on the employment effects of these two forces (see above), little is known about their effects on these two types of employment, particularly within a European context. Second, it sheds light on the role of labour market institutions in mediating the effects of both forces on the type of employment. Specifically, it uses information on labour market regulation, specifically employment protection legislation (EPL) for individual and collective dismissals as well as for the hiring of temporary workers, to show how legislation shapes the impact of both forces on the type of employment. Third, it looks at a set of technological changes – namely, robotisation and the three dimensions of ICT – for which the collective impact on the type of job has not been looked at. Fourth, it distinguishes between different types of offshoring, namely, 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' EU member states (EU13). This is important because it helps us to show which type of offshoring is important for the spread of atypical employment.

Our results show that both offshoring and technological change have had an important impact on European labour markets between 2009 and 2018. Offshoring has affected manufacturing and services workers differently, with a negative effect on employment in manufacturing but a positive effect on employment in services, due to a reduction in typical employment in manufacturing and an increase in atypical employment in services. Offshoring has thus been an important driver of the expansion of atypical employment in services. Moreover, an expansion of CT capital – i.e. communications equipment – has increased total employment, mainly through an increase in the demand for atypical employment, making it another important driver of atypical employment in Europe. By contrast, robotisation has had an important labour displacement effect, mainly at the expense of typical employment, with atypical employment declining only in the longer term, but to a similar extent. The negative employment effects from robotisation have been much more pronounced in the 'old' EU member states than in the less automated 'new' EU member states. Moreover, the strictness of EPL has also played an important, but differentiated, role in this context: for offshoring, stricter regulations have dampened employment adjustments of the more protected type of employment and encouraged stronger adjustments of the less protected type of employment. By contrast, although an increase in the demand for atypical employment in response to an increase in CT was observed only in countries with stricter EPL, the decline in the demand for both typical and atypical employment in response to increased robotisation was much stronger in countries with stricter EPL than in those with weaker EPL, making EPL an important amplifier of the negative employment effects of robotisation.

The remainder of the paper is structured as follows. Section 2 discusses the methodological approach, the different offshoring and technology indicators and the data sources used in the analysis. Section 3 provides, for each country and industry included in the analysis, a brief overview of changes in atypical employment, offshoring and technological change patterns between 2009 and 2018. Section 4 reports the main results from the analysis, while Section 5 deals with a number of endogeneity issues. Finally, Section 6 provides a summary of the results and sets out our conclusions.

# 2. Methodological approach and data

## 2.1. THE MODEL

In our 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, 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:

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

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, $\pi_{ic}$ refers to country-industry fixed effects and $\varepsilon_{ict}$ 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:

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

where Δ refers to the difference of a variable.

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

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). In this part of the analysis, we use gross annual wage by type of worker, i.e. gross annual wages for typical workers in the estimation of typical employment and gross annual wages for atypical workers in the estimation of atypical employment.

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 3 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 country dummies and offshoring and technological change.

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 industry level to correct for within-group serial correlation in the residuals.

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3 All self-employed persons are excluded.

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 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,

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.

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

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 5.

## 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:

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

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, in total and further broken down into annual gross wages for typical and atypical employees. 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 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

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

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 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).

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

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.

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.

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.

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13 Source: sbs_na_sca_r2 (Eurostat).

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.

