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Abstract

This paper analyses the impact of different types of offshoring and technological change as well as the mediating role of trade union representation at the firm level on the quality of workers' jobs in the EU in terms of atypical employment, which is further differentiated by type of atypical employment (i.e. temporary contracts and involuntary part-time work) as well as self-reported skills mismatch. It uses worker-firm-level data from the 2015 and 2021 European Working Conditions Surveys (EWCSs) merged with industry-level data on offshoring; the information and communication technologies (ICT) asset types of information technology (IT), communication technology (CT), and software and database (DB) technology; and robotisation. The results show that a worker's likelihood of being in atypical employment is related to both forces analysed but in different ways, as there is a higher probability of being in atypical employment due to offshoring or IT but a lower probability of being in atypical employment due to CT. The two types of atypical employment are affected differently, with strong differences being found between workers in manufacturing and services industries. Both forces are of limited importance for workers' self-reported skills mismatch and, as such, only temporarily lead to over-skilling in the case of offshoring but to under-skilling in the case of technological change. Trade union representation at the firm level only plays a limited mediating role in the likelihood that workers are either in atypical employment or report a skills mismatch.

Keywords: Trade unions, offshoring, technological change, atypical employment, skills mismatch, multilevel analysis

JEL classification: F16, F22, F66

CONTENTS

TABLES AND FIGURES

1. Introduction

Globalisation – and the expansion of global supply chains, in particular – as well as technological change (i.e. digitalisation and automation) are two key megatrends that have rapidly transformed the world of work. Specifically, both forces are seen as important drivers of, inter alia, the spread of atypical, non-standard forms of employment – such as temporary employment, marginal employment, part-time employment, temporary agency work or any other form of multi-party employment relationship, bogus employment or dependent self-employment (Eurofound, 2018a) – in sectors and occupations where they did not previously exist (ILO, 2016) or the emergence and widening of skills mismatches (Janeska and Lozanoska, 2021).

In Europe, temporary contracts and self-employment expanded strongly in the period between the late 1980s and the onset of the global financial crisis in 2007 (Eurofound, 2018b), with young, immigrant, low-skilled workers, those in elementary occupations and women being particularly affected by temporary contracts (Eurofound, 2015). Agency work expanded at a lower rate but has declined since the 2007 recession. Between 2010 and 2015, temporary contracts increased further but declined somewhat until 2020.

The spread of non-standard forms of work is a cause for concern, as workers in non-standard employment often have short job tenure and are more likely to move in and out of the labour market with a correspondingly high risk of low pay, (in-work) poverty and unemployment, all of which erode employability and exacerbate the likelihood of precarious employment careers 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 ‘standard’ workers to have interrupted or even no social insurance contribution records, their entitlement to benefits in the event of unemployment, sickness, maternity, disability and old age are also negatively affected (Schmid and Wagner, 2017).

Similarly, the emergence and widening of skills mismatches is also a cause for concern, as they are associated with a range of non-negligible economic costs for individuals, firms and the economy as a whole. These include wage penalties (Mavromaras et al., 2009), lower job satisfaction and higher turnover (see Quintini, 2011 for a review) among overeducated workers; negative productivity and competitiveness effects for firms (Bennett and McGuinness, 2009; Tang and Wang, 2005; Morris et al., 2020; Haskel and Martin, 1993, 1996); and potentially also higher unemployment at the economy level.

Empirical evidence on the effect of both megatrends on the spread of non-standard forms of work as well as the emergence and widening of skills mismatches is generally limited. For instance, Rutledge et al. (2019) show for the US that globalisation (captured by Chinese imports to the US) does not have a large effect, while automation does: 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. Kiyota and Maruyama (2017) find for the Japanese manufacturing sector that while ICT is associated with an increase in the demand for part-time workers, there is no significant effect from offshoring. Conversely, Machikita and Sato (2011) show that outsourcing tends to encourage the replacement of permanent workers with temporary workers in Japan. For 10 Central and Eastern European countries, Nikulin and

Szymczak (2020) show that greater integration into global value chains (GVCs) increases the likelihood of having temporary employment contracts (mainly in tradable sectors). Similarly, technological change and offshoring are found to have increased macroeconomic skills mismatches (Alonso and Zavakou, 2020) and tend to be associated with over-skilling among workers (Combier, 2021).

Theoretically, different mechanisms are considered relevant in this context. For instance, it is argued that offshoring promotes the spread of non-standard forms of work thorough various channels. For suppliers, offshoring may lead to worse labour standards (Nadvi, 2004; Plank et al., 2012) due to strong competitive pressures on suppliers to reduce (labour) costs or produce within short lead times. Suppliers then seek more numerical flexibility (Kalleberg, 2001) in their labour through non-standard forms of employment. Moreover, if task complexity in supplying firms is weaker, this may make workers more substitutable, leading employers to hire employees on temporary contracts (Lakhani et al., 2013). For firms that offshore, the need to respond flexibly to fluctuations in demand and to remain competitive are key incentives not only to offshore in the first place but also to resort to non-standard forms of employment (Shire et al., 2009). Conversely, if lower-skilled and more standardised jobs are relocated abroad, the quality of the remaining jobs may increase and employment may become more secure. Technological change may also lead to an increase in non-standard forms of employment, especially when technological change is rapid, as tasks and jobs need to be adjusted more frequently, which necessitates more flexible work arrangements. However, some jobs – particularly less complex jobs at the lower end of the skills hierarchy – may be more affected, especially if they have a high degree of substitutability and can be easily filled by other workers with little or no loss of human capital.

Similarly, both technological change (i.e. automation and digitalisation) and offshoring may also advance skills mismatches by changing the task content of jobs performed by workers. Theoretically, over- and under-skilling could occur as a result of both forces. Specifically, according to the routine-biased technological change (RBTC) hypothesis (formulated by Autor et al., 2003), new technologies make routine tasks – both manual and cognitive – redundant (‘substitution effect’), which mainly affects medium-skilled workers (Hardy et al., 2018). If substituted tasks are at the higher-skilled end of a worker’s task range, over-skilling occurs. At the same time, technological change also has a ‘reinstatement effect’ (Acemoglu and Restrepo, 2018, 2019), which leads to the emergence of new or re-engineered tasks. If these tasks are more complex (potentially complementing technology), a situation of under-skilling may arise, at least temporarily, until formal and informal training helps workers to acquire the necessary skills (McGuinness et al., 2023). Similar effects are also seen in offshoring – and the associated trade in tasks (Grossman and Rossi-Hansberg, 2008), with routine-based tasks and tasks that do not require much face-to-face contact (Blinder, 2009; Blinder and Krueger, 2013) being the easiest to offshore.

In view of the potentially negative effects of both forces, unions become of utmost importance, potentially mitigating – or even preventing altogether – negative effects on the quality of jobs. A key mechanism is the new (international) specialisation of tasks, which may strengthen the bargaining position of those workers whose jobs are not affected by offshoring or technological change and either remain in the country or cannot be digitised or automated, leading to better-quality jobs. Specifically, Landesmann and Leitner (2023) show that some workers gain from offshoring through an improvement in their bargaining power. Generally, however, empirical evidence on the mediating role of unions is scarce and often only found in the form of case studies (see e.g. Mailand and Larsen, 2011 on selected EU countries).

In view of the above, this paper contributes to the literature in several important ways. First, it analyses the labour market effects of offshoring and technological change in the EU, focusing on the quality of work and, in particular, of atypical employment – further differentiated by type of atypical employment in terms of temporary contracts and involuntary part-time work as well as skills mismatch, measured as a self-reported indicator. While there is a wealth of literature on the employment effects of these two forces (see e.g. Amiti and Wei, 2006; Crinò, 2010 and 2012; Egger et al., 2007; Foster-McGregor et al., 2013; Geishecker, 2008; Hijzen et al., 2005 and 2011; Liu and Trefler, 2011 for offshoring and the review article by Filippi et al. 2023 for technological change), little is known about their effects on the two indicators of quality of work, particularly within a European context. Second, it sheds light on the role of trade union representation at the firm level in mediating the effects of both forces on workers' job quality. Little is known about the role of trade unions for the type of job and the emergence and spread of non-standard forms of employment (see e.g. Landesmann and Leitner, 2023 or Mailand and Larsen, 2011) or skills mismatch, especially in view of the decline in union membership and density over the past decades (Dreher and Gaston, 2007). In recent years, as the strength of trade unions declined in their traditional constituencies, services expanded and 'new' groups of workers (e.g. women and immigrants) could no longer be ignored and non-standard workers were discovered as significant new constituencies (Aloisi and Gramano, 2019). Third, it looks at a set of technological changes – namely, robotisation and the different dimensions of information and communication technology – whose collective impact on job quality has not been looked at. Fourth, it distinguishes between different types of offshoring, namely, narrow (intra-industry) and broad (inter-industry) offshoring, manufacturing or services offshoring, and offshoring by sourcing region (from developed countries, developing countries or the 'new' EU member states (NMS13)).

The results differ depending on the year studied. Whereas neither an increase in total offshoring nor in technology – specifically, information technology (IT), communication technology (CT), or software and database (DB) technology – is significantly associated with atypical employment in 2021, our results show that a worker's probability of being in atypical employment in 2015 is related to both forces studied, but not necessarily by increasing the probability of having an atypical job. Specifically, in 2015, while an increase in offshoring (total and manufacturing offshoring) or IT exposure is associated with a higher probability of being in atypical employment (in the manufacturing sample only), an increase in CT is associated with a lower probability of being in atypical employment (in both samples). The two types of atypical employment (i.e. temporary contracts and involuntary part-time work) are affected differently, with strong differences between the two samples studied, which highlights that workers in manufacturing and services industries are affected differently. Moreover, both forces are of limited importance for workers' self-reported skills mismatch and, if at all, only temporarily, as in the case of total offshoring which is associated with over-skilling. In general, trade unions play a limited mediating role in influencing the likelihood that workers are either in atypical employment or report a skills mismatch. This does not change when endogeneity is taken into account.

The rest of the paper is structured as follows: In addition to discussing the various data sources, Section 2 lays out the methodological approach to testing the mediating role of trade unions in the effects of offshoring and technological change on workers' job quality in terms of atypical employment, further differentiated by type of atypical employment and skills mismatch. Section 3 provides a brief overview of the prevalence of atypical employment and skills mismatch in the EU by country, industry and occupation. The results are then presented and discussed in Section 4. Finally, Section 5 summarises our findings and sets out our conclusions.

2. Methodological approach and data

2.1. THE MODEL

To shed light on role of trade unions, offshoring and technological change in determining workers' job quality, the following specification is tested:

$$Out_{ijct}^{m} = \alpha_0 + \boldsymbol{X}'_{ijct}\boldsymbol{\beta} + \boldsymbol{Y}'_{jct}\boldsymbol{\gamma} + \beta_3 TU_{ijct} + \boldsymbol{OFF}'_{jct}\boldsymbol{\delta} + \boldsymbol{TC}'_{jct}\boldsymbol{\theta} + \vartheta_{jct} + \mu_{ct} + \varepsilon_{ijct}, \quad (1)$$

where Out_{ijct}^{m} refers to different job-quality outcomes of worker i in industry j and country c at time t (with $t = 2015$ or 2021). We distinguish between two different outcomes: (i) atypical employment, further differentiated by type of atypical employment; and (ii) skills mismatch (only for 2015, since the data for 2021 does not allow us to examine the perception of skills mismatch).

Atypical employment is captured by having a temporary contract or involuntarily working part-time. In the 2015 and 2021 European Working Conditions Surveys (EWCSs), the former is captured by the question '*What kind of employment contract do you have in your main job?*', with (i) temporary/fixed-term contract, (ii) temporary employment agency contract, and (iii) no contract being classified as atypical and (iv) contract of unlimited duration and (v) apprenticeship or other training scheme being classified as typical. Involuntary part-time employment refers to a situation in which an employee works part-time in the main job but would prefer to work more. The prevalence of part-time employment is captured by the question '*How many hours do you usually work per week in your main paid job?*', while the preference for more work is captured by the question '*Provided that you could make a free choice regarding your working hours and taking into account the need to earn a living: how many hours per week would you prefer to work at present?*'. We consider employees to be involuntarily employed part-time if they work less than 30 hours a week in their main job but would like to work more. In the analysis, we look at atypical employment as a whole, but we also differentiate between its constituent factors of temporary contract and involuntary part-time employment.

The prevalence of skills mismatch is measured by a self-reported[1] mismatch indicator derived from the following question: '*Which of the following statements would best describe your skills in your own work?*' Three different answer options were possible and were coded as follows: (1) '*I need further training to cope well with my duties*' is coded as *under-skilled*, (2) '*My present skills correspond well with my duties – perfectly matched*' as *well matched*, and (3) '*I have the skills to cope with more demanding duties*' as *over-skilled*.

The vector $\boldsymbol{X}_{ijct}$ contains a set of individual worker characteristics, including: gender (in terms of female, with male as the reference category); migrant (equal to one if the respondent was born outside the current country of residence and zero otherwise);[2] age, which is classified into young (aged 15-24),

1 It is important to note, however, that the way mismatch is measured matters and that self-reporting is associated with higher over-skilling as compared to a measure based on 'realized matches' (i.e. a comparison of attained values with average or median values in an occupation) (Pellizzari and Fichen, 2017).

2 Migrant status is not included in the X vector for 2021 due to limited data availability.

middle-aged (aged 25-49) and old (aged 50 and above; as reference); the highest level of education (ISCED-11 based), classified into low (ISCED-0 to ISCED-2, as reference), medium (ISCED-3 and ISCED-4) and high (ISCED-5 to ISCED-8); occupation (ISCO-2008 based), classified into high (ISCO-1 to ISCO-3; as reference), medium (ISCO-4 to ISCO-7), and low (ISCO-8 and ISCO-9); and tenure (as the log of the number of years in the company).

The vector $\boldsymbol{Y}_{jct}$ contains firm characteristics, including: firm size, based on the number of employees at the local site where the respondent works, classified into micro and small (1-49 employees; as reference), medium-sized (50-249 employees) and large (250 and more employees); and firm type, classified according to the respondent's sector of employment into private (private sector), public (public sector; as reference) or other (in the case of either a joint private-public company, the not-for-profit sector, an NGO or other).

In the analysis carried out on the 2021 sample, a score measuring the number of pro-worker reforms during the COVID-19 lockdown year has been added. These reforms relate to short-time working schemes, sickness schemes, in-work benefits, income tax, etc.

TU_{ijct} refers to trade union representation. It is captured by the question '*Does the following exist at your company or organisation…?*', with one of the three answer options being (A) *Trade union, works council or a similar committee representing employees*. Answers are coded as one in the case of an affirmative answer and zero otherwise.[3]

OFF_{jct} and TC_{jct} are the two industry-level indicators[4] of interest and refer to offshoring and technological change, respectively, in industry j and country c at time t. Offshoring is measured using information from international input-output tables, from which intermediate input purchases by each sector and country from each sector and country can be measured. In our analysis, we distinguish between various offshoring measures. Our initial indicator for offshoring is a measure of *total offshoring*, defined as the share of imported intermediate inputs from all industries as a share of gross output:

$$IIM_{i,c}^{T} = \frac{\sum_{j=1}^{J} O_{j,c}}{GO_{i,c}}, \quad (2)$$

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 broken down further along three different dimensions. First, following Feenstra and Hanson (1999), we differentiate between *narrow (N) (or intra-industry)* and *broad (B) (or inter-industry) offshoring*. While narrow offshoring only considers imports of intermediates in each industry from the same industry, 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. Second, we differentiate between *manufacturing (M)* and *services (S) offshoring* to account for

3 Other answer options also include (B) *Health and safety delegate or committee*. Since trade unions are also represented in such health and safety delegates/committees in many countries, we have carried out a robustness check using answer options (A) and (B) together. The results are qualitatively similar except for temporary contracts in 2021, which turns significant. For the sake of brevity, the results are not presented here but are available from the authors upon request.

4 Since the EWCS is a worker-level survey and does not contain a firm identifier, it was not possible to do a firm-level analysis. The key indicators of interest were therefore merged at the industry level.

the growing importance of services offshoring over the past two decades (Jensen and Kletzer, 2005). Most services were traditionally considered untradable, but many services have now become tradable due to developments in new information and communication technologies. While manufacturing offshoring refers to imports of intermediates in each industry from all manufacturing industries, services offshoring refers to imports of intermediates in each industry from all services industries. Third, we differentiate by sourcing country and – following the classification of countries in the 2009 World Development Report (World Bank, 2009) – according to income levels, with the categories being *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 EU Member States (NMS13)*,[5] which, with the exception of Cyprus, Malta, Slovakia and Slovenia, were not classified as high-income countries in 2009. From a European perspective, this further differentiation of the group of NMS countries is important, as the new member states have become important source countries for intermediate inputs for Western Europe.[6]

As concerns technological change, we distinguish between two different measures: (i) information and communication technologies (ICT), especially its three components, namely, information technology (IT), communication technology (CT), and software and database (DB) technology;[7] and (ii) industrial robots, defined as the stock of industrial robots per 1,000 employees.

Finally, ϑ_{jct} and μ_{ct} are the random effects corresponding to the intercepts of industries in a country and of countries, while ε_{ijct} is the remaining error term, all of which are assumed to be normally distributed.

In the analysis, we use the relative change in the industry-level variables (defined in very general terms as $\Delta OFF/OFF$ and $\Delta TC/TC$) to take into account the fact that changes take time to materialise. We use different differencing periods (Δ) – 1 year, 2 years, 3 years – which allows us to determine and compare the effects of short- versus longer-term changes on the prevalence of atypical employment and skills mismatch. We use different differencing periods for each of the two EWCS waves, namely, 1 year, 2 years, and 3 years for the 2015 EWCS, but only one year for the 2021 EWCS. In the case of the latter, this is due to data limitations, particularly the limited data availability of several industry-level variables after 2018, resulting in a data gap between the year in which the dependent variables are observed (i.e. 2021) and the period of the relative change in the industry-level variable. This limits the comparability of results across the two EWCS waves used in this study. The EWCS-based indicators cannot be differenced, as they are observed at the level of the individual worker, and the EWCS is not designed as a panel in which the same workers would be (re-)interviewed in some (or all) EWCS waves.

In a second step, we add interaction terms to equation (1) between each of the industry-level indicators OFF_{jct} and TC_{jct} and the dummies for employee representation TU_{ijct} to test whether trade union representation mediates the relationship between offshoring and technological change, on the one hand, and job quality (i.e. atypical employment, skills mismatch), on the other.

5 For the NMS in our sample, the 'offshoring to the NMS13' indicator is calculated excluding the own country.

6 The group of developed countries comprises Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Japan, Luxembourg, the Netherlands, Norway, Portugal, South Korea, Spain, Sweden, Switzerland, Taiwan, the UK and the US. The group of developing countries comprises Albania, Bosnia and Herzegovina, China, India, Indonesia, Mexico, Montenegro, North Macedonia, Russia, Serbia, Turkey and Ukraine.

7 While IT broadly refers to computer hardware, CT refers to telecommunications equipment.

Methodologically, we apply a three-level multilevel regression model to take into account that the different outcome variables (plus other worker and firm characteristics) are available at the individual level while the offshoring and technological change measures are only available at the industry level (with countries as the third level). Hence, we can appropriately incorporate explanatory variables at all levels of aggregation and separately consider the within-country, across-country and industry variation. In addition to improving the estimates' efficiency (Gelman and Hill, 2006), this also produces unbiased estimates because it explicitly takes into account that individuals are nested in industries nested in countries, which allows for correlation among workers in the same industries and countries. Ordinary least squares (OLS) standard errors, which do not account for the intra-cluster correlation arising from the existing data hierarchy, are biased (usually downward) and inconsistent. The intraclass correlation coefficient (ICC) of intercept-only models points to non-negligible within-group/-cluster correlation, which justifies a multilevel approach. The multilevel approach also helps us to reduce the potential simultaneity problem of both offshoring and technological change, as we can expect that while offshoring and technological change affect the prevalence of atypical employment and skills mismatch, the job situation of individual workers (e.g. holding an atypical job or a job characterised by an imperfect job-skills match) conversely has a much smaller effect on offshoring and technological change. However, we do not use industry- or country-fixed effects, as our interest is primarily in modelling industry-level (but also country-level) processes.

Depending on the nature of the dependent variable, we will apply different multilevel regression methods: for atypical employment (in total and by constituent elements), a multilevel logit model is taken; and for skills mismatch, a multilevel multinomial logit model is taken, with 'well-matched' as the reference category and 'under-skilled' and 'over-skilled' as the two outcomes of interest. The cross-level interaction terms (between level-1 employee representation and level-2 industry indicators) are added in each case, with all industry-level indicators centred to ease interpretation. We report odds ratios with heteroscedasticity-robust standard errors. We use Stata version 16.1 and follow the approach suggested by Buis (2012) to calculate odds ratios for the cross-level interaction terms.

There are some potential methodological issues in our analysis. One issue is related to the simultaneity between the outcome variable and the different variables at the industry level. However, as mentioned above, this is reduced by the multilevel approach we take. Another issue relates to selection and the fact that all industry-level measures may also affect individuals' decisions regarding labour market participation (e.g. unemployment due to offshoring activities). However, since our sample only includes employed individuals and, by construction, excludes unemployed individuals, it cannot be taken into consideration. Lastly, there may also be an endogeneity issue between trade union representation and the different job-quality-outcome variables examined in this study, although this is difficult to address in a cross-section setting such as ours. In the context of our multilevel approach, where reverse causality of lower- to higher-level indicators is limited, we address this issue by using information on trade unions – specifically, trade union density – at the higher level. We explored several industry-level indicators from relevant sources, such as (i) the database on Institutional Characteristics of Trade Unions, Wage Setting, State Intervention and Social Pacts (ICTWSS)[8] and (ii) the European Social Survey (ESS)[9], which, among other things, include information on trade union membership (current and previous) and industry affiliation (at the 2-digit level). However, both proved inadequate because of either missing data

[8] In 2021, the ICTWSS database was rebranded as the OECD/AIAS ICTWSS database, which is publicly available at https://www.oecd.org/employment/ictwss-database.htm.

[9] https://www.europeansocialsurvey.org/.

or limited sample size. We therefore used information on trade union density at the country level (from the ICTWSS), which is not ideal because we cannot make use of the variation in trade union density across industries. Although trade union density changes little in the short run, we use it in a similar way to the industry-level indicators, namely, centred and in lagged form (specifically, with 1-, 2- and 3-year lags, each corresponding to the 1-, 2- and 3-year differences we use in the analysis). We discuss the results in section 5.

2.2. DATA SOURCES

We construct our database from six different data sources. First, we use the *European Working Conditions Survey (EWCS)*, which was launched in 1990 and has since been conducted every five years in a growing number of European countries (EU member states, EU candidate countries, EFTA countries).[10] Specifically, we use two editions of the European Working Conditions Survey (EWCS), namely, the 2015 EWCS (6th edition) and the 2021 EWCTS (extraordinary edition) addition to detailed information on worker and firm characteristics, both editions also provide information on employee representation at the company/organisational level in terms of: (i) trade unions, works councils or a similar committee representation (in addition to (ii) health and safety delegate or committee, and (iii) regular meetings in which employees can express their views about what is happening in the organisation). Previous EWCS editions did not include information on employee representation. Typically, the survey is carried out by means of face-to-face interviews using computer-aided personal interviewing (CAPI) with a sample size that varies between a required minimum of 1,000 and over 3,000 persons per country, using a multi-stage, stratified clustered sampling design used in each country, with stratification based on geographic regions (NUTS 2 level or below) and degree of urbanisation. However, owing to the COVID-19 pandemic, the 2021 EWCTS was carried out by computer-assisted telephone interviewing (CATI) with a sample size for each country ranging from 1,000 to 4,200 interviews and a single-stage, un-clustered sampling strategy based on random direct dialling to mobile (cell) telephone numbers (Random Digital Dialling – RDD).[11] The change in interview mode may affect the comparability of the two waves, as respondents may answer differently depending on the interview mode. Generally, the sample used in the EWC(T)S is representative of individuals aged 15 and over[12] who live in private households and are employed (i.e. who did at least one hour of work for pay or profit during the week before the interview took place, from Monday to Sunday). Information about workers' industry affiliation (according to the one- and two-digit NACE Rev. 2 classification) is used to match the EWC(T)S with other industry-level data, in particular the various measures of offshoring and technological change. Generally, the sample includes those participants who were employed at the time of the survey. We excluded the group of self-employed for whom the question on employee representation was not available, as it was only addressed to employees.

Second, trade-related data is taken from the 2020 release of the *World Input-Output Database (WIOD)*,[13] which provides information on international linkages of production processes and structures of final goods trade across 38 industries (NACE Rev. 2, A38) and 51 countries, covering all 27 EU member

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10 To date, there have been seven editions of the EWCS – in 1991, 1995, 2000/2001, 2005, 2010, 2015 and 2021 – in a growing number of European countries.

11 In Sweden, both mobile and landlines from a population register were used.

12 The age was 16 and over in Bulgaria, Norway, Spain and the UK.

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

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 for the 2005-2018 period. We use information for both domestic and imported inputs at the one- and two-digit industry level to construct the different offshoring measures.

Third, information on the real net capital stock (in 2015 prices) of computer hardware (IT), telecommunications equipment (CT), and computer software and database (DB) is taken from the 2021 edition of the *EU-KLEMS Growth and Productivity Accounts*, which is available for all 27 EU member states (as of 2020) plus Norway, Japan, the US and the UK for the 1995-2019 period and for 40 detailed industries (plus 23 industry aggregates), according to the NACE Rev. 2 industry classification.[14] For some EU member states, net capital stocks in total and by asset type are only available for the total economy (i.e. all NACE activities) or are incomplete at the more detailed NACE level. Hence, we imputed the missing data using information on the capital stock for the total economy by asset type of the country for which the imputation was performed and the shares at the more detailed NACE level of one or two reference EU countries.[15] This allowed us to determine the real net capital stock by asset type for all EU member states (as of 2020) plus the United Kingdom, with the exception of Croatia, Cyprus and Malta, for which we had no information on the total net capital stock.

Fourth, information on industrial robots[16] is taken from the *World Robotics Industrial Robots* statistics, which are compiled and published by the International Federation of Robotics (IFR)[17] and available for the 1993-2022 period.[18] The 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[19]), six broad non-manufacturing industries (at the section-level), and one 'Unspecified' category. Rather than corresponding to any particular industry class, the latter contains all data for which the exact industry in which the robots are used is either unknown or cannot be disclosed due to compliance rules. To make full use of the data, we have split up the 'Unspecified' category and allocated the data for each country and year to the 11 broad manufacturing and six broad non-manufacturing industries according to their share in the total.

Fifth, information on employment by detailed industry (used to compute the robot density) is taken from the *Structural Business Statistics (SBS)* available from Eurostat,[20] which describe the detailed structure,

14 The EU KLEMS is the main source for industry-level information on ICT – and its asset types IT, CT and DB – which is closely linked to the Third Industrial Revolution (AKA the Digital Revolution). Although this data source was not mentioned in the proposal, its inclusion in the analysis allows us to compare not only the impact of the three asset types with each other but also the impact of a technology of the next (i.e. Fourth) Industrial Revolution, namely, robotics.

15 We used the following reference countries: EL and SK for BG, UK for DK, FI and LV for EE, CZ and AT for HU, UK and NL for IE, FI for LT, NL for LU, CZ and SK for PL, ES and FR for PT, EL and SK for RO, FI for SE and SK, and AT for SI.

16 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: 29).

17 See https://ifr.org/worldrobotics.

18 The robots data is collected from nearly all industrial robot suppliers worldwide and supplemented with (secondary) data provided by several national robot associations, 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), the Russian Federation (RAR), and the People's Republic of China (CRIA).

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

20 Source: sbs_na_sca_r2 (Eurostat).

economic activity and performance of businesses over time.[21] These statistics are available for all EU member states, Iceland, Norway and Switzerland as well as some candidate and potential candidate countries at the 1- and 2-digit industry level, according to the NACE Rev. 2 industry classification.

Finally, information on per-worker reforms during the COVID-19 lockdown is taken from the *Labour Market Reform Database* (LABREF) provided by the European Commission's Directorate-General for Employment, Social Affairs and Inclusion (DG EMPL). LABREF is an open-access descriptive database covering labour market and social policy measures introduced by EU member states. It has become one of the standard references in the employment field, providing information on the reform measures adopted and their main design features.[22]

Owing to certain data limitations related to EU-KLEMS capital stock data (e.g. there is no information on real capital stocks at the detailed two-digit industry level for industries G and H for several countries) and to WIOD data (e.g. information for non-manufacturing industries is mainly available at the 1-digit level), we use an industry classification scheme that closely follows the 2019 edition of EU-KLEMS accounts, although it is less detailed for the services industries. Moreover, we exclude industries T and U, as the EU-KLEMS accounts do not contain information on the three types of ICT capital types. The list of industries is provided in Table A.1 in the annex.

In our analysis, we use two different data samples: (i) the total economy sample at the one- and two-digit industry level, 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, since 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. Specifically, while we use the three ICT asset types in our estimations for the total economy sample, we use both the three ICT asset types and robot density (in addition to all other indicators mentioned in equation (1)) in our estimations for the manufacturing sample. This allows us to also compare the effects of the two different measures of technological change for the manufacturing sample.

The sample for the descriptive part of this study (see next section) includes all 28 (pre-Brexit) EU member states. However, the econometric analyses are carried out on a sample of 25 countries due to the limited availability of some of the data in the EU-KLEMS (see above). In particular, the econometric analyses exclude Croatia, Cyprus and Malta.

In the analysis, we use weights as provided in the dataset.[23]

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21 Since Eurostat's SBS data is available at the more detailed NACE 2-digit level, it is preferable to other data sources, such as the EU LFS, which is only available at the crude 1-digit level.

22 This data source (not mentioned in the proposal) contains important policy information and was included to control for the effects of the COVID-19 pandemic (i.e. reforms implemented during lockdowns) and its effect on the quality of work.

23 Summary statistics of the main variables from the EWC(T)S are reported in Table A.2 in the annex.

3. Descriptive analysis

The prevalence of atypical types of employment (excluding self-employment) – by country, industry and occupation – is shown in Panels A, B and C of Figure 1 (for 2015) and Figure 2 (for 2021) below. The height of each bar captures the share of atypical employment in total employment, which is then further broken down by its constituent parts. This is done while taking into account the fact that the two types of atypical employment can also overlap, as workers can simultaneously have jobs of a temporary nature and can work part-time involuntarily. Hence, we distinguish between (i) temporary contract only, (ii) involuntary part-time only, and (iii) both (when both types overlap).

The two figures point to significant differences between EU member states (Panel A).[24] In 2015, the prevalence of atypical employment was highest in Cyprus, at 55%, indicating that every second employee was in an atypical job. This is followed by Spain, Greece, Malta, Poland and the Netherlands, where between 32% and 37% of employees were in atypical employment. However, in the majority of EU member states, the share of employees in atypical employment was below 30%. Atypical employment was least common in Lithuania, where only 10% of employees were in atypical employment. Overall, temporary contracts were the most common form of atypical employment, while involuntary part-time work or both forms of atypical employment together only played a minor role. A notable exception was Luxembourg, where involuntary part-time only was as common as temporary contracts only (with very little overlap between the two). In 2021, the share of employees in atypical employment had decreased compared to 2015. This decrease mainly stemmed from a decrease in the share of employees in temporary contracts, which can be attributed to the severe impact of the economic crisis associated with COVID-19 on employees in atypical employment (OECD and ILO, 2021). Similar to 2015, in 2021, Cyprus had the highest share of employees in atypical employment (36%), while all other countries had shares below 30%. Romania had the lowest share (8%). Temporary contracts remained the most prevalent form of atypical employment, even in Luxembourg.

The importance of atypical employment also varied between industries (Panel B), ranging in 2015 from 70% in industry T (Activities of households as employers) to 7% in industry B (Mining and quarrying) (Panel B). A similar observation can be made for 2021, but the share was smaller and varied from 43% to 4%. Again, temporary contracts were the most common form of atypical employment, while involuntary part-time work or both forms of atypical employment together only played a minor role. In 2015, an important exception was industry 19 (Coke and refined petroleum products), where involuntary part-time only was as common as temporary contracts only (with no overlap between the two). In 2021, this exception disappeared and only temporary contracts were recorded in industry 19. However, in activities of households as employers (industry T), involuntary part-time was as common as temporary contracts.

[24] This is, of course, contingent upon national employment protection legislation (OECD, 2020).

Similarly, the importance of atypical employment also varied between occupations (Panel C). As expected, atypical employment was less prevalent among highly skilled workers (managers, Occ1) and more prevalent among low-skilled workers (elementary occupations, Occ9). However, there are differences depending on the year studied. In 2015, skilled agricultural, forestry and fishery workers (Occ6) were the most affected by atypical work, whereas they were one of the three occupation groups least affected by this form of work in 2021. This finding is consistent with the sectoral results mentioned earlier. Industry A (Agriculture, forestry and fishing), which employs the majority of skilled agricultural workers, had the second-highest proportion of atypical employees in 2015 and was one of the sectors least affected by atypical employment in 2021. Again, temporary contracts were the most common form of atypical employment, while involuntary part-time work or both forms of atypical employment together only played a minor role. However, involuntary part-time only was relatively common among elementary occupations (Occ9) and also, in 2021, among skilled agricultural, forestry and fishery workers (Occ6).

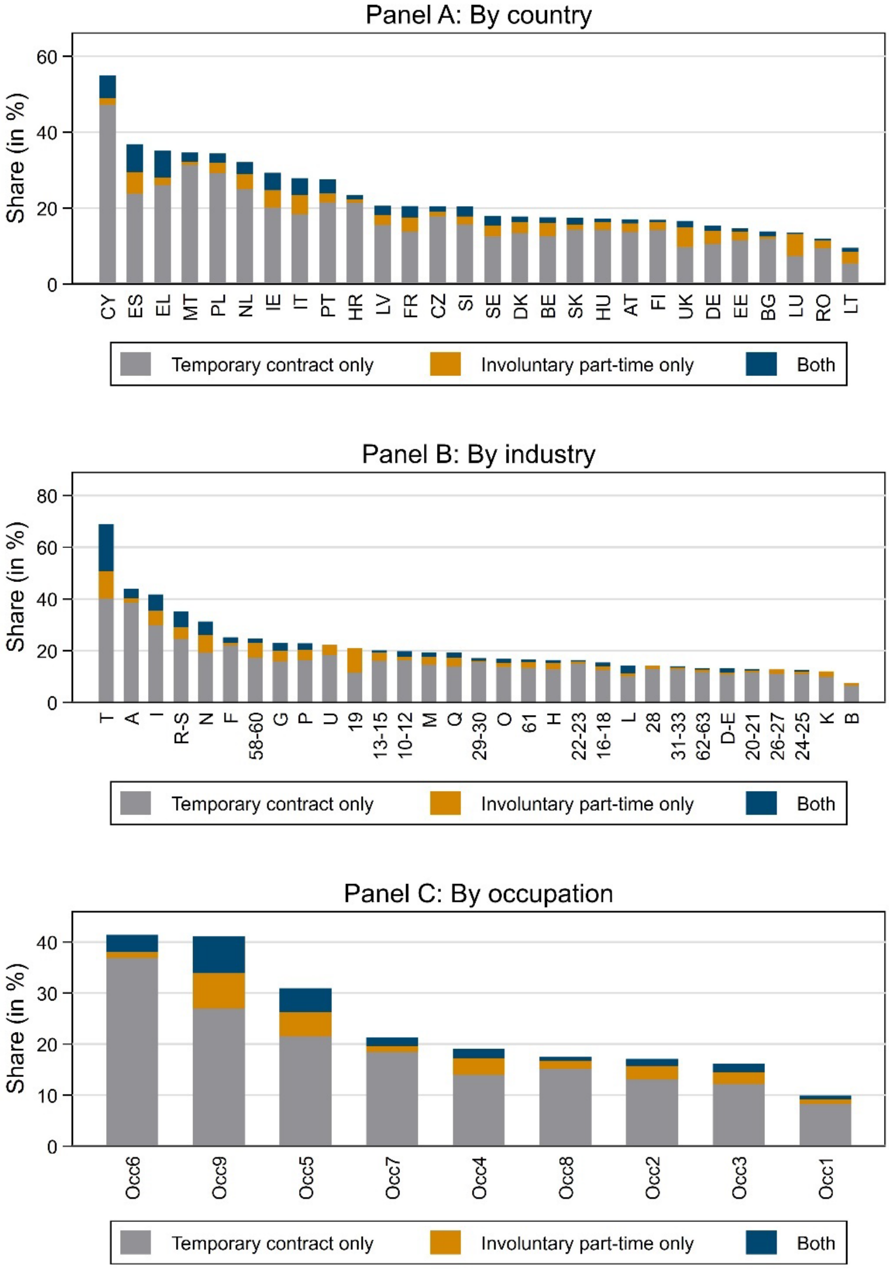
The prevalence of self-reported skills mismatch among workers (excluding the self-employed) – by country, industry and occupation – is shown in Panels A, B and C of Figure 3 below, which distinguishes between three categories: (i) skills match, where a worker's current skills correspond well with her/his duties; (ii) under-skilled, where a worker feels that she/he needs training to perform her/his duties well; and (iii) over-skilled, where a workers feels that she/he has skills that would allow her/him to perform more demanding tasks.