# 3. 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 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.

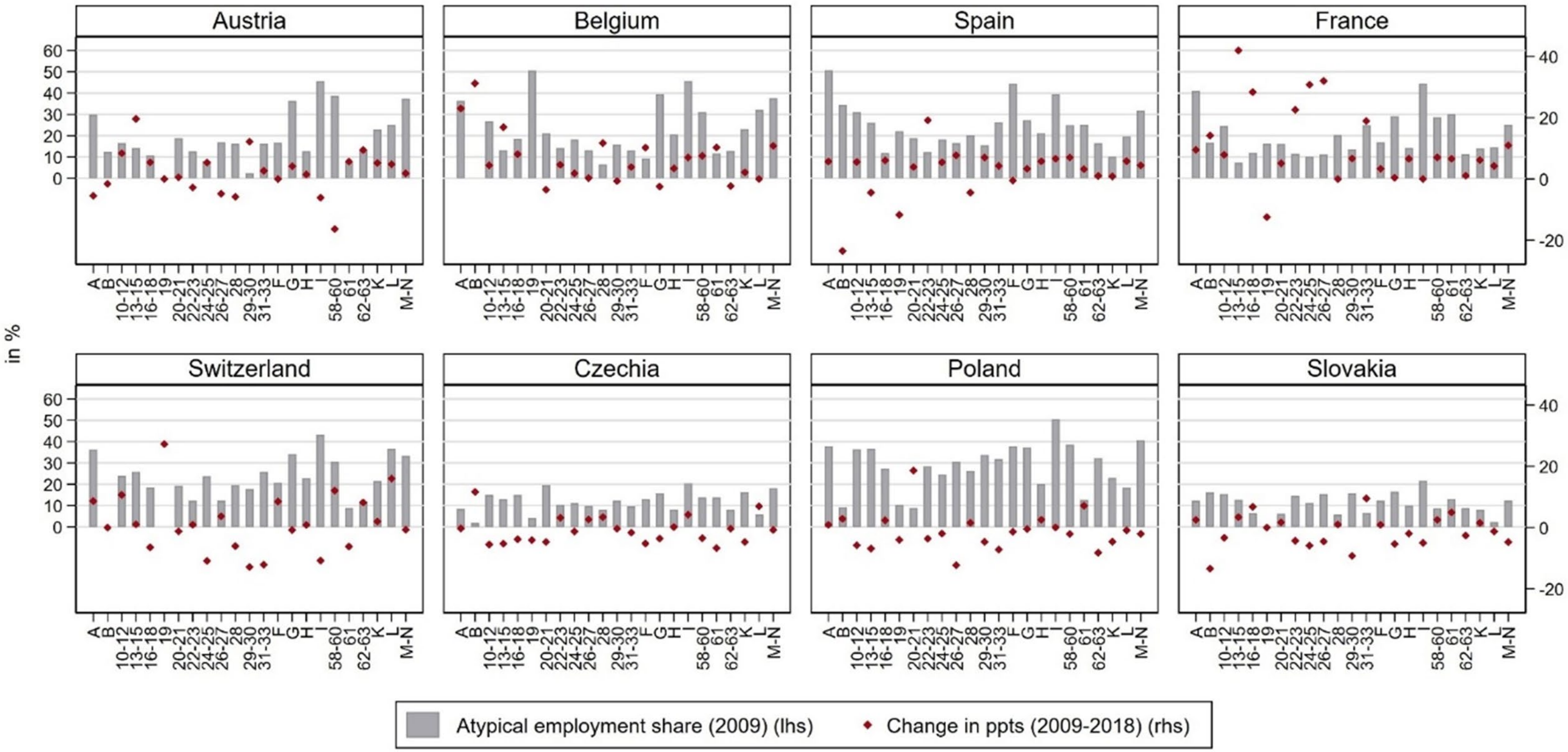
Robot density was generally higher in the manufacturing industries of the EU15 than the EU13 in 2009. A notable exception is industry 29-30 (transport equipment) in Slovakia, where the robot density was similar to that in France or Switzerland. Generally, robot density in industry 29-30 (transport equipment) 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).