Figure 3 shows that skills mismatch – in terms of both under- and over-skilled – varies across EU member states; is highest in Austria, where 54% of workers consider themselves mismatched; and is lowest in Portugal, where only 25% of workers consider themselves mismatched (Panel A). Despite this broad range, the majority of EU member states fall within the 40-50% mismatch range. Moreover, with a few exceptions (Austria, Estonia, Malta and Lithuania), over-skilling is more common than under-skilling. Over-skilling is most common in Romania, followed by Cyprus and Greece.

At the industry-level, skills mismatch is similarly common but in a narrower range than at the country level, varying from 53% in industries 19 (Coke and refined petroleum products) and 61 (Telecommunications) to 31% in industry U (Activities of extraterritorial organisation and bodies) (Panel B). Again, over-skilling is much more common than under-skilling without exception and most prevalent in industries 19 (Coke and refined petroleum products) and T (Activities of households as employers).

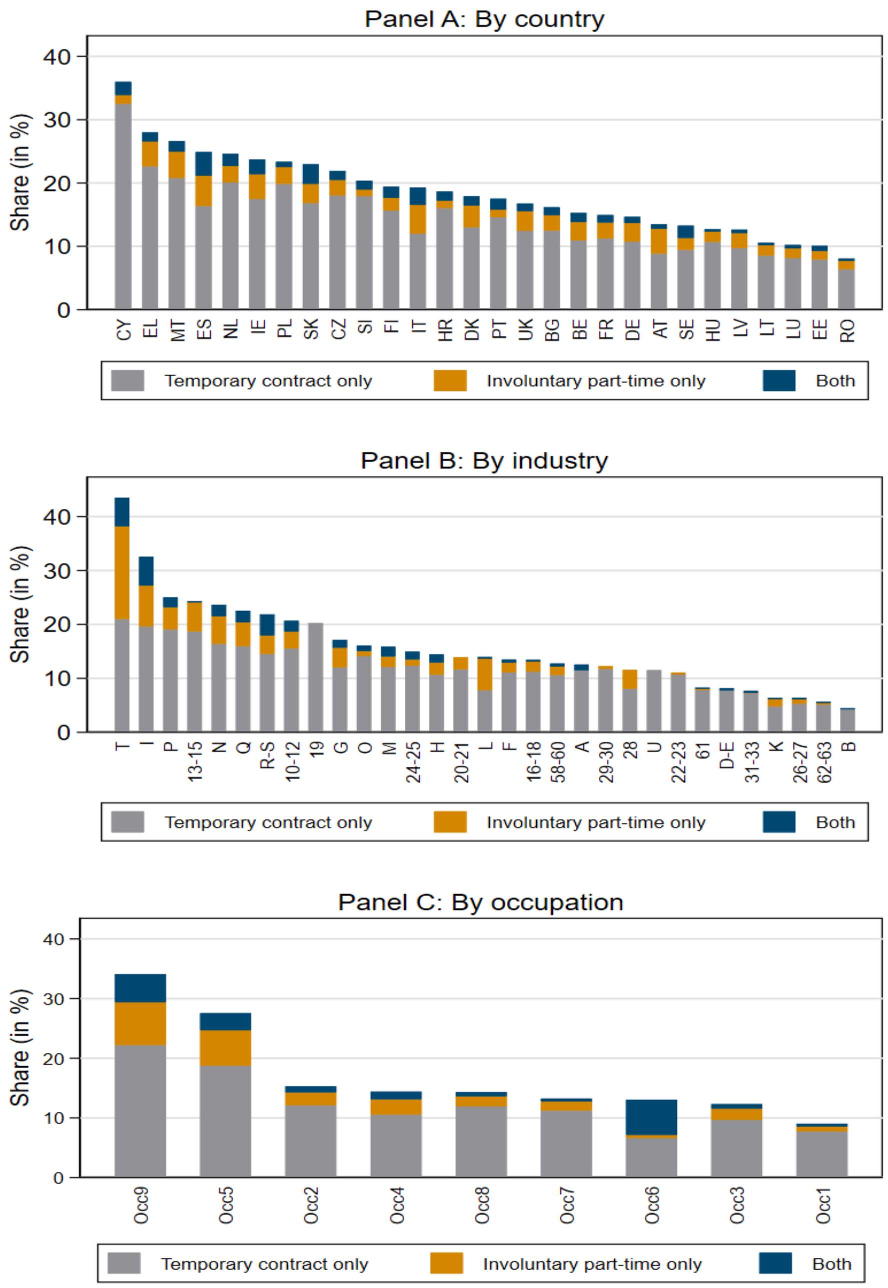
Finally, the prevalence of skills mismatch at the occupational level is quite similar, in the range of 50-60% (Panel C). As expected, skills mismatch is highest in the high-skilled occupations: professionals (Occ2), managers (Occ1), and technicians and associate professionals (Occ3). Interestingly, over- and under-skilling are of similar importance in the high-skilled occupations, while over-skilling dominates in the medium- to low-skilled occupations and is most common among clerical support workers (Occ4) and in elementary occupations (Occ9).

Figure 1 / Prevalence of atypical types of work in 2015, by country, industry and occupation



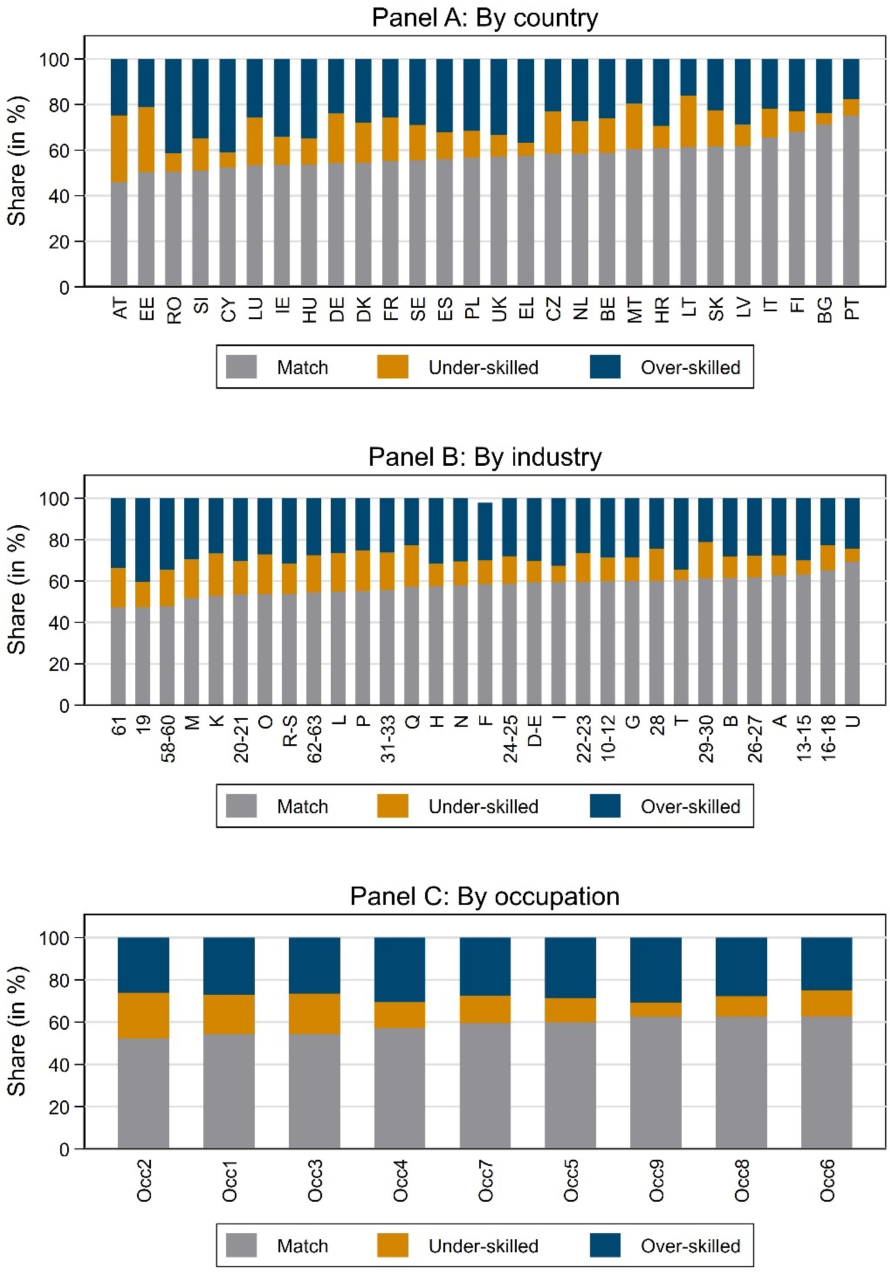
Note: Atypical employment refers to either the presence of a temporary contract or involuntary part-time work. The industry classifications in Panel B follow the NACE Rev. 2 classification; see Table A.1 for the list of industries. Occupations are classified according to ISCO-08, where Occ1 refers to ‘Managers’, Occ2 to ‘Professionals’, Occ3 to ‘Technicians and associate professionals’, Occ4 to ‘Clerical support workers’, Occ5 to ‘Service and sales workers’, Occ6 to ‘Skilled agricultural, forestry and fishery workers’, Occ7 to ‘Craft and related trades workers’, Occ8 to ‘Plant and machine operators and assemblers’, and Occ9 to ‘Elementary occupations’. Occ0 (Armed forces) was excluded due to insufficient data. Weights are used in the calculations.
Source: European Working Conditions Survey 2015, own calculations.

Figure 2 / Prevalence of atypical types of work in 2021, by country, industry and occupation



Note: Atypical employment refers to either the presence of a temporary contract or involuntary part-time work. The industry classifications in Panel B follow the NACE Rev. 2 classification; see Table A.1 for the list of industries. Occupations are classified according to ISCO-08, where Occ1 refers to ‘Managers’, Occ2 to ‘Professionals’, Occ3 to ‘Technicians and associate professionals’, Occ4 to ‘Clerical support workers’, Oc5 to ‘Service and sales workers’, Occ6 to ‘Skilled agricultural, forestry and fishery workers’, Occ7 to ‘Craft and related trades workers’, Occ8 to ‘Plant and machine operators and assemblers’, and Occ9 to ‘Elementary occupations’. Occ0 (Armed forces) was excluded due to insufficient data. Weights are used in the calculations.
Source: European Working Conditions Telephone Survey 2021, own calculations.

Figure 3 / Frequency of skills mismatch, by country, industry and occupation



Note: The prevalence of skills mismatch is measured by the following question from the EWCS-2015: *'Which of the following statements would best describe your skills in your own work?'*. The three different answer options were coded as follows: 'match' refers to a situation in which the present skills correspond well with the respondent's duties, 'under-skilled' to a situation in which further training is needed to cope well with the respondent's duties, and 'over-skilled' to a situation in which the respondent has skills to cope with more demanding duties. The industry classifications in Panel B follow the NACE Rev. 2 classification; see Table A.1 for the list of industries. Occupations are classified according to ISCO-08, where Occ1 refers to 'Managers', Occ2 to 'Professionals', Occ3 to 'Technicians and associate professionals', Occ4 to 'Clerical support workers', Occ5 to 'Service and sales workers', Occ6 to 'Skilled agricultural, forestry and fishery workers', Occ7 to 'Craft and related trades workers', Occ8 to 'Plant and machine operators and assemblers', and Occ9 to 'Elementary occupations'. Occ0 (Armed forces) was excluded due to insufficient data. Weights are used in the calculations.
Source: European Working Conditions Survey 2015, own calculations.

4. Results

Results are presented separately for the two outcomes considered, namely, *atypical employment* (see Sections 4.1 and 4.2), which is further differentiated by the type of atypical employment (temporary contract and involuntary part-time employment) and self-reported *skills mismatch* (see Section 4.3), which distinguishes between well matched (as the reference category), under-skilled and over-skilled. While Section 4.1 refers to the results for atypical employment of the 2015 EWCS, Section 4.2 refers to those of the 2021 EWCTS. Section 4.3 refers to the results for skills mismatch, but only for the 2015 EWCS, as there is no comparable skills mismatch indicator for the 2021 EWCTS. For reasons discussed in the Data chapter (Section 2.2), we present two sets of results: one including the entire group of industries covered in the analysis, and another that focuses only on manufacturing industries. For the 2021 EWCTS, due to data and convergence issues, we only present results for the entire group of industries. Moreover, for each outcome and sample, we present results for two models: the main model specified in equation (1) and the model including interaction terms between each of the industry-level indicators (OFF_{jct} and TC_{jct}) and the dummy for employee representation TU_{ijct} to shed light on the potential mediating role of trade union representation on employment outcomes. In discussing our results, we focus on 1-, 2- and 3-year differences in industry-level variables (for 2015), which allows us to compare the effects of short- versus longer-term changes in offshoring and technological change on the prevalence of atypical employment and skills mismatch. As highlighted above, for the 2021 EWCTS, we only use 1-year differences which refer to changes between 2017 and 2018, while the outcomes (i.e. atypical employment, temporary contract and involuntary part-time employment) refer to 2021.

4.1. ATYPICAL EMPLOYMENT – RESULTS FROM THE 2015 EWCS

The results (see Table 1 and Table 2 below) show that the existence of a trade union at the firm level is associated with a lower probability of being in atypical employment. However, this finding is only observed in the total sample – and for both having a temporary contract and working part-time involuntarily – while it is absent in the manufacturing sample, suggesting that trade union representation mainly makes a difference for workers in non-manufacturing industries, specifically private and public services industries, which make up the bulk of non-manufacturing industries in our sample.

An increase in total offshoring is associated with a higher probability of being in atypical employment, but only in the manufacturing sample and then consistently for all three differencing periods, which suggests that both short- and longer-term changes in total offshoring in manufacturing increase the likelihood of being in atypical employment. This is mainly related to an increase in the probability of a temporary contract but is unrelated to involuntary part-time work.

The results for technology not only differ by sample but also by technology measure – ICT, further broken down by its three asset types, and automation. Specifically, an increase in IT is associated with a higher probability of being in atypical employment only in manufacturing, but then for short- and longer-term changes. This is mainly due to the higher probability of a temporary contract. Conversely, an increase in CT is associated with a lower probability of being in atypical employment in both samples.

Table 1 / Atypical employment – in total and by type (total sample, 2015): Total offshoring

	(1) Atypical D1	(2) Atypical D2	(3) Atypical D3	(4) Temp. Contr D1	(5) Temp. Contr D2	(6) Temp. Contr D3	(7) Invol. Part-time D1	(8) Invol. Part-time D2	(9) Invol. Part-time D3
TU	0.713***	0.713***	0.712***	0.730***	0.729***	0.729***	0.735***	0.736***	0.737***
	(0.041)	(0.041)	(0.041)	(0.048)	(0.048)	(0.048)	(0.051)	(0.051)	(0.051)
D.OFF^{tot}	1.051	1.352*	1.054	1.039	1.281	1.006	1.127	1.370	1.010
	(0.167)	(0.222)	(0.121)	(0.172)	(0.234)	(0.131)	(0.164)	(0.293)	(0.120)
D.IT	1.147*	1.012	0.971	1.109	1.007	0.966	1.320**	1.115	1.077
	(0.089)	(0.116)	(0.110)	(0.086)	(0.116)	(0.120)	(0.149)	(0.143)	(0.113)
D.CT	0.886**	1.004	1.037	0.887**	1.012	1.059	0.921	0.962	0.907
	(0.049)	(0.024)	(0.075)	(0.052)	(0.023)	(0.086)	(0.086)	(0.033)	(0.061)
D.DB	1.241	1.016	0.999	1.270	0.979	0.955	0.909	1.047**	1.041
	(0.244)	(0.020)	(0.049)	(0.293)	(0.025)	(0.047)	(0.262)	(0.022)	(0.063)
Female	1.234***	1.233***	1.235***	1.018	1.018	1.019	1.873***	1.866***	1.870***
	(0.066)	(0.066)	(0.066)	(0.054)	(0.054)	(0.054)	(0.160)	(0.160)	(0.160)
Migrant	1.235***	1.235***	1.236***	1.185**	1.185**	1.186**	1.295**	1.294**	1.293**
	(0.078)	(0.077)	(0.077)	(0.089)	(0.088)	(0.089)	(0.144)	(0.144)	(0.143)
15-24 yrs old	1.120	1.121	1.119	1.034	1.034	1.033	1.252	1.251	1.248
	(0.143)	(0.143)	(0.143)	(0.118)	(0.117)	(0.117)	(0.220)	(0.219)	(0.218)
25-49 yrs old	0.704***	0.703***	0.704***	0.687***	0.687***	0.687***	0.847*	0.847*	0.846*
	(0.038)	(0.038)	(0.038)	(0.050)	(0.050)	(0.050)	(0.074)	(0.074)	(0.074)
ISCED: medium	0.807***	0.806***	0.806***	0.814**	0.814**	0.814**	0.763**	0.762**	0.763**
	(0.064)	(0.064)	(0.064)	(0.073)	(0.073)	(0.073)	(0.104)	(0.104)	(0.103)
ISCED: high	0.666***	0.666***	0.666***	0.679***	0.679***	0.679***	0.675***	0.674***	0.675***
	(0.065)	(0.064)	(0.065)	(0.086)	(0.085)	(0.086)	(0.092)	(0.091)	(0.091)
Tenure (ln)	0.406***	0.406***	0.406***	0.363***	0.363***	0.363***	0.662***	0.662***	0.662***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.024)	(0.024)	(0.024)
ISCO: medium	0.801***	0.800***	0.801***	0.847**	0.847**	0.849**	0.740**	0.736**	0.736**
	(0.046)	(0.046)	(0.046)	(0.056)	(0.056)	(0.056)	(0.100)	(0.100)	(0.100)
ISCO: high	0.655***	0.653***	0.657***	0.719***	0.719***	0.723***	0.575***	0.568***	0.572***
	(0.061)	(0.061)	(0.061)	(0.077)	(0.078)	(0.078)	(0.077)	(0.077)	(0.077)
Firm size: medium	0.939	0.938	0.938	0.989	0.988	0.987	0.807*	0.807*	0.809*
	(0.051)	(0.051)	(0.051)	(0.082)	(0.082)	(0.082)	(0.093)	(0.093)	(0.094)
Firm size: large	0.994	0.993	0.992	1.168*	1.166*	1.165*	0.508***	0.510***	0.511***
	(0.081)	(0.080)	(0.080)	(0.108)	(0.107)	(0.107)	(0.076)	(0.076)	(0.076)
Firm type: private	0.698***	0.700***	0.697***	0.668***	0.668***	0.665***	0.776***	0.779***	0.776***
	(0.047)	(0.047)	(0.047)	(0.056)	(0.057)	(0.057)	(0.069)	(0.068)	(0.067)
Firm type: other	1.113	1.116	1.112	1.100	1.101	1.097	1.093	1.098	1.095
	(0.110)	(0.111)	(0.110)	(0.114)	(0.114)	(0.113)	(0.161)	(0.160)	(0.160)
var(country)	1.396***	1.379***	1.401***	1.563***	1.540***	1.561***	1.219***	1.207***	1.226***
	(0.096)	(0.096)	(0.092)	(0.150)	(0.151)	(0.150)	(0.082)	(0.081)	(0.085)
var(country>nace)	1.420***	1.423***	1.419***	1.540***	1.542***	1.532***	1.424***	1.429***	1.437***
	(0.075)	(0.076)	(0.074)	(0.099)	(0.098)	(0.092)	(0.095)	(0.093)	(0.094)
Constant	1.578**	1.569**	1.602**	1.361	1.370*	1.400*	0.121***	0.118***	0.121***
	(0.302)	(0.296)	(0.302)	(0.257)	(0.252)	(0.259)	(0.026)	(0.024)	(0.025)
No. of obs.	24,653	24,650	24,650	24,614	24,611	24,611	24,234	24,231	24,231
Log likelihood	-9,439	-9,439	-9,440	-8,205	-8,205	-8,205	-4,587	-4,587	-4,588

Note: Weights are used in estimations. D1, D2 and D3 refer to 1-, 2- and 3-year differences of the industry-level variables. Odds ratios are reported. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 2 / Atypical employment – in total and by type (manufacturing only, 2015): Total offshoring

	(1) Atypical D1	(2) Atypical D2	(3) Atypical D3	(4) Temp. Contr D1	(5) Temp. Contr D2	(6) Temp. Contr D3	(7) Invol. Part-time D1	(8) Invol. Part-time D2	(9) Invol. Part-time D3
TU	0.965	1.018	1.014	1.088	1.157	1.147	0.636	0.641	0.606*
	(0.160)	(0.175)	(0.175)	(0.176)	(0.197)	(0.200)	(0.200)	(0.202)	(0.182)
D.OFF^{tot}	1.358*	1.604***	1.356**	1.924***	2.187***	1.112	0.647	0.833	1.209
	(0.223)	(0.293)	(0.169)	(0.377)	(0.424)	(0.246)	(0.434)	(0.640)	(0.285)
D.RobDens	0.855	1.012	0.982	0.925	1.028	0.986	0.695	0.705**	0.672**
	(0.181)	(0.031)	(0.015)	(0.221)	(0.046)	(0.015)	(0.211)	(0.112)	(0.132)
D.IT	2.750***	2.102***	1.689***	2.726***	2.062***	1.708***	1.885**	1.393	1.310
	(0.752)	(0.394)	(0.193)	(0.833)	(0.471)	(0.198)	(0.607)	(0.403)	(0.271)
D.CT	0.732**	0.822	0.781**	0.764*	0.880	0.822*	0.520	0.371**	0.524***
	(0.098)	(0.132)	(0.091)	(0.107)	(0.145)	(0.095)	(0.405)	(0.151)	(0.116)
D.DB	1.211	1.351	0.827	1.534	1.556	0.873	1.628	2.158	2.052
	(0.590)	(0.469)	(0.223)	(0.816)	(0.607)	(0.234)	(1.870)	(1.416)	(1.150)
Female	1.212	1.210	1.240*	1.092	1.078	1.113	2.167***	2.256***	2.327***
	(0.155)	(0.152)	(0.155)	(0.160)	(0.158)	(0.164)	(0.601)	(0.624)	(0.642)
Migrant	1.288	1.348	1.407	1.273	1.333	1.388	1.247	1.217	1.333
	(0.380)	(0.375)	(0.405)	(0.461)	(0.463)	(0.500)	(0.676)	(0.649)	(0.707)
15-24 yrs old	0.669*	0.625**	0.697	0.679	0.627*	0.696	0.873	0.884	0.945
	(0.146)	(0.139)	(0.160)	(0.164)	(0.156)	(0.178)	(0.330)	(0.337)	(0.369)
25-49 yrs old	0.699***	0.639***	0.652***	0.777	0.701	0.704	0.697*	0.673**	0.761
	(0.095)	(0.093)	(0.106)	(0.161)	(0.161)	(0.172)	(0.138)	(0.136)	(0.155)
ISCED: medium	1.103	1.214	1.216	1.139	1.269	1.249	0.867	0.930	0.977
	(0.189)	(0.145)	(0.156)	(0.235)	(0.188)	(0.189)	(0.181)	(0.185)	(0.189)
ISCED: high	0.632*	0.701	0.721	0.658	0.738	0.751	0.636	0.670	0.698
	(0.174)	(0.182)	(0.190)	(0.204)	(0.210)	(0.216)	(0.226)	(0.248)	(0.266)
Tenure (ln)	0.296***	0.289***	0.284***	0.263***	0.256***	0.252***	0.721**	0.728**	0.722***
	(0.028)	(0.027)	(0.028)	(0.029)	(0.027)	(0.027)	(0.091)	(0.095)	(0.090)
ISCO: medium	0.797	0.778	0.734*	0.807	0.781	0.739*	1.012	1.039	1.009
	(0.125)	(0.131)	(0.132)	(0.130)	(0.132)	(0.134)	(0.303)	(0.311)	(0.321)
ISCO: high	0.314***	0.310***	0.302***	0.311***	0.309***	0.301***	0.395	0.403	0.396
	(0.056)	(0.052)	(0.054)	(0.051)	(0.047)	(0.048)	(0.238)	(0.247)	(0.249)
Firm size: medium	0.627	0.687	0.726	0.738	0.826	0.885	0.242**	0.243**	0.256**
	(0.188)	(0.197)	(0.215)	(0.237)	(0.248)	(0.273)	(0.143)	(0.141)	(0.150)
Firm size: large	0.688	0.714	0.726	0.763	0.800	0.822	0.283**	0.290**	0.288**
	(0.185)	(0.181)	(0.190)	(0.220)	(0.213)	(0.229)	(0.149)	(0.150)	(0.144)
Firm type: private	0.450	0.439	0.451	0.372*	0.363*	0.371	0.392	0.377	0.351
	(0.233)	(0.228)	(0.252)	(0.207)	(0.203)	(0.224)	(0.338)	(0.319)	(0.296)
Firm type: other	0.297*	0.272*	0.254*	0.228**	0.207**	0.193**	0.347	0.323	0.301
	(0.200)	(0.184)	(0.190)	(0.158)	(0.144)	(0.152)	(0.531)	(0.484)	(0.459)
var(country)	1.842***	1.878***	2.229**	2.030***	2.031***	2.630**	1.509	1.489	1.375
	(0.387)	(0.389)	(0.817)	(0.508)	(0.490)	(1.119)	(0.414)	(0.412)	(0.366)
var(country>nace)	1.365	1.350	1.339	1.482*	1.445*	1.425	1.355	1.241	1.290
	(0.279)	(0.256)	(0.283)	(0.337)	(0.304)	(0.330)	(0.395)	(0.384)	(0.370)
Constant	3.277*	2.753	2.864	2.734	2.252	2.403	0.158**	0.166**	0.180**
	(2.286)	(1.880)	(2.132)	(2.035)	(1.650)	(1.895)	(0.140)	(0.149)	(0.154)
No. of obs.	3,089	3,000	2,862	3,088	2,999	2,861	3,043	2,955	2,820
Log likelihood	-969.3	-934.2	-889.7	-873.8	-838.0	-799.4	-309.4	-301.8	-288.2

Note: Weights are used in estimations. D1, D2 and D3 refer to 1-, 2- and 3-year differences of the industry-level variables. Odds ratios are reported. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

However, CT effects differ by type of atypical employment and are associated with a lower probability of a temporary contract in the total sample and a lower probability of involuntary part-time work in manufacturing. A change in DB or robot density is statistically unrelated to the likelihood of being in atypical employment. However, a further differentiation by type of atypical employment shows that both are related to the probability of involuntary part-time work, but in different ways. Specifically, while a higher likelihood of involuntary part-time work is associated with DB in the total sample, a lower likelihood of involuntary part-time work is associated with robot density in manufacturing.

Hence, our results are partly at odds with what is found in the related literature, which shows that different forms of non-standard employment tend to increase in response to offshoring, ICT and robotisation (Rutledge et al., 2019 for the US; Kiyota and Maruyama, 2017 as well as Machikita and Sato, 2011 for Japan; Nikulin and Szymczak, 2020 for several Central and Eastern European countries).

In terms of worker and firm characteristics, there are important differences but also similarities between the atypical employment measures and samples studied. By and large, however, our results are in line with what is typically found in the literature (see e.g. Eurofound, 2015). Specifically, as concerns differences, in the full sample (Table 1), we observe that females and migrants are more likely to be in atypical employment than males and non-migrants. For females, this is mainly related to their higher likelihood of working part-time involuntarily, while migrants are doubly affected, as they are more likely to have a temporary contract and to work part-time involuntarily. This is in contrast to what can be observed for the manufacturing sample, where females are more likely than males to work part-time involuntarily, while there are no differences by country of birth (i.e. migrant status). Moreover, higher educational attainment is associated with a lower probability of being in atypical employment, but only in the total sample, while in the manufacturing sample (Table 2), there are no differences by highest level of educational attainment. In the total sample, higher educational attainment is related to both a lower likelihood of having a temporary contract and of involuntary part-time work. In addition, workers in private firms are less likely to be in atypical employment than those in public firms, but this only holds true for the total sample (results for the manufacturing sample are only marginally significant for other firms). In the total sample, the lower likelihood of workers in private firms is associated with both a lower probability of a temporary contract and of involuntary part-time work.

There are also similarities, which are mainly related to the age, tenure and occupation of employees as well as the size of the firm they work for. Specifically, middle-aged employees (25-49 years old) are less likely to be in atypical employment than older employees (aged 50 and above). In the total sample, this is mainly related to the lower probability of having a temporary contract (while the lower probability of involuntary part-time work is only marginally significant in both samples). Similarly, tenure is associated with a lower probability of being in atypical employment, both in terms of a lower likelihood of having a temporary contract and of involuntary part-time work. Workers in higher skilled occupations are also less likely to be in atypical employment. In the total sample, this is related to both a lower likelihood of having a temporary contract and of involuntary part-time work, while in the manufacturing sample, this mainly related to a lower probability of having a temporary contract. By contrast, there are no effects of firm size on the probability of being in atypical employment in general. However, for one type of atypical employment (i.e. involuntary part-time work), the size of the firm does matter, and a larger firm size is associated with a lower probability of working part-time involuntarily.

Table 3 and Table 4 below report the results when total offshoring is further split into (i) narrow and broad offshoring (OFF^{N}, OFF^{B}), (ii) manufacturing and services offshoring (OFF^{Manuf}, OFF^{Serv}), and (iii) offshoring by source country (developed countries – OFF^{Devd}, developing countries – OFF^{Devg}, and NMS13 – OFF^{NMS13}), as defined in Section 2.2. The results are again reported for the three year differences: 1, 2 and 3 years. Since the coefficients for the other control variables are similar to what we observed above (see Table 1 and Table 2 above), we concentrate on the different offshoring indicators.[25]

Table 3 / Atypical employment – in total and by type (total sample, 2015): Other offshoring measures

	(1) Atypical D1	(2) Atypical D2	(3) Atypical D3	(4) Temp. contr D1	(5) Temp. contr D2	(6) Temp. contr D3	(7) Invol. part-time D1	(8) Invol. part-time D2	(9) Invol. part-time D3
Narrow and broad offshoring									
D.OFF^{N}	1.015	1.030	0.991	0.993	1.027	0.989	1.044	0.996	1.007
	(0.025)	(0.023)	(0.026)	(0.029)	(0.039)	(0.033)	(0.107)	(0.084)	(0.044)
D.OFF^{B}	1.037	1.248	1.073	1.044	1.211	1.050	1.101	1.273	1.076
	(0.142)	(0.183)	(0.115)	(0.139)	(0.187)	(0.157)	(0.179)	(0.304)	(0.129)
No. of obs.	24,653	24,650	24,650	24,614	24,611	24,611	24,234	24,231	24,231
Log likelihood	-9,439	-9,439	-9,440	-8,205	-8,205	-8,205	-4,587	-4,587	-4,587
Manufacturing and services offshoring									
D.OFF^{Manuf}	0.995	1.111	1.065	0.911	1.017	1.006	1.184**	1.300***	1.085*
	(0.074)	(0.080)	(0.078)	(0.096)	(0.107)	(0.097)	(0.099)	(0.085)	(0.051)
D.OFF^{Serv}	1.050	1.103	1.016	1.135	1.199	1.025	0.949	0.824	1.035
	(0.158)	(0.156)	(0.066)	(0.176)	(0.176)	(0.086)	(0.156)	(0.164)	(0.123)
No. of obs.	24,653	24,650	24,650	24,614	24,611	24,611	24,234	24,231	24,231
Log likelihood	-9,439	-9,439	-9,439	-8,205	-8,205	-8,205	-4,587	-4,586	-4,587
Offshoring to developed countries, developing countries and NMS13									
D.OFF^{Devd}	1.140	1.360	1.127	1.072	1.273	1.056	1.448	1.723**	1.222
	(0.250)	(0.286)	(0.200)	(0.295)	(0.283)	(0.212)	(0.361)	(0.398)	(0.210)
D.OFF^{Devg}	1.372	1.074	0.994	1.513	1.186	1.040	1.016	0.879	0.907
	(0.304)	(0.184)	(0.125)	(0.389)	(0.172)	(0.103)	(0.263)	(0.195)	(0.127)
D.OFF^{NMS13}	0.704**	0.782*	0.852*	0.687	0.715	0.836	0.768	0.918	0.881
	(0.115)	(0.114)	(0.083)	(0.181)	(0.157)	(0.106)	(0.170)	(0.108)	(0.089)
No. of obs.	24,653	24,650	24,650	24,614	24,611	24,611	24,234	24,231	24,231
Log likelihood	-9,437	-9,438	-9,439	-8,203	-8,204	-8,204	-4,587	-4,586	-4,587

Note: Weights are used in estimations. D1, D2 and D3 refer to 1-, 2- and 3-year differences of the industry-level variables. All calculations also include all other control variables. Odds ratios are reported. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

The results show that an increase in offshoring (measured by different offshoring indicators) remains unrelated to atypical employment in the total sample. The only exception is offshoring to the NMS13, which is associated with a lower probability of being in atypical employment, but only for very recent increases. In manufacturing, increases in manufacturing offshoring are associated with a higher probability of being in atypical employment, but again only for very recent increases. By contrast, offshoring to the NMS13 is associated with a lower probability of being in atypical employment. Further differentiation by type of atypical employment shows that both manufacturing offshoring and offshoring to

25 The full results tables are available from the authors upon request.

developed countries make involuntary part-time work more likely in both samples. Overall, the differences in results by sourcing region suggest that different tasks and jobs are offshored to the different regions analysed, with offshoring to the NMS13 (presumably of tasks that require more flexibility) helping to reduce the 'risk' of being in temporary employment.

Table 4 / Atypical employment – in total and by type (manufacturing only, 2015): Other offshoring measures

	(1) Atypical D1	(2) Atypical D2	(3) Atypical D3	(4) Temp. contr D1	(5) Temp. contr D2	(6) Temp. contr D3	(7) Invol. part-time D1	(8) Invol. part-time D2	(9) Invol. part-time D3
				Narrow and broad offshoring					
D.OFF^{N}	2.786	1.653	1.276	2.810	1.586	1.124	0.303	0.858	1.108
	(2.147)	(0.714)	(0.207)	(2.178)	(0.593)	(0.216)	(0.457)	(0.826)	(0.109)
D.OFF^{B}	0.726	1.101	1.128	0.874	1.387	1.370	2.372	1.212	1.196
	(0.389)	(0.411)	(0.424)	(0.526)	(0.556)	(0.667)	(1.965)	(0.691)	(0.576)
No. of obs.	3,089	3,000	2,862	3,088	2,999	2,861	3,043	2,955	2,820
Log likelihood	-968.0	-933.9	-889.2	-873.0	-837.9	-799.1	-309.0	-301.8	-288.2
				Manufacturing and services offshoring					
D.OFF^{Manuf}	1.770**	2.142***	1.704*	1.145	1.461	1.436	3.201***	3.113***	2.735***
	(0.417)	(0.450)	(0.505)	(0.317)	(0.454)	(0.474)	(0.885)	(0.978)	(0.791)
D.OFF^{Serv}	0.518	0.623	0.682	1.296	1.358	0.957	0.157	0.182	0.290*
	(0.235)	(0.276)	(0.191)	(1.133)	(0.926)	(0.370)	(0.322)	(0.226)	(0.207)
No. of obs.	3,089	3,000	2,862	3,088	2,999	2,861	3,043	2,955	2,820
Log likelihood	-968.6	-933.1	-889.0	-874.1	-838.0	-799.2	-307.5	-299.2	-284.9
				Offshoring to developed countries, developing countries and NMS13					
D.OFF^{Devd}	9.759*	2.964	2.735*	7.419	2.649	2.488	4.733	1.253	2.860
	(12.760)	(3.166)	(1.587)	(10.274)	(2.955)	(1.666)	(7.127)	(1.596)	(2.959)
D.OFF^{Devg}	1.824	2.257	1.198	1.474	2.467	1.022	2.282	0.662	1.024
	(1.963)	(2.603)	(0.352)	(1.491)	(2.988)	(0.351)	(3.674)	(0.680)	(0.311)
D.OFF^{NMS13}	0.064**	0.176*	0.382*	0.150	0.253	0.488	0.055	1.059	0.434
	(0.073)	(0.162)	(0.205)	(0.212)	(0.242)	(0.296)	(0.097)	(1.337)	(0.229)
No. of obs.	3,089	3,000	2,862	3,088	2,999	2,861	3,043	2,955	2,820
Log likelihood	-966.6	-932.2	-887.9	-872.8	-836.8	-798.4	-308.3	-301.7	-287.7

Note: Weights are used in estimations. D1, D2 and D3 refer to 1-, 2- and 3-year differences of the industry-level variables. All calculations also include all other control variables. Odds ratios are reported. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 5 (Panels A and B) below displays the results from the interaction models to shed light on the potential mediating role of trade union representation on the probability of being in atypical employment. While Panel A refers to the total sample, Panel B refers to the smaller manufacturing sample. The results are again reported for the three year differences (1, 2 and 3 years) but only for the main variables of interest (i.e. main effects and interaction effects), as the coefficients for the other control variables are similar to those reported above (see Table 1 and Table 2 above).[26]

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

It shows that trade union representation at the firm level plays little role in mediating the effects of either offshoring or technological change on atypical employment. As indicated by the lack of significance of the interaction terms, this is particularly true for total offshoring for both samples as well as for both types of atypical employment considered (i.e. temporary contract and involuntary part-time work). As concerns technological change, we find very few significant interaction terms and, if so, then often positive ones, as in the case of IT (for both samples). This highlights that trade union representation in industries exposed to IT capital growth is associated with a higher likelihood of atypical employment. In manufacturing, this also holds for the likelihood of a temporary contract and of involuntary part-time work. An important exception is robot density with negatively significant interaction terms, which indicates that trade union representation in manufacturing industries exposed to robot density growth is associated with a significantly lower likelihood of atypical employment.