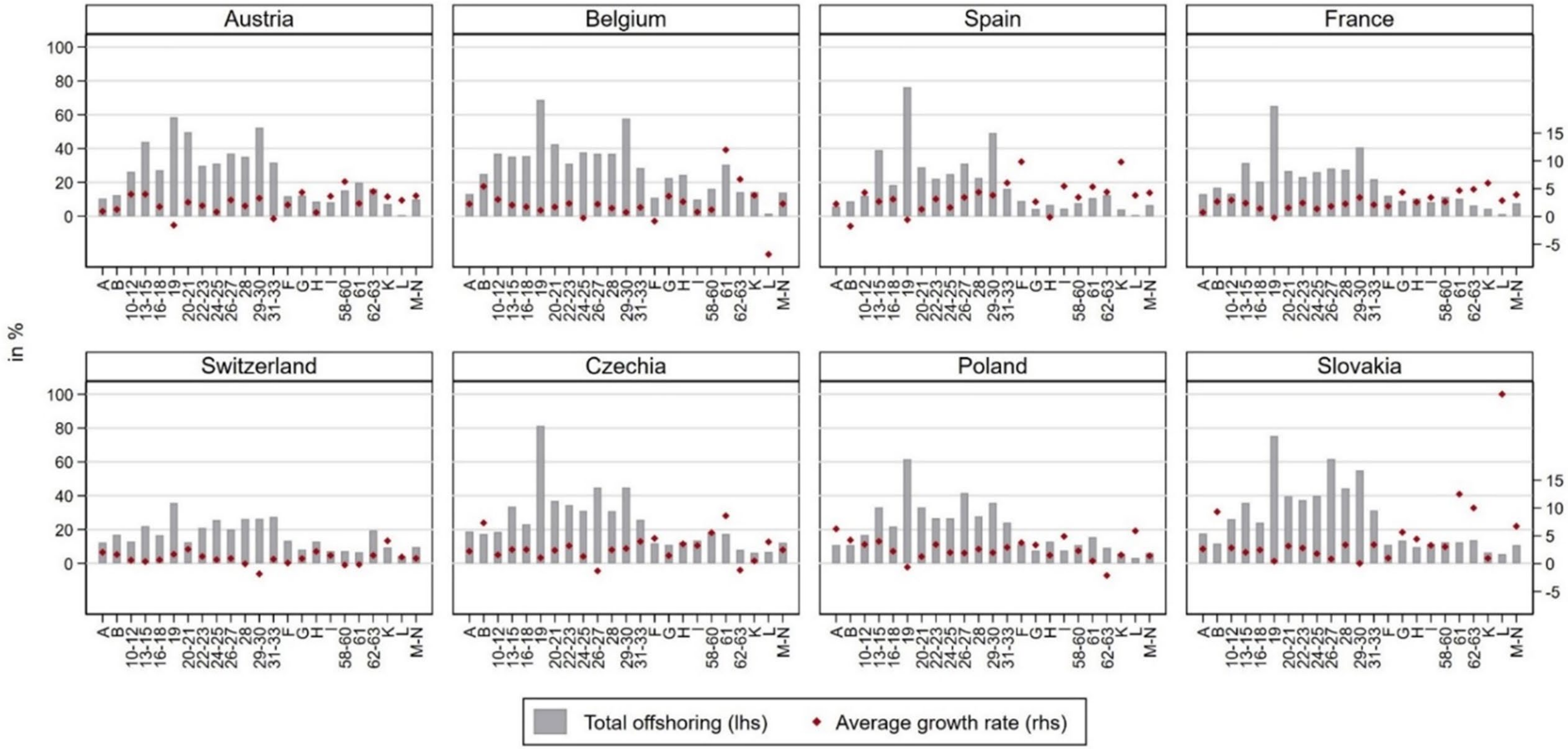
Although the average growth rates of IT, CT and DB were quite different between 2009 and 2018, it is nevertheless possible to make some general observations. With the exception of Slovakia, the average growth rates in DB were mostly positive, but generally of relatively low magnitude (except for Poland, 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)**