A limited mediating role of trade union representation on atypical employment is also observed for the other offshoring measures (see Table 6 and Table 7 below). In some cases, a positive significant interaction effect can again be observed, such as for narrow offshoring for the total sample or manufacturing offshoring for the manufacturing sample, which suggests that trade union representation in industries exposed to the growth in these types of offshoring is associated with a higher likelihood of atypical employment. In both samples, this is related to different types of atypical employment, namely, to a temporary contract for the total sample but to involuntary part-time work for the manufacturing sample. By contrast, trade union representation appears to reduce the likelihood of being in atypical employment (which is related to a lower likelihood of having a temporary contract) in industries exposed to the growth in offshoring to the NMS13.

Generally, the positive interaction terms need to be interpreted with caution because causality can run both ways. They more likely indicate that trade unions are more strongly present in industries where the quality of jobs is deteriorating due to offshoring or technological change.

Table 5 / Mediating effect of trade unions on atypical employment – in total and by type (total and manufacturing only, 2015): Total offshoring

	Panel A: Total									Panel B: Manufacturing								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	Atypical	Atypical	Atypical	Temp. contr	Temp. contr	Temp. contr	Invol. part-time	Invol. part-time	Invol. part-time	Atypical	Atypical	Atypical	Temp. contr	Temp. contr	Temp. contr	Invol. part-time	Invol. part-time	Invol. part-time
	D1	D2	D3	D1	D2	D3	D1	D2	D3	D1	D2	D3	D1	D2	D3	D1	D2	D3
TU	0.713***	0.718***	0.712***	0.729***	0.731***	0.726***	0.745***	0.749***	0.740***	0.962	0.993	1.026	1.086	1.154	1.181	0.641	0.590	0.502**
	(0.039)	(0.041)	(0.040)	(0.046)	(0.047)	(0.047)	(0.054)	(0.055)	(0.054)	(0.167)	(0.184)	(0.184)	(0.186)	(0.223)	(0.221)	(0.195)	(0.199)	(0.153)
D.OFF^{tot}	1.355**	1.790***	1.068	1.380	1.606***	1.018	1.395**	1.695**	1.065	1.311	1.959*	1.407	2.227	3.172**	1.081	0.481	0.749	1.427
	(0.191)	(0.242)	(0.162)	(0.290)	(0.261)	(0.162)	(0.227)	(0.391)	(0.156)	(0.654)	(0.727)	(0.301)	(1.272)	(1.600)	(0.358)	(0.219)	(0.531)	(0.419)
TU*D.OFF^{tot}	0.972	1.079	1.043	0.959	1.071	1.002	0.972	1.050	0.934	1.351	1.312	1.248	1.521	1.455	1.110	1.188	0.976	0.904
	(0.175)	(0.283)	(0.167)	(0.182)	(0.304)	(0.177)	(0.183)	(0.281)	(0.152)	(0.866)	(0.867)	(0.207)	(1.198)	(1.182)	(0.235)	(1.342)	(1.230)	(0.236)
D.RobDens										0.883	1.163**	1.041	0.964	1.220**	1.051	0.412	0.583	0.726
										(0.167)	(0.077)	(0.038)	(0.224)	(0.116)	(0.042)	(0.354)	(0.253)	(0.201)
TU*D.RobDens										0.777	0.861***	0.893***	0.813	0.853***	0.886***	1.083	0.894	0.596
										(0.384)	(0.037)	(0.032)	(0.407)	(0.035)	(0.030)	(0.274)	(0.207)	(0.202)
D.IT	1.123	0.976	0.995	1.054	0.948	0.961	1.383**	1.212	1.202	2.163**	1.928***	1.723***	2.230**	2.100**	1.883***	1.213	0.899	1.085
	(0.205)	(0.181)	(0.158)	(0.210)	(0.180)	(0.175)	(0.191)	(0.176)	(0.139)	(0.785)	(0.490)	(0.293)	(0.848)	(0.608)	(0.331)	(0.636)	(0.436)	(0.319)
TU*D.IT	1.164**	1.034	0.955	1.153*	1.048	0.979	1.257	1.023	0.949	3.449***	2.344***	1.807***	3.402***	2.174***	1.802***	2.980**	2.103*	1.496
	(0.084)	(0.099)	(0.100)	(0.096)	(0.105)	(0.111)	(0.210)	(0.156)	(0.141)	(1.153)	(0.607)	(0.302)	(1.349)	(0.639)	(0.301)	(1.418)	(0.840)	(0.778)
D.CT	0.787**	1.000	1.005	0.765*	1.011	1.032	0.977	0.938***	0.871	0.585	0.799	0.728	0.593	0.778	0.698*	0.715	0.601	0.689
	(0.084)	(0.041)	(0.121)	(0.109)	(0.045)	(0.145)	(0.094)	(0.022)	(0.079)	(0.375)	(0.232)	(0.142)	(0.395)	(0.230)	(0.145)	(0.506)	(0.253)	(0.225)
TU*D.CT	0.959	1.014	1.066	0.990	1.017	1.089*	0.846	0.988	0.935	0.824	0.867	0.841	0.872	0.969	0.923	0.438	0.204**	0.352*
	(0.053)	(0.017)	(0.049)	(0.047)	(0.027)	(0.054)	(0.137)	(0.053)	(0.078)	(0.153)	(0.129)	(0.091)	(0.163)	(0.150)	(0.102)	(0.509)	(0.154)	(0.198)
D.DB	1.182	1.031	1.009	1.287	1.008	0.982	0.755	1.041	1.018	1.006	1.008	0.614	1.271	1.226	0.705	1.568	2.016	1.446
	(0.309)	(0.030)	(0.075)	(0.354)	(0.030)	(0.063)	(0.183)	(0.034)	(0.102)	(0.743)	(0.501)	(0.243)	(1.053)	(0.691)	(0.313)	(1.868)	(1.637)	(1.126)
TU*D.DB	1.403	1.001	0.989	1.309	0.941	0.921	1.246	1.050**	1.058	1.949	1.616	0.946	2.404	1.658	0.894	2.129	2.989	3.337
	(0.413)	(0.021)	(0.038)	(0.445)	(0.037)	(0.053)	(0.701)	(0.021)	(0.041)	(1.511)	(0.802)	(0.482)	(1.945)	(0.898)	(0.430)	(2.760)	(2.233)	(3.475)
No. of obs.	24,653	24,650	24,650	24,614	24,611	24,611	24,234	24,231	24,231	3,089	3,000	2,862	3,088	2,999	2,861	3,043	2,955	2,820
Log likelihood	-9,435	-9,435	-9,439	-8,200	-8,202	-8,204	-4,585	-4,585	-4,586	-967.8	-928.5	-884.8	-872.4	-831.6	-794.1	-308.0	-300.4	-287.3

Note: Weights are used in estimations. D1, D2 and D3 refer to 1-, 2- and 3-year differences of the industry-level variables. All calculations also include all other control variables. Odds ratios are reported. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 6 / Mediating effect of trade unions on atypical employment – in total and by type (total sample, 2015): Other offshoring measures

	(1) Atypical D1	(2) Atypical D2	(3) Atypical D3	(4) Temp. contr D1	(5) Temp. contr D2	(6) Temp. contr D3	(7) Invol. part-time D1	(8) Invol. part-time D2	(9) Invol. part-time D3
Narrow and broad offshoring									
TU	0.713***	0.716***	0.712***	0.729***	0.730***	0.727***	0.746***	0.749***	0.742***
	(0.038)	(0.039)	(0.040)	(0.044)	(0.045)	(0.047)	(0.055)	(0.054)	(0.052)
$D.OFF^{N}$	0.990	0.958	0.983	0.944*	0.951	0.981	1.062	1.009	1.029
	(0.026)	(0.033)	(0.034)	(0.033)	(0.042)	(0.035)	(0.108)	(0.083)	(0.055)
$TU*D.OFF^{N}$	1.070*	1.114***	1.003	1.093	1.117***	1.000	1.020	0.980	0.973
	(0.041)	(0.037)	(0.027)	(0.064)	(0.039)	(0.040)	(0.129)	(0.109)	(0.055)
$D.OFF^{B}$	1.489***	1.741***	1.120	1.602***	1.642***	1.117	1.337	1.492*	1.070
	(0.206)	(0.219)	(0.152)	(0.228)	(0.224)	(0.188)	(0.262)	(0.359)	(0.151)
$TU*D.OFF^{B}$	0.877	0.929	1.026	0.843	0.928	0.984	0.971	1.036	1.084
	(0.147)	(0.232)	(0.188)	(0.176)	(0.249)	(0.203)	(0.177)	(0.326)	(0.221)
No. of obs.	24,653	24,650	24,650	24,614	24,611	24,611	24,234	24,231	24,231
Log likelihood	-9,433	-9,430	-9,439	-8,197	-8,198	-8,204	-4,585	-4,586	-4,586
Manufacturing and services offshoring									
TU	0.712***	0.716***	0.709***	0.727***	0.730***	0.724***	0.744***	0.745***	0.735***
	(0.038)	(0.038)	(0.037)	(0.044)	(0.044)	(0.044)	(0.054)	(0.055)	(0.052)
$D.OFF^{Manuf}$	1.020	1.121**	1.047	0.926	1.009	0.994	1.197***	1.321***	1.067
	(0.083)	(0.063)	(0.090)	(0.086)	(0.074)	(0.092)	(0.081)	(0.086)	(0.072)
$TU*D.OFF^{Manuf}$	0.983	1.122	1.112	0.907	1.042	1.041	1.185	1.280**	1.131
	(0.142)	(0.154)	(0.125)	(0.214)	(0.227)	(0.180)	(0.155)	(0.153)	(0.107)
$D.OFF^{Serv}$	1.379	1.460**	1.083	1.442	1.491**	1.093	1.187	0.994	1.076
	(0.293)	(0.241)	(0.084)	(0.327)	(0.248)	(0.108)	(0.231)	(0.249)	(0.143)
$TU*D.OFF^{Serv}$	0.966	0.839	0.906	1.066	0.977	0.912	0.798	0.618**	0.954
	(0.132)	(0.138)	(0.065)	(0.172)	(0.156)	(0.079)	(0.172)	(0.144)	(0.108)
No. of obs.	24,653	24,650	24,650	24,614	24,611	24,611	24,234	24,231	24,231
Log likelihood	-9,434	-9,431	-9,436	-8,200	-8,200	-8,202	-4,585	-4,583	-4,585
Offshoring to developed countries, developing countries and NMS13									
TU	0.709***	0.718***	0.714***	0.726***	0.729***	0.727***	0.742***	0.754***	0.746***
	(0.038)	(0.040)	(0.041)	(0.045)	(0.048)	(0.047)	(0.053)	(0.056)	(0.057)
$D.OFF^{Devd}$	1.050	1.601**	1.014	0.719	1.407	1.042	2.831**	2.148***	1.012
	(0.287)	(0.336)	(0.216)	(0.210)	(0.368)	(0.277)	(1.225)	(0.491)	(0.294)
$TU*D.OFF^{Devd}$	1.471	1.250	1.242	1.898**	1.223	1.074	0.605	1.370	1.497*
	(0.419)	(0.323)	(0.257)	(0.564)	(0.331)	(0.244)	(0.284)	(0.565)	(0.332)
$D.OFF^{Devg}$	1.546*	1.265	1.112	2.362**	1.345	1.097	0.592	1.021	1.055
	(0.400)	(0.244)	(0.112)	(0.908)	(0.349)	(0.111)	(0.207)	(0.233)	(0.146)
$TU*D.OFF^{Devg}$	1.135	0.886	0.876	0.850	1.027	0.980	2.177**	0.708	0.716
	(0.303)	(0.187)	(0.178)	(0.266)	(0.206)	(0.188)	(0.862)	(0.307)	(0.177)
$D.OFF^{NMS13}$	0.844	0.768	0.840	0.817	0.714	0.802	0.776	0.867	0.950
	(0.200)	(0.171)	(0.119)	(0.288)	(0.233)	(0.150)	(0.301)	(0.153)	(0.138)
$TU*D.OFF^{NMS13}$	0.580***	0.779**	0.872	0.541**	0.700**	0.877	0.740	0.954	0.820
	(0.118)	(0.097)	(0.090)	(0.146)	(0.101)	(0.116)	(0.185)	(0.148)	(0.118)
No. of obs.	24,653	24,650	24,650	24,614	24,611	24,611	24,234	24,231	24,231
Log likelihood	-9,432	-9,433	-9,436	-8,194	-8,200	-8,203	-4,581	-4,583	-4,582

Note: Weights are used in estimations. D1, D2 and D3 refer to 1-, 2- and 3-year differences of the industry-level variables. All calculations also include all other control variables. Odds ratios are reported. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 7 / Mediating effect of trade unions on atypical employment – in total and by type (manufacturing only, 2015): Other offshoring measures

	(1) Atypical D1	(2) Atypical D2	(3) Atypical D3	(4) Temp. contr D1	(5) Temp. contr D2	(6) Temp. contr D3	(7) Invol. part-time D1	(8) Invol. part-time D2	(9) Invol. part-time D3
Narrow and broad offshoring									
TU	0.985	1.001	1.018	1.089	1.140	1.183	0.719	0.618	0.498**
	(0.163)	(0.176)	(0.184)	(0.183)	(0.214)	(0.223)	(0.257)	(0.221)	(0.149)
D.OFF^{N}	0.995	1.555	1.214	1.392	1.855	1.029	0.105*	0.650	1.197
	(0.827)	(0.806)	(0.177)	(1.291)	(0.849)	(0.162)	(0.136)	(0.708)	(0.146)
TU*D.OFF^{N}	5.782*	1.622	1.288	4.614	1.096	1.178	0.798	1.250	0.967
	(5.735)	(0.989)	(0.308)	(4.799)	(0.631)	(0.315)	(1.654)	(1.639)	(0.115)
D.OFF^{B}	1.346	1.541	1.223	1.468	1.851	1.407	3.505	1.309	1.343
	(1.075)	(0.924)	(0.968)	(1.413)	(1.256)	(1.466)	(3.236)	(1.018)	(0.884)
TU*D.OFF^{B}	0.447	0.761	1.019	0.536	1.027	1.345	2.207	1.112	0.757
	(0.291)	(0.524)	(0.526)	(0.442)	(0.946)	(0.835)	(1.901)	(0.761)	(0.603)
No. of obs.	3,089	3,000	2,862	3,088	2,999	2,861	3,043	2,955	2,820
Log likelihood	-964.5	-927.9	-884.4	-870.7	-831.3	-793.7	-307.1	-300.3	-287.4
Manufacturing and services offshoring									
TU	0.966	1.022	1.066	1.078	1.171	1.212	0.670	0.621	0.483**
	(0.172)	(0.191)	(0.200)	(0.189)	(0.227)	(0.248)	(0.232)	(0.230)	(0.175)
D.OFF^{Manuf}	1.936*	3.030***	2.659***	1.035	1.885*	2.039*	3.253**	3.272***	2.875***
	(0.729)	(0.906)	(1.005)	(0.355)	(0.630)	(0.852)	(1.514)	(1.377)	(1.130)
TU*D.OFF^{Manuf}	1.415	1.487	0.917	1.170	1.196	0.840	2.574**	2.196	2.178
	(0.724)	(0.680)	(0.500)	(0.952)	(0.861)	(0.617)	(1.012)	(1.476)	(1.119)
D.OFF^{Serv}	0.649	0.498	0.454**	1.899	1.058	0.666	0.192	0.235	0.364
	(0.461)	(0.398)	(0.176)	(2.832)	(1.218)	(0.368)	(0.454)	(0.334)	(0.279)
TU*D.OFF^{Serv}	0.433	0.708	0.988	0.968	1.577	1.409	0.127	0.111	0.174*
	(0.333)	(0.446)	(0.374)	(0.785)	(1.111)	(0.584)	(0.297)	(0.196)	(0.172)
No. of obs.	3,089	3,000	2,862	3,088	2,999	2,861	3,043	2,955	2,820
Log likelihood	-966.8	-926.7	-881.6	-872.6	-831.7	-792.4	-306.3	-297.6	-283.9
Offshoring to developed countries, developing countries and NMS13									
TU	0.980	0.991	1.046	1.113	1.151	1.212	0.496**	0.569	0.412***
	(0.175)	(0.174)	(0.185)	(0.204)	(0.195)	(0.214)	(0.173)	(0.197)	(0.138)
D.OFF^{Devd}	2.583	1.080	1.482	2.133	0.630	1.118	1.396	0.858	3.234
	(4.108)	(1.084)	(1.094)	(3.944)	(0.665)	(1.100)	(3.776)	(1.600)	(4.750)
TU*D.OFF^{Devd}	30.791	7.410	4.467*	17.600	7.872	4.754*	16.801	2.958	0.749
	(65.194)	(9.600)	(3.978)	(38.204)	(10.056)	(4.326)	(36.656)	(4.815)	(1.001)
D.OFF^{Devg}	22.070***	9.840**	1.725	35.567***	27.560***	1.593	0.337	0.148	0.824
	(20.756)	(10.697)	(0.617)	(35.474)	(30.387)	(0.744)	(0.648)	(0.212)	(0.332)
TU*D.OFF^{Devg}	0.134	0.596	0.829	0.050	0.303	0.649	72.688**	8.075	2.461**
	(0.244)	(0.862)	(0.312)	(0.095)	(0.467)	(0.269)	(135.594)	(16.403)	(1.095)
D.OFF^{NMS13}	0.020***	0.148*	0.331	0.024**	0.134*	0.383	1.288	11.612*	1.131
	(0.027)	(0.149)	(0.237)	(0.041)	(0.147)	(0.302)	(3.211)	(15.753)	(0.956)
TU*D.OFF^{NMS13}	0.267	0.150	0.452	1.424	0.275	0.677	0.001***	0.014**	0.047***
	(0.594)	(0.193)	(0.380)	(3.299)	(0.353)	(0.540)	(0.001)	(0.028)	(0.055)
No. of obs.	3,089	3,000	2,862	3,088	2,999	2,861	3,043	2,955	2,820
Log likelihood	-958.3	-923.1	-881.4	-861.2	-823.7	-791.1	-303.6	-295.2	-283.4

Note: Weights are used in estimations. D1, D2 and D3 refer to 1-, 2- and 3-year differences of the industry-level variables. All calculations also include all other control variables. Odds ratios are reported. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

4.2. ATYPICAL EMPLOYMENT – RESULTS FROM THE 2021 EWCTS

The results for the total sample (see Table 8 below) show that, as in 2015, the existence of a trade union at the firm level in 2021 is associated with a lower probability of being in atypical employment. However, the further breakdown by type of atypical employment suggests that it is mainly associated with a lower probability of involuntary part-time employment, but not of temporary contracts.