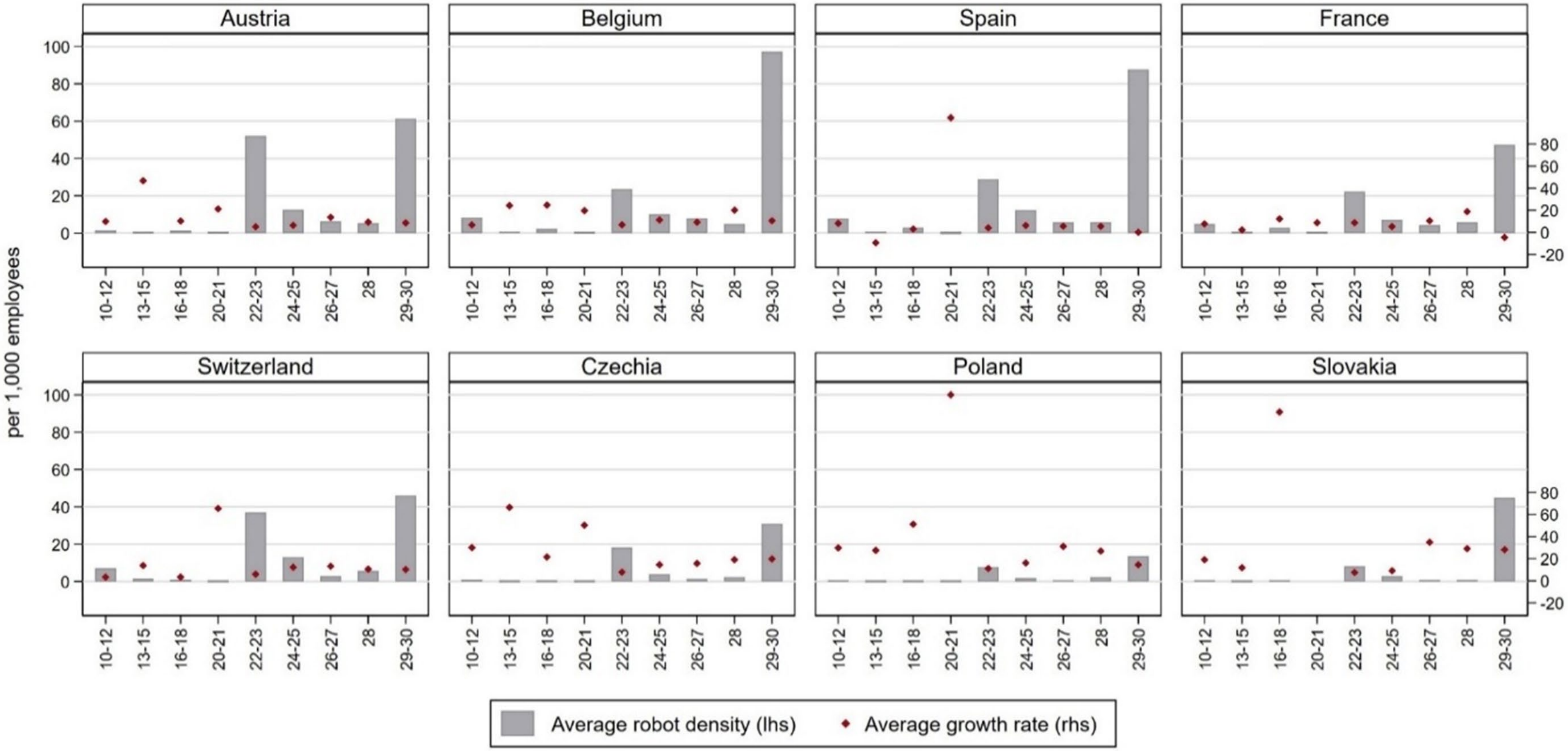

Note: The grey bar refers to the atypical employment share in 2009; the red diamonds to the change (in ppts) between 2009 and 2018. A refers to agriculture, forestry and fishing; B to mining and quarrying; 10-12 to food products, beverages and tobacco; 13-15 to textiles, wearing apparel, leather and 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)**