However, neither an increase in total offshoring nor in technology (IT, CT and DB) is significantly associated with atypical employment or the two types of atypical employment. Given the lagged structure of the industry-level variables, this suggests that past changes (between 2017 and 2018) are unrelated to workers' probability of being in atypical employment in 2021.

As concerns worker and firm characteristics, we observe several similarities with the results for 2015. For example, females were more likely to be in atypical employment than males, mainly due to their higher likelihood of having involuntary part-time work. Similarly, tenure was associated with a lower probability of being in atypical employment, in terms of both a lower likelihood of having a temporary contract and of involuntary part-time work. Workers in higher-skilled occupations were also less likely to be in atypical employment, which is related to both a lower likelihood of having a temporary contract and of involuntary part-time work. Firm-size only matters for involuntary part-time work, making workers in larger firms less likely to work part-time involuntarily.

There are also several differences vis-à-vis the results for 2015. Specifically, young employees aged 15-24 were more likely to be in atypical employment, such as temporary or involuntary part-time work, than older employees (50 and above). There were no differences by highest level of educational attainment. Workers in private firms were less likely to be in atypical employment than those in public firms, which is mainly related to a lower probability of having a temporary contract.

Table 9 below report the results when total offshoring is further split into (i) narrow and broad offshoring, (ii) manufacturing and services offshoring, and (iii) offshoring by source country, as defined in Section 2.2. The results are again reported for 1-year differences only, referring to changes between 2017 and 2018. We focus on the different offshoring indicators, as the coefficients for the other control variables are similar to what we observed above.[27]

The results show that only offshoring by source region matters, and it is only associated with a lower probability of being in atypical employment for offshoring to developing countries, mainly due to a lower probability of involuntary part-time employment. However, both are only marginally statistically significant. By contrast, offshoring to developed countries is associated with a higher probability of involuntary part-time employment.

27 The full results tables are available from the authors upon request.

Table 8 / Atypical employment – in total and by type (total sample, 2021): Total offshoring

	(1) Atypical D1	(2) Temp. contr D1	(3) Invol. part-time D1
TU	0.888**	0.943	0.740**
	(0.049)	(0.064)	(0.092)
D.OFF^{tot}	1.402	1.483	3.221
	(1.760)	(2.151)	(4.189)
D.IT	1.039	1.118	0.750
	(0.184)	(0.210)	(0.278)
D.CT	0.867	0.684	1.264
	(0.237)	(0.241)	(0.449)
D.DB	0.922	1.099	0.509
	(0.217)	(0.344)	(0.213)
Female	1.141**	0.944	2.094***
	(0.071)	(0.069)	(0.447)
15-24 yrs old	1.613***	1.607***	1.663**
	(0.203)	(0.185)	(0.364)
25-49 yrs old	0.965	0.934	1.024
	(0.059)	(0.063)	(0.209)
ISCED: medium	0.944	0.834	1.241
	(0.105)	(0.135)	(0.316)
ISCED: high	0.953	0.946	1.010
	(0.161)	(0.161)	(0.339)
Tenure (ln)	0.475***	0.420***	0.717***
	(0.038)	(0.045)	(0.062)
ISCO: medium	0.690**	0.749*	0.588***
	(0.117)	(0.114)	(0.105)
ISCO: high	0.462***	0.511***	0.407***
	(0.070)	(0.063)	(0.083)
Firm size: medium	0.795	0.877	0.523***
	(0.115)	(0.140)	(0.071)
Firm size: large	0.736**	0.840	0.364***
	(0.088)	(0.095)	(0.067)
Firm type: private	0.575***	0.444***	1.154
	(0.067)	(0.068)	(0.140)
Firm type: other	0.730***	0.638***	1.182
	(0.072)	(0.080)	(0.184)
Country covid-19 reforms	1.139**	1.156**	1.094
	(0.064)	(0.075)	(0.063)
var(country)	1.142**	1.175**	1.059
	(0.075)	(0.078)	(0.055)
var(country>nace)	1.511***	1.494***	1.711***
	(0.119)	(0.100)	(0.312)
Constant	0.734**	0.747*	0.051***
	(0.104)	(0.126)	(0.016)
No. of obs.	22,451	22,342	22,402
Log likelihood	-8,109	-6,967	-3,472

Note: Weights are used in estimations. D1 refers to 1-year differences of the industry-level variables. Odds ratios are reported. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 9 / Atypical employment – in total and by type (total sample, 2021): Other offshoring measures

	(1) Atypical D1	(2) Temp. contr D1	(3) Invol. part-time D1
Narrow and broad offshoring			
TU	0.888**	0.943	0.741**
	(0.049)	(0.064)	(0.092)
D.OFF^{N}	0.973	0.936	1.299
	(0.248)	(0.267)	(0.338)
D.OFF^{B}	1.786	2.282	2.041
	(2.314)	(3.297)	(2.749)
No. of obs.	22,451	22,342	22,402
Log likelihood	-8,109	-6,966	-3,472
Manufacturing and services offshoring			
TU	0.888**	0.943	0.740**
	(0.049)	(0.064)	(0.092)
D.OFF^{Manuf}	2.901	5.532*	0.997
	(3.366)	(5.098)	(2.196)
D.OFF^{Serv}	0.490	0.281	2.751
	(0.736)	(0.406)	(6.284)
No. of obs.	22,451	22,342	22,402
Log likelihood	-8,109	-6,966	-3,472
Offshoring to developed countries, developing countries and NMS13			
TU	0.888**	0.943	0.741**
	(0.048)	(0.064)	(0.091)
D.OFF^{Devd}	4.686	5.360	6.093**
	(4.948)	(5.706)	(5.615)
D.OFF^{Devg}	0.464*	0.520	0.367*
	(0.186)	(0.211)	(0.199)
D.OFF^{NMS13}	0.755	0.561	1.975
	(0.488)	(0.318)	(1.582)
No. of obs.	22,451	22,342	22,402
Log likelihood	-8,107	-6,965	-3,470

Note: Weights are used in estimations. D1 refers to 1-year differences of the industry-level variables. All calculations also include all other control variables. Odds ratios are reported. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 10 and Table 11 below display the results from the interaction models, namely, for total offshoring and the various offshoring measures, respectively.[28] Similar to 2015, the results show that trade union representation at the firm level played little role in mediating the effects of either offshoring or technological change on atypical employment. The only exception was DB, which shows a positive interaction with trade union representation. This highlights that trade union representation in industries exposed to DB capital growth is associated with a higher likelihood of atypical employment, especially temporary contracts. Again, this result must be interpreted with caution, as causality may run in both directions.

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

A limited mediating role of trade union representation in atypical employment is also observed for the other offshoring measures (see Table 11 below). In contrast to 2015, positive and negative significant interaction effects are observed in some cases, although these are mainly associated with the two different types of atypical employment analysed in this study. It is important to recognise that the strength of certain relationships may be questionable due to large standard errors and the infrequency of the phenomena being studied.

Table 10 / Mediating effect of trade unions on atypical employment – in total and by type (total, 2021): Total offshoring

	(1) Atypical D1	(2) Temp. contr D1	(3) Invol. part-time D1
TU	0.901*	0.979	0.715***
	(0.056)	(0.074)	(0.073)
$D.OFF^{tot}$	3.057	3.456	7.930
	(5.263)	(7.259)	(11.341)
$TU*D.OFF^{tot}$	0.221	0.201	0.111
	(0.285)	(0.333)	(0.181)
D.IT	1.367	1.306	1.090
	(0.469)	(0.427)	(0.508)
TU*D.IT	0.398	0.490	0.269
	(0.235)	(0.280)	(0.272)
D.CT	0.633	0.331*	1.846
	(0.289)	(0.202)	(1.009)
TU*D.CT	1.871	2.667	0.507
	(1.050)	(1.652)	(0.500)
D.DB	0.601**	0.503**	0.661
	(0.143)	(0.141)	(0.308)
TU*D.DB	2.768**	4.661**	0.521
	(1.164)	(3.037)	(0.405)
No. of obs.	22,451	22,342	22,402
Log likelihood	-8,104	-6,958	-3,468

Note: Weights are used in estimations. D1 refers to 1-year differences of the industry-level variables. All calculations also include all other control variables. Odds ratios are reported. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 11 / Mediating effect of trade unions on atypical employment – in total and by type (total sample, 2021): Other offshoring measures

	(1) Atypical D1	(2) Temp. contr D1	(3) Invol. part-time D1
	Narrow and broad offshoring		
TU	0.903*	0.982	0.745***
	(0.053)	(0.070)	(0.072)
$D.OFF^{N}$	0.816	0.728	0.088**
	(0.496)	(0.515)	(0.089)
$TU*D.OFF^{N}$	1.205	1.312	19.979***
	(0.696)	(0.907)	(21.037)
$D.OFF^{B}$	4.303	6.354	52.398*
	(8.877)	(15.681)	(108.451)
$TU*D.OFF^{B}$	0.216	0.176	0.011**
	(0.344)	(0.350)	(0.023)
No. of obs.	22,451	22,342	22,402
Log likelihood	-8,104	-6,958	-3,465
	Manufacturing and services offshoring		
TU	0.900*	0.978	0.712***
	(0.056)	(0.074)	(0.071)
$D.OFF^{Manuf}$	11.265	60.240***	0.011
	(20.174)	(92.961)	(0.038)
$TU*D.OFF^{Manuf}$	0.062**	0.007***	4,202.422**
	(0.085)	(0.009)	(17,352.629)
$D.OFF^{Serv}$	0.292	0.060	347.199*
	(0.551)	(0.119)	(1,042.273)
$TU*D.OFF^{Serv}$	3.442	34.964**	0.000**
	(4.383)	(61.163)	(0.000)
No. of obs.	22,451	22,342	22,402
Log likelihood	-8,103	-6,955	-3,465
	Offshoring to developed countries, developing countries and NMS13		
TU	0.892*	0.975	0.693***
	(0.052)	(0.073)	(0.076)
$D.OFF^{Devd}$	3.832	5.820	2.112
	(4.458)	(6.342)	(3.165)
$TU*D.OFF^{Devd}$	1.632	0.696	14.968
	(1.566)	(0.534)	(31.763)
$D.OFF^{Devg}$	0.832	0.983	0.663
	(0.631)	(0.739)	(0.626)
$TU*D.OFF^{Devg}$	0.314	0.305	0.225
	(0.301)	(0.293)	(0.331)
$D.OFF^{NMS13}$	0.707	0.804	1.242
	(0.548)	(0.441)	(1.812)
$TU*D.OFF^{NMS13}$	1.115	0.579	2.193
	(0.693)	(0.481)	(2.880)
No. of obs.	22,451	22,342	22,402
Log likelihood	-8,101	-6,954	-3,464

Note: Weights are used in estimations. D1 refers to 1-year differences of the industry-level variables. All calculations also include all other control variables. Odds ratios are reported. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

4.3. SKILLS MISMATCH – RESULTS FROM THE 2015 EWCS

As concerns skills mismatch, we find that trade union representation at the firm level has no significant effect on the presence and/or nature (i.e. under- and over-skilled) of skills mismatch (see Table 12 below: Panel A refers to the total sample, Panel B to the smaller manufacturing sample).

Similarly, both offshoring and technological change play a limited role. For instance, an increase in total offshoring is associated with a higher probability of being over-skilled in the total sample but a lower probability of being over-skilled in the manufacturing sample. Differences between samples suggest that the higher likelihood of over-skilling in the total sample is mainly related to services industries in which, starting from a low level, offshoring has expanded strongly over recent years, predominantly in non-public services industries. In addition, the higher likelihood of over-skilling further suggests that offshoring leads to the substitution of the more skilled tasks within a worker's job. However, the higher probability of over-skilling in the total sample is observed for shorter-term changes in total offshoring (i.e. D1 and D2) but not for longer-term changes, suggesting that the effect may only be temporary and eventually disappears. An increase in CT and DB is associated with a higher probability of being under-skilled in the total sample, pointing to the importance of a 'reinstatement effect' and the emergence of new or re-engineered tasks and job requirements, which make workers under-skilled. In manufacturing, only an increase in DB is significant and is associated with a higher probability of being over-skilled, suggesting that more complex and demanding tasks may be replaced by DB ('substitution effect').

As concerns worker and firm characteristics, our results are mixed and differ by sample. For instance, in the full sample (Table 12, Panel A), we observe that females are less likely to be either over- or under-skilled than males, while migrants are more likely to be under-skilled than non-migrants. By contrast, there are no differences by either gender or country of birth in the manufacturing sample (Table 12, Panel B). Furthermore, the highly educated are more likely to be either over- or under-skilled in the total sample but more likely to be over-skilled only in the manufacturing sample. This contrasts with what is observed for workers in high-skilled occupations, who are more likely to be under-skilled (in both samples) but only over-skilled in the total sample only. Generally, job tenure is associated with a lower probability of a mismatch, suggesting that individual skills and job requirements become more aligned as more time is spent in the same firm. By contrast, there are not any differences across samples related to age. Compared with older workers, young (15-24 years of age) and prime-age (25-49 years) workers are more likely to indicate a job-skills mismatch; this mainly relates to being under-skilled for young workers and over-skilled for prime-age workers.

Table 12 / Skills mismatch (total & manufacturing only): Total offshoring

	Panel A: Total						Panel B: Manufacturing					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Under-skilled	Over-skilled	Under-skilled	Over-skilled	Under-skilled	Over-skilled	Under-skilled	Over-skilled	Under-skilled	Over-skilled	Under-skilled	Over-skilled
	D1		D2		D3		D1		D2		D3	
TU	1.101	0.997	1.111	0.993	1.110	0.994	0.999	0.981	0.987	0.966	0.975	0.927
	(0.096)	(0.053)	(0.098)	(0.052)	(0.098)	(0.052)	(0.189)	(0.136)	(0.182)	(0.131)	(0.178)	(0.123)
D.OFF^{tot}	1.129	1.219**	1.116	1.398**	1.173	0.929	0.689	1.306	0.579	1.256	0.942	0.786**
	(0.185)	(0.118)	(0.249)	(0.198)	(0.174)	(0.102)	(0.233)	(0.364)	(0.207)	(0.330)	(0.152)	(0.084)
D.RobDens							1.151	0.961	1.022	0.972	0.988	0.972
							(0.134)	(0.142)	(0.022)	(0.042)	(0.031)	(0.026)
D.IT	1.139	1.067	1.033	1.065	1.081	1.030	1.439	1.216	0.876	1.079	0.957	1.052
	(0.149)	(0.059)	(0.073)	(0.043)	(0.067)	(0.035)	(0.364)	(0.285)	(0.255)	(0.175)	(0.169)	(0.103)
D.CT	1.071	0.963	1.055***	1.014	1.020	0.956	0.949	0.903	0.981	0.824*	1.045	0.916
	(0.078)	(0.064)	(0.020)	(0.023)	(0.032)	(0.032)	(0.068)	(0.066)	(0.080)	(0.090)	(0.081)	(0.063)
D.DB	0.887	1.232	1.038**	1.010	1.064*	1.039	0.907	1.596	1.058	1.677**	0.937	1.022
	(0.226)	(0.186)	(0.016)	(0.011)	(0.035)	(0.037)	(0.427)	(0.558)	(0.286)	(0.439)	(0.314)	(0.213)
Female	0.841***	0.849***	0.840***	0.847***	0.836***	0.850***	0.722	0.886	0.714	0.872	0.680**	0.891
	(0.040)	(0.031)	(0.041)	(0.031)	(0.041)	(0.031)	(0.145)	(0.079)	(0.146)	(0.082)	(0.132)	(0.088)
Migrant	1.169***	1.054	1.163**	1.058	1.167**	1.055	1.187	1.132	1.219	1.092	1.111	1.065
	(0.071)	(0.063)	(0.073)	(0.059)	(0.072)	(0.059)	(0.217)	(0.164)	(0.223)	(0.157)	(0.180)	(0.149)
15-24 yrs old	1.762***	1.062	1.759***	1.063	1.761***	1.060	1.857**	1.015	1.818**	1.025	1.771*	1.036
	(0.293)	(0.120)	(0.291)	(0.120)	(0.289)	(0.118)	(0.506)	(0.287)	(0.506)	(0.281)	(0.518)	(0.290)
25-49 yrs old	1.109	1.100**	1.109	1.101**	1.111	1.100**	1.022	1.318***	0.991	1.288***	0.973	1.296**
	(0.071)	(0.051)	(0.071)	(0.051)	(0.071)	(0.051)	(0.161)	(0.125)	(0.147)	(0.127)	(0.147)	(0.136)
ISCED: medium	1.091	1.076	1.086	1.077	1.084	1.076	1.101	1.434**	1.071	1.462**	1.163	1.424**
	(0.122)	(0.084)	(0.123)	(0.084)	(0.119)	(0.082)	(0.182)	(0.221)	(0.177)	(0.230)	(0.212)	(0.229)
ISCED: high	1.335**	1.687***	1.331**	1.687***	1.319**	1.698***	1.346	2.191***	1.269	2.237***	1.391	2.160***
	(0.185)	(0.136)	(0.185)	(0.136)	(0.180)	(0.135)	(0.385)	(0.425)	(0.362)	(0.445)	(0.420)	(0.448)

Contd.