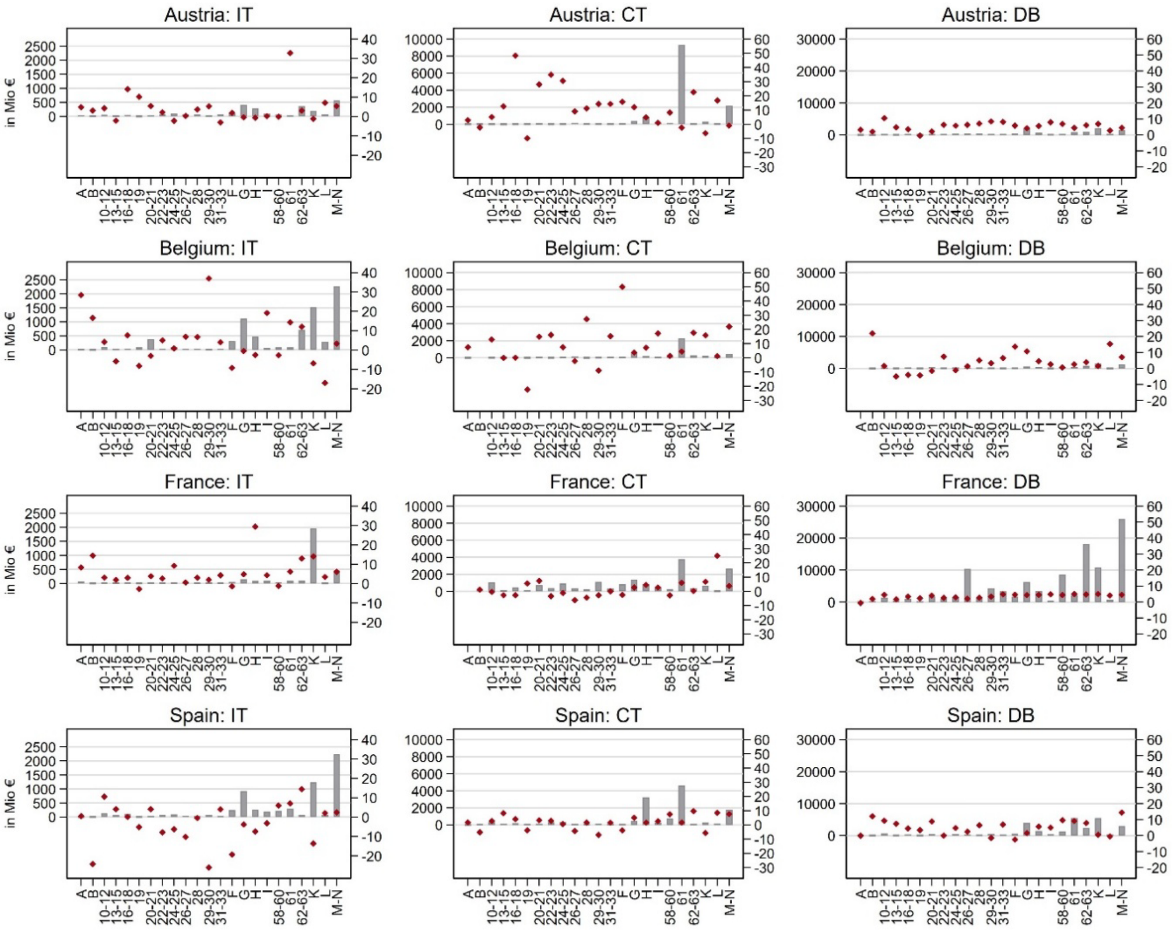

Note: The grey bar refers to total offshoring (as % of gross output) in 2009; the red diamonds to the growth rate (in %) between 2009 and 2018. A refers to agriculture, forestry and fishing; B to mining and quarrying; 10-12 to food products, beverages and tobacco; 13-15 to textiles, wearing apparel, 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)**



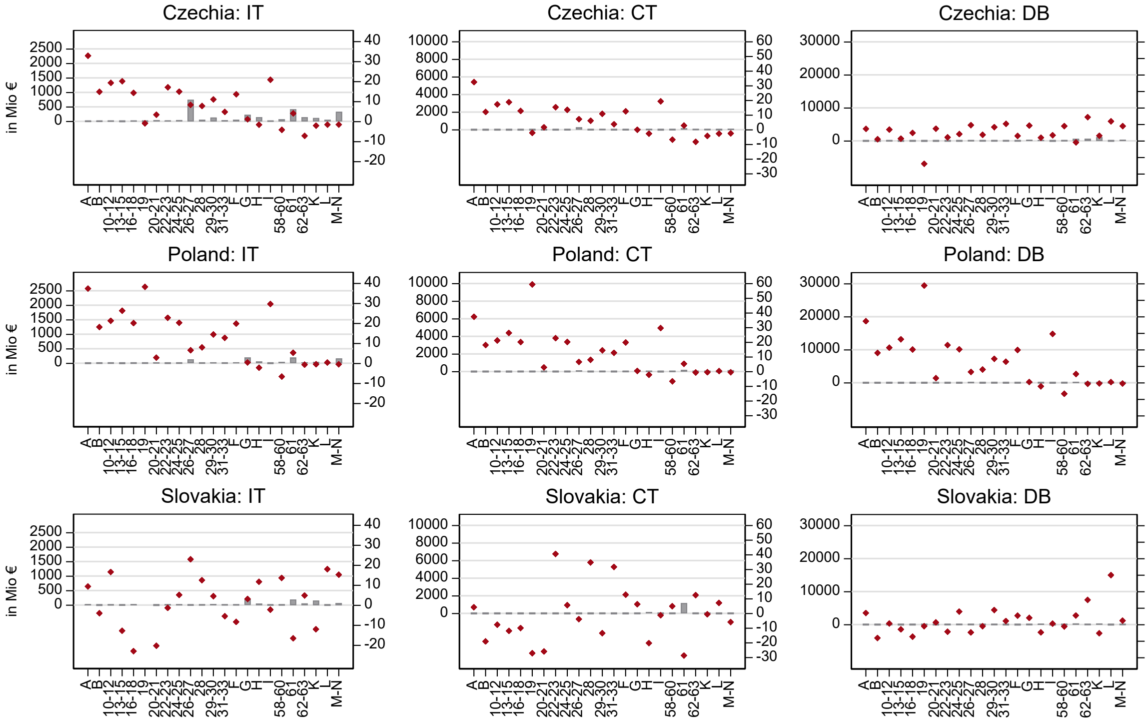

Note: Robot density is defined as the number of robots per 1,000 employees. The grey bar refers to the average of the first three years (2009-2011); the red diamonds to the average growth rate. A refers to agriculture, forestry and fishing; B to mining and quarrying; 10-12 to food products, beverages 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.