Table 12 / Continued

	Panel A: Total						Panel B: Manufacturing					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Under-skilled	Over-skilled	Under-skilled	Over-skilled	Under-skilled	Over-skilled	Under-skilled	Over-skilled	Under-skilled	Over-skilled	Under-skilled	Over-skilled
	D1		D2		D3		D1		D2		D3	
Tenure (ln)	0.887***	0.950**	0.887***	0.950**	0.887***	0.950**	0.840***	0.921	0.836***	0.909	0.816***	0.901*
	(0.026)	(0.021)	(0.026)	(0.021)	(0.026)	(0.021)	(0.046)	(0.053)	(0.048)	(0.053)	(0.045)	(0.055)
ISCO: medium	1.611***	1.039	1.600***	1.036	1.605***	1.040	1.011	0.901	1.080	0.893	1.113	0.891
	(0.117)	(0.060)	(0.119)	(0.060)	(0.119)	(0.060)	(0.115)	(0.130)	(0.120)	(0.130)	(0.125)	(0.132)
ISCO: high	2.689***	0.844***	2.663***	0.842***	2.668***	0.848**	1.981***	0.843	2.066***	0.849	2.030***	0.825
	(0.315)	(0.055)	(0.318)	(0.055)	(0.316)	(0.054)	(0.376)	(0.165)	(0.414)	(0.170)	(0.412)	(0.161)
Firm size: medium	1.005	1.101*	1.006	1.101*	1.002	1.105*	1.054	0.973	1.053	0.959	1.023	0.960
	(0.092)	(0.057)	(0.091)	(0.056)	(0.092)	(0.057)	(0.224)	(0.160)	(0.233)	(0.160)	(0.230)	(0.161)
Firm size: large	0.972	1.047	0.979	1.045	0.973	1.051	1.101	0.908	1.082	0.900	1.092	0.889
	(0.124)	(0.070)	(0.123)	(0.070)	(0.123)	(0.069)	(0.291)	(0.162)	(0.297)	(0.158)	(0.298)	(0.164)
Firm type: private	0.798***	1.087*	0.812***	1.084	0.801***	1.088*	1.841	1.550*	1.668	1.532	1.960	1.425
	(0.047)	(0.054)	(0.050)	(0.054)	(0.049)	(0.055)	(0.866)	(0.393)	(0.764)	(0.397)	(0.989)	(0.359)
Firm type: other	1.021	0.999	1.037	0.994	1.035	0.991	3.329*	0.780	3.044*	0.766	3.497*	0.739
	(0.105)	(0.103)	(0.108)	(0.102)	(0.109)	(0.105)	(2.067)	(0.368)	(1.799)	(0.360)	(2.332)	(0.355)
var(country)	1.073***		1.075***		1.074**		1.177*		1.191*		1.165	
	(0.029)		(0.029)		(0.030)		(0.107)		(0.116)		(0.115)	
var(country>nace)	1.079***		1.074***		1.079***		1.077*		1.079*		1.068	
	(0.020)		(0.020)		(0.021)		(0.044)		(0.048)		(0.050)	
Constant	0.157***	0.410***	0.153***	0.408***	0.153***	0.416***	0.119***	0.196***	0.144***	0.210***	0.128***	0.268***
	(0.021)	(0.066)	(0.020)	(0.066)	(0.021)	(0.067)	(0.058)	(0.092)	(0.067)	(0.095)	(0.069)	(0.118)
No. of obs.	24,434	24,434	24,431	24,431	24,431	24,431	3,078	3,078	2,990	2,990	2,852	2,852
Log likelihood	-23,188	-23,188	-23,180	-23,180	-23,182	-23,182	-2,996	-2,996	-2,906	-2,906	-2,823	-2,823

Note: Weights are used in estimations. D1, D2 and D3 refer to one1-, 2- and 3-year differences of the industry-level variables. Odds ratios are reported. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 13 / Skills mismatch (total & manufacturing only): Other offshoring measures

	Panel A: Total						Panel B: Manufacturing					
	(1) Under-skilled	(2) Over-skilled	(3) Under-skilled	(4) Over-skilled	(5) Under-skilled	(6) Over-skilled	(7) Under-skilled	(8) Over-skilled	(9) Under-skilled	(10) Over-skilled	(11) Under-skilled	(12) Over-skilled
	D1		D2		D3		D1		D2		D3	
Narrow and broad offshoring												
$D.OFF^{N}$	0.896*	0.966	1.013	1.007	1.003	0.991	0.604	0.760	0.671	0.762	0.908	0.855**
	(0.050)	(0.042)	(0.045)	(0.031)	(0.028)	(0.017)	(0.297)	(0.299)	(0.276)	(0.248)	(0.089)	(0.065)
$D.OFF^{B}$	1.227	1.223*	1.088	1.315**	1.195	1.007	0.807	1.355	0.694	1.299	1.090	0.923
	(0.154)	(0.144)	(0.202)	(0.171)	(0.168)	(0.128)	(0.277)	(0.590)	(0.186)	(0.535)	(0.353)	(0.267)
No. of obs.	24,434	24,434	24,431	24,431	24,431	24,431	3,078	3,078	2,990	2,990	2,852	2,852
Log likelihood	-23,185	-23,185	-23,181	-23,181	-23,183	-23,183	-2,996	-2,996	-2,905	-2,905	-2,823	-2,823
Manufacturing and services offshoring												
$D.OFF^{Man}$	0.876	0.921	0.878	0.952	0.905	0.844**	1.185	1.532	1.118	1.251	1.195	0.857
	(0.134)	(0.118)	(0.124)	(0.113)	(0.078)	(0.061)	(0.341)	(0.493)	(0.328)	(0.333)	(0.263)	(0.197)
$D.OFF^{Serv}$	1.094	1.252	1.008	1.183*	1.109	1.068	1.050	0.624	1.079	0.874	1.017	1.071
	(0.157)	(0.186)	(0.116)	(0.110)	(0.090)	(0.060)	(0.494)	(0.207)	(0.412)	(0.262)	(0.280)	(0.179)
No. of obs.	24,434	24,434	24,431	24,431	24,431	24,431	3,078	3,078	2,990	2,990	2,852	2,852
Log likelihood	-23,186	-23,186	-23,180	-23,180	-23,179	-23,179	-2,996	-2,996	-2,906	-2,906	-2,823	-2,823
Offshoring to developed countries, developing countries and NMS13												
$D.OFF^{Devd}$	1.338	1.092	1.169	1.486*	1.216	0.936	4.980	3.864*	3.742	1.809	3.084*	1.675
	(0.406)	(0.211)	(0.215)	(0.340)	(0.160)	(0.140)	(6.936)	(3.034)	(3.285)	(1.104)	(1.921)	(0.820)
$D.OFF^{Devg}$	0.988	1.126	0.999	0.937	0.968	0.923	0.394	0.655	0.725	0.819	0.832	0.699**
	(0.265)	(0.228)	(0.104)	(0.112)	(0.091)	(0.058)	(0.267)	(0.302)	(0.479)	(0.395)	(0.154)	(0.118)
$D.OFF^{NMS13}$	0.834	1.055	0.947	1.038	0.963	1.072	0.405	0.493	0.213**	0.779	0.417**	0.879
	(0.230)	(0.110)	(0.111)	(0.063)	(0.078)	(0.052)	(0.428)	(0.267)	(0.150)	(0.298)	(0.172)	(0.289)
No. of obs.	24,434	24,434	24,431	24,431	24,431	24,431	3,078	3,078	2,990	2,990	2,852	2,852
Log likelihood	-23,185	-23,185	-23,177	-23,177	-23,181	-23,181	-2,995	-2,995	-2,902	-2,902	-2,819	-2,819

Note: Weights are used in estimations. D1, D2 and D3 refer to 1-, 2- and 3-year differences of the industry-level variables. All calculations also include all other control variables. Odds ratios are reported. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 14 / Mediating effect of trade union representation on skills mismatch (total & manufacturing only): Total offshoring

	Panel A: Total						Panel B: Manufacturing					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
	Under-skilled	**Over-skilled**	**Under-skilled**	**Over-skilled**	**Under-skilled**	**Over-skilled**	**Under-skilled**	**Over-skilled**	**Under-skilled**	**Over-skilled**	**Under-skilled**	**Over-skilled**
	D1		**D2**		**D3**		**D1**		**D2**		**D3**	
TU	1.105	1.000	1.111	0.994	1.110	0.996	0.961	0.956	1.017	0.995	1.004	0.937
	(0.094)	(0.054)	(0.099)	(0.053)	(0.102)	(0.054)	(0.200)	(0.100)	(0.203)	(0.115)	(0.177)	(0.117)
$D.OFF^{tot}$	1.158	1.272	0.989	1.383*	1.043	0.768*	0.942	1.701**	0.169	1.794**	0.677	0.884
	(0.369)	(0.267)	(0.282)	(0.239)	(0.179)	(0.106)	(1.145)	(0.443)	(0.225)	(0.495)	(0.272)	(0.235)
$TU*D.OFF^{tot}$	1.123	1.196**	1.208	1.405**	1.297*	1.111	0.622	1.159	0.768	0.918	1.098	0.695*
	(0.182)	(0.095)	(0.255)	(0.197)	(0.194)	(0.102)	(0.252)	(0.687)	(0.272)	(0.486)	(0.151)	(0.131)
D.RobDens							1.159	0.716	1.040	0.957	0.998	0.960
							(0.166)	(0.189)	(0.040)	(0.061)	(0.034)	(0.038)
TU*D.RobDens							1.174	1.189	0.989	1.007	0.966	0.990
							(0.179)	(0.130)	(0.040)	(0.044)	(0.039)	(0.028)
D.IT	1.006	1.088	1.034	1.114	1.063	1.023	1.910	2.679**	1.056	1.925***	1.097	1.410**
	(0.224)	(0.120)	(0.146)	(0.096)	(0.107)	(0.068)	(0.980)	(1.095)	(0.412)	(0.436)	(0.198)	(0.212)
TU*D.IT	1.212*	1.039	1.034	1.040	1.082	1.024	1.246	0.835	0.734	0.750	0.909	0.802
	(0.123)	(0.067)	(0.073)	(0.046)	(0.077)	(0.035)	(0.274)	(0.295)	(0.255)	(0.194)	(0.261)	(0.125)
D.CT	1.284***	1.114**	1.069***	1.042***	1.078	1.011	1.873**	1.361	1.007	0.685	0.917	0.769
	(0.099)	(0.059)	(0.018)	(0.015)	(0.053)	(0.052)	(0.592)	(0.496)	(0.260)	(0.176)	(0.122)	(0.124)
TU*D.CT	0.961	0.887	1.044	0.984	0.985	0.919**	0.860**	0.835**	0.958	0.814**	1.083	0.923
	(0.082)	(0.072)	(0.033)	(0.033)	(0.047)	(0.033)	(0.063)	(0.064)	(0.115)	(0.084)	(0.144)	(0.067)
D.DB	0.841	1.259	1.026	0.986	1.033	1.007	0.794	1.031	1.640*	1.764*	0.793	1.103
	(0.215)	(0.212)	(0.025)	(0.021)	(0.065)	(0.046)	(0.425)	(0.418)	(0.479)	(0.571)	(0.225)	(0.341)
TU*D.DB	0.945	1.195	1.044***	1.020**	1.084***	1.061	0.712	1.589	0.689	1.445	1.077	1.077
	(0.281)	(0.241)	(0.014)	(0.010)	(0.025)	(0.044)	(0.626)	(0.747)	(0.327)	(0.431)	(0.552)	(0.295)
No. of obs.	24,434	24,434	24,431	24,431	24,431	24,431	3,078	3,078	2,990	2,990	2,852	2,852
Log likelihood	-23,180	-23,180	-23,177	-23,177	-23,173	-23,173	-2,984	-2,984	-2,895	-2,895	-2,816	-2,816

Note: Weights are used in estimations. D1, D2 and D3 refer to 1-, 2- and 3-year differences of the industry-level variables. All calculations also include all other control variables. Odds ratios are reported. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

In terms of firm characteristics, while there are not any differences in firm size in either sample, the type of firm does matter, but again there are differences across samples. While in the total sample workers in private firms are less likely to be under-skilled than those in public firms, workers in manufacturing industries working in other firms are more likely to be under-skilled than those working in public firms.

The results for the further differentiation of total offshoring into (i) narrow and broad offshoring, (ii) manufacturing and services offshoring, and (iii) offshoring by source country are shown in Table 13 (Panels A and B). We again concentrate on the different offshoring indicators since the coefficients for the other control variables are similar to what we observed in Table 12 above.[29]

Similar to the results in Table 12 for total offshoring, other offshoring measures mainly affect the probability of being over-skilled. Specifically, for the total sample, an increase in broad offshoring is associated with a higher probability of being over-skilled, particularly for shorter-term changes, while, conversely, an increase in manufacturing offshoring is associated with a lower probability of being over-skilled. In manufacturing, an increase in both narrow offshoring and offshoring to developing countries is associated with a lower probability of being over-skilled. By contrast, an increase in offshoring to the NMS13 is associated with a lower probability of being under-skilled. In summary, for the total sample and specifically for the services industries, offshoring – when significant – is associated with a higher skills mismatch (i.e. higher over-skilling), while in manufacturing, it is associated with a lower skills mismatch (i.e. lower over-skilling or under-skilling).

Table 14 below report the results from the interaction models, with Panel A referring to the total sample and Panel B to the manufacturing sample. The results are again reported for the three year differences (1, 2 and 3 years) but only for the main variables of interest (i.e. main effects and interaction effects) since the coefficients for the other control variables are similar to those observed above (see Table 12).[30]

Similar to atypical employment, it shows that trade union representation at the firm level plays little role in mediating the effects of either total offshoring or technological change on the presence and/or nature (i.e. under-skilled and over-skilled) of skills mismatch. Where the interaction terms are statistically significant (at least at the 5% level of statistical significance), they are often positive, as in the case of total offshoring or DB, indicating that trade union representation in industries exposed to total offshoring or DB capital growth is associated with a higher probability of a skills mismatch, specifically, a higher probability of over-skilling in the case of total offshoring and a higher probability of both under- and over-skilling in the case of DB. By contrast, in the case of CT, trade unions seem to make a difference and are associated with a lower probability of a skills mismatch, both in terms of under- and over-skilling (specifically in manufacturing). Again, this result must be interpreted with caution, as causality may run in both directions.

The limited mediating role of trade union representation also holds for the other offshoring measures (see Table 15 and Table 16). We find few statistically significant interaction terms. However, the ones we do find are mostly positive and related to under-skilling, as in the case of broad offshoring or services offshoring for the total sample and of manufacturing offshoring, services offshoring and offshoring to developed countries for manufacturing. In the manufacturing sample, the interaction term for offshoring

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

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

to the NMS13 is negative, suggesting that trade union representation in industries with increasing offshoring to the NMS13 is associated with a lower probability of under-skilling.

Table 15 / Mediating effect of trade union representation on skills mismatch (total sample): Other offshoring measures

	(1) Under-skilled	(2) Over-skilled	(3) Under-skilled	(4) Over-skilled	(5) Under-skilled	(6) Over-skilled
	D1		D2		D3	
Narrow and broad offshoring						
TU	1.107	0.999	1.109	0.995	1.111	0.996
	(0.094)	(0.054)	(0.099)	(0.053)	(0.103)	(0.054)
D.OFF^{N}	0.882*	0.990	1.033	1.031	0.995	0.988
	(0.067)	(0.044)	(0.063)	(0.048)	(0.031)	(0.026)
TU*DOFF^{N}	0.900*	0.939	0.996	0.989	1.010	0.996
	(0.054)	(0.051)	(0.048)	(0.035)	(0.033)	(0.018)
D.OFF^{B}	1.160	1.243	0.892	1.266	1.046	0.834
	(0.294)	(0.244)	(0.217)	(0.193)	(0.183)	(0.126)
TU*D.OFF^{B}	1.254*	1.234*	1.241	1.347**	1.343**	1.202*
	(0.148)	(0.147)	(0.202)	(0.197)	(0.173)	(0.134)
No. of obs.	24,434	24,434	24,431	24,431	24,431	24,431
Log likelihood	-23,176	-23,176	-23,176	-23,176	-23,173	-23,173
Manufacturing and services offshoring						
TU	1.107	1.000	1.113	0.995	1.110	1.000
	(0.094)	(0.053)	(0.098)	(0.053)	(0.098)	(0.053)
D.OFF^{Manuf}	0.995	0.890	0.955	0.925	0.970	0.766***
	(0.111)	(0.117)	(0.118)	(0.118)	(0.069)	(0.072)
TU*D.OFF^{Manuf}	0.815	0.932	0.836	0.963	0.858	0.907
	(0.147)	(0.132)	(0.137)	(0.123)	(0.091)	(0.076)
D.OFF^{Serv}	0.942	1.302	0.894	1.162	1.014	1.006
	(0.283)	(0.297)	(0.158)	(0.136)	(0.077)	(0.056)
TU*D.OFF^{Serv}	1.172	1.237	1.090	1.207*	1.212**	1.156*
	(0.142)	(0.182)	(0.129)	(0.123)	(0.118)	(0.095)
No. of obs.	24,434	24,434	24,431	24,431	24,431	24,431
Log likelihood	-23,175	-23,175	-23,175	-23,175	-23,166	-23,166
Offshoring to developed countries, developing countries and NMS13						
TU	1.108	0.997	1.110	0.994	1.115	0.994
	(0.095)	(0.053)	(0.097)	(0.051)	(0.100)	(0.051)
D.OFF^{Devd}	1.400	1.219	0.934	1.408	1.158	0.711**
	(0.801)	(0.464)	(0.317)	(0.367)	(0.239)	(0.121)
TU*D.OFF^{Devd}	1.324	1.044	1.347*	1.550*	1.270*	1.172
	(0.399)	(0.201)	(0.233)	(0.382)	(0.182)	(0.171)
D.OFF^{Devg}	0.947	1.039	1.139	0.959	0.996	0.981
	(0.378)	(0.243)	(0.135)	(0.118)	(0.120)	(0.077)
TU*D.OFF^{Devg}	1.016	1.185	0.916	0.918	0.947	0.883*
	(0.270)	(0.265)	(0.138)	(0.123)	(0.109)	(0.062)
D.OFF^{NMS13}	0.818	1.094	0.948	1.051	0.906	1.069
	(0.373)	(0.168)	(0.196)	(0.101)	(0.124)	(0.085)
TU*D.OFF^{NMS13}	0.836	1.029	0.945	1.021	1.005	1.081
	(0.195)	(0.107)	(0.099)	(0.072)	(0.087)	(0.062)
No. of obs.	24,434	24,434	24,431	24,431	24,431	24,431
Log likelihood	-23,176	-23,176	-23,172	-23,172	-23,169	-23,169