# 4. Results

In what follows, we discuss the results of our estimations, first without taking endogeneity issues into account. Specifically, Section 4.1 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 4.2, 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 4.3, 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 5, 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]

## 4.1. 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 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.

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.

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.

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).

**Table 1 / Employment effect (total economy): Total offshoring**

| | 3-year differences (D3) | | | 5-year differences (D5) | | | 9-year differences (D9) | | |
|---|---|---|---|---|---|---|---|---|---|
| | total (1) | typical (2) | atypical (3) | total (4) | typical (5) | atypical (6) | total (7) | typical (8) | atypical (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 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 (1) | typical (2) | atypical (3) | total (4) | typical (5) | atypical (6) | total (7) | typical (8) | atypical (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 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.

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 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 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 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.

## 4.2. 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

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

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.

**Table 5 / Employment effect (total economy): Other offshoring measures**

| | 3-year differences (D3) | | | 5-year differences (D5) | | | 9-year differences (D9) | | |
|---|---|---|---|---|---|---|---|---|---|
| | total (1) | typical (2) | atypical (3) | total (4) | typical (5) | atypical (6) | total (7) | typical (8) | atypical (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 |
| R² | 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 |
| R² | 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 |
| R² | 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 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 (1) | typical (2) | atypical (3) | total (4) | typical (5) | atypical (6) | total (7) | typical (8) | atypical (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 |
| | **Offshorig 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 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.

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 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 7 / Employment effect (total economy): Other offshoring measures – EU15 vs. EU13

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

## 4.3. 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 (1) | typical (2) | atypical (3) | total (4) | typical (5) | atypical (6) | total (7) | typical (8) | atypical (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 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 (1) | typical (2) | atypical (3) | total (4) | typical (5) | atypical (6) | total (7) | typical (8) | atypical (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 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 (1) | typical (2) | atypical (3) | total (4) | typical (5) | atypical (6) | total (7) | typical (8) | atypical (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 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 (1) | typical (2) | atypical (3) | total (4) | typical (5) | atypical (6) | total (7) | typical (8) | atypical (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 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.

# 5. 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.

## 5.1. 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) total | (2) typical | (3) atypical | (4) total | (5) typical | (6) atypical | (7) total | (8) typical | (9) 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** | | |
| $I\text{-}IIM^T$ | | 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*** | | |
| $I\text{-}IIM^T$ | | 0.137*** | 0.083 | | -0.010 | -0.010 | | 0.514* | 0.432 |

Note: All variables are in logs. Standard errors clustered at the 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). $I\text{-}IIM^T$ 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) total | (2) typical | (3) atypical | (4) total | (5) typical | (6) atypical | (7) total | (8) typical | (9) 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 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 communication 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). 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) total | (2) typical | (3) atypical | (4) total | (5) typical | (6) atypical | (7) total | (8) typical | (9) 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 |
| R² | 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 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.

## 5.2. 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.

# 6. 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 a group of 'old' and 'new' EU member states between 2009 and 2018. The novelty of this paper 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 employment protection legislation (EPL), which has so far received little attention in this line of literature.

The 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 several 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.

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# 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 (1) | typical (2) | atypical (3) | total (4) | typical (5) | atypical (6) | total (7) | typical (8) | atypical (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 |
| **Offshoring to developed, developing 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 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). EPL refers 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 |
| **Offshoring to developed, developing 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 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). EPL refers 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 (1) | typical (2) | atypical (3) | total (4) | typical (5) | atypical (6) | total (7) | typical (8) | atypical (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 |
| **Offshoring to developed countries, developing 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 industry level. Robust standard ererors 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). EPL to refers to 'strict' employment protection legislation; $IIM^N$ 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 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 (1) | typical (2) | atypical (3) | total (4) | typical (5) | atypical (6) | total (7) | typical (8) | atypical (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 |
| **Offshoring to developed countries, 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 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). EPL refers to 'strict' employment protection legislation; $IIM^N$ 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 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 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 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 (1) | typical (2) | atypical (3) | total (4) | typical (5) | atypical (6) | total (7) | typical (8) | atypical (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 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 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).

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