Note: Weights are used in estimations. D1, D2 and D3 refer to 1-, 2- and 3-year differences of the industry-level variables. All calculations also include all other control variables. Odds ratios are reported. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 16 / Mediating effect of trade union representation on skills mismatch (manufacturing only): Other offshoring measures

	(1) Under-skilled	(2) Over-skilled	(3) Under-skilled	(4) Over-skilled	(5) Under-skilled	(6) Over-skilled
	D1		D2		D3	
Narrow and broad offshoring						
TU	1.001	0.961	1.056	0.996	1.045	0.919
	(0.209)	(0.101)	(0.203)	(0.112)	(0.186)	(0.118)
$D.OFF^{N}$	0.210	0.631	0.331**	0.781	0.635*	0.935
	(0.213)	(0.360)	(0.186)	(0.347)	(0.173)	(0.149)
$TU*D.OFF^{N}$	0.927	0.776	1.043	0.737	1.036	0.779*
	(0.473)	(0.345)	(0.470)	(0.291)	(0.107)	(0.106)
$D.OFF^{B}$	1.177	2.014	0.284	1.821	0.894	1.171
	(1.434)	(0.860)	(0.252)	(0.876)	(0.429)	(0.332)
$TU*D.OFF^{B}$	0.695	1.122	0.736	0.938	1.136	0.688
	(0.251)	(0.793)	(0.228)	(0.575)	(0.445)	(0.343)
No. of obs.	3,078	3,078	2,990	2,990	2,852	2,852
Log likelihood	-2,982	-2,982	-2,893	-2,893	-2,814	-2,814
Manufacturing and services offshoring						
TU	0.948	0.958	0.979	0.996	1.003	0.929
	(0.201)	(0.099)	(0.201)	(0.112)	(0.185)	(0.127)
$D.OFF^{Manuf}$	0.505	1.476	0.548	1.273	0.941	0.978
	(0.319)	(0.505)	(0.293)	(0.352)	(0.327)	(0.238)
$TU*D.OFF^{Manuf}$	1.693**	1.468	1.415	1.206	1.325	0.733
	(0.440)	(0.679)	(0.475)	(0.522)	(0.312)	(0.258)
$D.OFF^{Serv}$	7.457***	0.887	1.862	1.128	1.042	1.022
	(4.151)	(0.685)	(0.927)	(0.744)	(0.292)	(0.258)
$TU*D.OFF^{Serv}$	0.432	0.572*	0.756	0.675	0.981	1.059
	(0.290)	(0.172)	(0.409)	(0.180)	(0.345)	(0.197)
No. of obs.	3,078	3,078	2,990	2,990	2,852	2,852
Log likelihood	-2,980	-2,980	-2,895	-2,895	-2,816	-2,816
Offshoring to developed countries, developing countries and NMS13						
TU	0.944	0.978	0.978	0.985	0.943	0.914
	(0.197)	(0.095)	(0.182)	(0.107)	(0.157)	(0.109)
$D.OFF^{Devd}$	1.867	12.086***	0.473	1.787	0.930	1.389
	(3.398)	(11.336)	(0.601)	(1.438)	(0.721)	(0.778)
$TU*D.OFF^{Devd}$	7.636	1.784	10.385**	1.785	7.289**	2.059
	(12.834)	(2.593)	(11.167)	(1.806)	(5.952)	(1.617)
$D.OFF^{Devg}$	0.130**	0.566	0.619	1.061	0.792	0.782
	(0.121)	(0.539)	(0.489)	(0.869)	(0.197)	(0.263)
$TU*D.OFF^{Devg}$	0.861	0.907	0.750	0.738	0.839	0.628*
	(0.946)	(0.781)	(0.600)	(0.463)	(0.215)	(0.167)
$D.OFF^{NMS13}$	3.662	0.228*	1.036	0.903	1.101	1.044
	(4.175)	(0.179)	(0.932)	(0.665)	(0.400)	(0.490)
$TU*D.OFF^{NMS13}$	0.107	0.680	0.066***	0.599	0.180***	0.664
	(0.157)	(0.483)	(0.067)	(0.332)	(0.112)	(0.251)
No. of obs.	3,078	3,078	2,990	2,990	2,852	2,852
Log likelihood	-2,978	-2,978	-2,888	-2,888	-2,808	-2,808

Note: Weights are used in estimations. D1, D2 and D3 refer to 1-, 2- and 3-year differences of the industry-level variables. All calculations also include all other control variables. Odds ratios are reported. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

5. Endogeneity

The analysis also addresses the potential endogeneity of trade union representation at the firm level. In our multilevel approach, we use country-level information on union density (ICTWSS), centred and lagged, since reverse causality from lower- to higher-level indicators is limited. Section 5.1 refers to results for atypical employment, while Section 5.2 refers to those for skills mismatch. For the sake of brevity, we only report results for the model with total offshoring.[31]

Similar to a standard instrumental variable approach, we first establish the ‘relevance’ of trade union density by means of a multilevel logit regression model with trade union representation at the firm level as dependent variable and union density as control variable, in addition to all other control variables used in the analysis. The results for both survey rounds (2015 and 2021), both samples (total and manufacturing only), and all three differencing periods are shown in Table A.3 in the annex. It shows that trade union representation at the firm level and union density at the country level are highly positively correlated – at the 1% level of statistical significance – making union density a highly relevant ‘alternative’ to the potentially endogenous trade union representation at the firm level.

5.1. ATYPICAL EMPLOYMENT

Table 17 below shows that union density was generally unrelated to the probability of being in atypical employment.[32] The only exception is the manufacturing sample (for 2015), where higher union density is associated with a higher probability of involuntary part-time work.

Moreover, similar to findings above (see Table 5 and Table 10 above), Table 18 shows that union density plays little role in mediating the effects of either offshoring or technological change on atypical employment. In fact, even fewer interaction terms are significant. However, when they are, they are negative, suggesting that union density plays a mediating role, such as for CT (in 2015 and 2021) and DB (in 2015 only).

31 The results for the remaining offshoring indicators are available from the authors upon request.

32 The full results are reported in Tables A.4, A.5 and A.6 in the annex.

Table 17 / Atypical employment – in total and by type (total and manufacturing sample for 2015 and total for 2021): Endogeneity – the role of union density

	(1) Atypical D1	(2) Atypical D2	(3) Atypical D3	(4) Temp. contract D1	(5) Temp. contract D2	(6) Temp. contract D3	(7) Invol. part-time D1	(8) Invol. part-time D2	(9) Invol. part-time D3
				Panel A: Total (2015)					
L.Union density	0.999	0.998	0.998	0.997	0.997	0.996	1.003	1.003	1.003
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
No. of obs.	24,653	24,650	24,650	24,614	24,611	24,611	24,234	24,231	24,231
Log likelihood	-9,467	-9,467	-9,468	-8,225	-8,225	-8,225	-4,597	-4,596	-4,597
				Panel B: Manufacturing (2015)					
L.Union density	0.998	1.000	1.001	0.993	0.996	0.997	1.019***	1.017***	1.015***
	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)	(0.012)	(0.007)	(0.006)	(0.006)
No. of obs.	3,089	3,000	2,862	3,088	2,999	2,861	3,043	2,955	2,820
Log likelihood	-969.3	-934.2	-889.7	-873.8	-838.4	-799.8	-309.2	-301.7	-288.8
				Panel C: Total (2021)					
L.Union density	0.999			0.998			1.005		
	(0.004)			(0.004)			(0.004)		
No. of obs.	22,451			22,342			22,402		
Log likelihood	-8,114			-6,968			-3,479		

Note: Weights are used in estimations. D1, D2 and D3 refer to 1-, 2- and 3-year differences of the industry-level variables. All calculations also include all other control variables. Odds ratios are reported. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 18 / Mediating effect of trade unions on atypical employment – in total and by type (total and manufacturing only for 2015 and total for 2021): Endogeneity – the role of union density

	(1) Atypical D1	(2) Atypical D2	(3) Atypical D3	(4) Temp. contract D1	(5) Temp. contract D2	(6) Temp. contract D3	(7) Invol. part-time D1	(8) Invol. part-time D2	(9) Invol. part-time D3
				Panel A: Total (2015)					
L.Union density	0.997	0.998	0.998	0.995	0.995	0.996	1.003	1.003	1.003
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
D.OFF^{tot}	1.039	1.333**	1.007	1.024	1.253	0.981	1.142	1.385	0.918
	(0.155)	(0.192)	(0.123)	(0.159)	(0.192)	(0.147)	(0.157)	(0.278)	(0.122)
D.OFF^{tot}*L.Union density	0.975	0.985	0.992	0.975	0.982	1.000	0.988	0.996	0.978**
	(0.016)	(0.014)	(0.009)	(0.019)	(0.016)	(0.011)	(0.022)	(0.014)	(0.010)
D.IT	1.113	1.005	0.905	1.061	0.993	0.887	1.342	1.125	1.098
	(0.118)	(0.106)	(0.091)	(0.116)	(0.105)	(0.095)	(0.273)	(0.135)	(0.097)
D.IT*L.Union density	0.998	1.000	1.001	0.999	1.000	1.002	0.996	1.005	1.003
	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.008)	(0.005)	(0.003)
D.CT	0.962	0.946**	1.054	0.970	0.950*	1.080	0.968	0.922*	0.912
	(0.072)	(0.024)	(0.071)	(0.079)	(0.026)	(0.082)	(0.121)	(0.038)	(0.063)
D.CT*L.Union density	0.995	0.994***	0.988***	0.995	0.995***	0.987***	0.994	0.993***	0.994
	(0.004)	(0.001)	(0.004)	(0.004)	(0.001)	(0.005)	(0.005)	(0.003)	(0.005)
D.DB	0.819	1.019	0.995	0.820	0.994	0.953	0.790	1.010	0.997
	(0.197)	(0.043)	(0.050)	(0.218)	(0.047)	(0.051)	(0.287)	(0.066)	(0.057)
D.DB*L.Union density	0.950**	0.999	1.001	0.948**	0.995	0.997	0.987	1.007	1.012
	(0.020)	(0.006)	(0.006)	(0.021)	(0.006)	(0.006)	(0.023)	(0.009)	(0.008)
No. of obs.	24,653	24,650	24,650	24,614	24,611	24,611	24,234	24,231	24,231
Log likelihood	-9,462	-9,464	-9,462	-8,221	-8,223	-8,220	-4,596	-4,595	-4,593

Contd.

Table 18 / Continued

	(1) Atypical D1	(2) Atypical D2	(3) Atypical D3	(4) Temp. contract D1	(5) Temp. contract D2	(6) Temp. contract D3	(7) Invol. part-time D1	(8) Invol. part-time D2	(9) Invol. part-time D3
				Panel B: Manufacturing (2015)					
L.Union density	1.000	0.996	1.000	0.994	0.990	0.998	1.024***	1.022***	1.010
	(0.008)	(0.008)	(0.011)	(0.010)	(0.010)	(0.013)	(0.007)	(0.007)	(0.007)
D.OFF^{tot}	1.455	1.795	1.345	2.067	3.206*	1.313	0.333	0.618	1.141
	(1.091)	(0.998)	(0.249)	(1.789)	(2.074)	(0.337)	(0.412)	(0.850)	(0.439)
D.OFF^{tot}*L.Union density	1.005	0.988	1.001	1.003	0.960	1.027	1.087	1.053	0.976
	(0.086)	(0.065)	(0.017)	(0.095)	(0.068)	(0.021)	(0.129)	(0.130)	(0.027)
D.RobDens	1.096	1.021	0.962	1.179	1.091	1.015	0.653	0.714	0.710**
	(0.305)	(0.101)	(0.100)	(0.373)	(0.162)	(0.127)	(0.484)	(0.148)	(0.119)
D.RobDens*L.Union density	1.030	1.000	0.998	1.032	1.004	1.002	0.985	0.994	0.990
	(0.019)	(0.008)	(0.008)	(0.021)	(0.011)	(0.009)	(0.044)	(0.013)	(0.014)
D.IT	4.748**	1.648	1.601**	4.148**	1.587	1.685**	3.549**	1.613	1.240
	(2.924)	(0.592)	(0.343)	(2.992)	(0.669)	(0.382)	(1.951)	(0.743)	(0.370)
D.IT*L.Union density	0.957*	1.002	0.995	0.967	1.007	1.000	0.953*	0.977	0.977
	(0.023)	(0.015)	(0.010)	(0.027)	(0.017)	(0.009)	(0.024)	(0.021)	(0.015)
D.CT	0.410	1.030	0.775	0.436	1.132	0.823	0.124	0.264**	0.399***
	(0.395)	(0.461)	(0.157)	(0.473)	(0.539)	(0.176)	(0.162)	(0.148)	(0.135)
D.CT*L.Union density	1.013	0.987	0.997	1.014	0.987	0.999	1.016	0.990	0.990
	(0.036)	(0.015)	(0.008)	(0.041)	(0.016)	(0.009)	(0.052)	(0.032)	(0.021)
D.DB	0.569	1.059	0.838	0.771	1.074	0.866	2.693	3.198	2.244
	(0.407)	(0.461)	(0.232)	(0.569)	(0.465)	(0.250)	(3.868)	(2.272)	(1.241)
D.DB*L.Union density	0.939	0.977	0.998	0.938*	0.967	0.994	1.046	1.056	1.015
	(0.044)	(0.027)	(0.020)	(0.036)	(0.022)	(0.018)	(0.072)	(0.043)	(0.027)
No. of obs.	3,089	3,000	2,862	3,088	2,999	2,861	3,043	2,955	2,820
Log likelihood	-965.5	-933.3	-889.5	-871.0	-837.1	-799.5	-308.0	-300.6	-287.7
				Panel C: Total (2021)					
L.Union density	1.000			0.998			1.006		
	(0.004)			(0.004)			(0.004)		
D.OFF^{tot}	1.625			1.761			2.487		
	(1.808)			(2.262)			(3.424)		
D.OFF^{tot}*L.Union density	1.014			1.012			0.991		
	(0.032)			(0.034)			(0.040)		
D.IT	0.836			0.888			0.707		
	(0.159)			(0.183)			(0.261)		
D.IT*L.Union density	0.981			0.981			0.996		
	(0.011)			(0.013)			(0.019)		
D.CT	0.627			0.455**			1.172		
	(0.199)			(0.181)			(0.482)		
D.CT*L.Union density	0.967*			0.959*			0.986		
	(0.019)			(0.021)			(0.023)		
D.DB	1.066			1.156			0.700		
	(0.338)			(0.487)			(0.265)		
D.DB*L.Union density	1.018			1.009			1.035		
	(0.022)			(0.033)			(0.022)		
No. of obs.	22,451			22,342			22,402		
Log likelihood	-8,112			-6,967			-3,479		

Note: Weights are used in estimations. D1, D2 and D3 refer to 1-, 2- and 3-year differences of the industry-level variables. All calculations also include all other control variables. Odds ratios are reported. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

5.2. SKILLS MISMATCH

Similar to findings above, union density is unrelated to the presence and/or nature of skills mismatch[33] (see Table 19) and plays little role in mediating the effects of either total offshoring or technological change on the presence and/or nature of skills mismatch (see Table 20). We again find fewer statistically significant interaction terms than above (see Table 14), but where the interaction terms are statistically significant, they are often positive, as in the case of IT (in manufacturing), indicating that union density in manufacturing industries exposed to IT capital growth is associated with a higher probability of a skills mismatch.

Table 19 / Skills mismatch (total and manufacturing only, 2015): Endogeneity – the role of union density

	(1) Under-skilled	(2) Over-skilled	(3) Under-skilled	(4) Over-skilled	(5) Under-skilled	(6) Over-skilled
	D1		D2		D3	
	Panel A: Total					
L.Union density	0.995	1.000	0.996	1.000	0.996	1.000
	(0.005)	(0.003)	(0.005)	(0.003)	(0.005)	(0.003)
No of obs.	24,434	24,434	24,431	24,431	24,431	24,431
Log likelihood	-23182	-23182	-23177	-23177	-23179	-23179
	Panel B: Manufacturing					
L.Union density	1.002	1.006	1.002	1.005	1.002	1.002
	(0.005)	(0.006)	(0.006)	(0.006)	(0.005)	(0.007)
No of obs.	3,078	3,078	2,990	2,990	2,852	2,852
Log likelihood	-2996	-2996	-2905	-2905	-2823	-2823

Note: Weights are used in estimations. D1, D2 and D3 refer to 1-, 2- and 3-year differences of the industry-level variables. All calculations also include all other control variables. Odds ratios are reported. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

33 The full results are reported in Tables A.7 in the annex.

Table 20 / Mediating effect of trade unions on skills mismatch (total and manufacturing only, 2015): Endogeneity – the role of union density

	Panel A: Total						Panel B: Manufacturing					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
	Under-skilled	Over-skilled	Under-skilled	Over-skilled	Under-skilled	Over-skilled	Under-skilled	Over-skilled	Under-skilled	Over-skilled	Under-skilled	Over-skilled
	D1		D2		D3		D1		D2		D3	
L.Union density	0.996	1.000	0.997	0.999	0.997	0.999	0.998	1.006	1.001	1.008	1.001	1.003
	(0.005)	(0.003)	(0.004)	(0.003)	(0.005)	(0.003)	(0.005)	(0.006)	(0.007)	(0.007)	(0.005)	(0.007)
D.OFF^{tot}	1.142	1.232*	1.136	1.419**	1.108	0.954	1.623	0.792	0.505	0.836	0.966	0.853**
	(0.197)	(0.136)	(0.269)	(0.207)	(0.154)	(0.104)	(0.872)	(0.478)	(0.301)	(0.396)	(0.220)	(0.068)
D.OFF^{tot}*L.Union density	0.995	0.995	0.995	0.989	0.994	1.005	0.928**	1.047	1.017	1.049	0.997	1.017*
	(0.016)	(0.011)	(0.015)	(0.010)	(0.007)	(0.005)	(0.034)	(0.056)	(0.051)	(0.045)	(0.018)	(0.009)
D. RobDens							1.063	0.901	0.998	0.979	1.055	0.978
							(0.144)	(0.106)	(0.062)	(0.079)	(0.048)	(0.045)
D.RobDens*L.Union density							0.989	0.994	0.998	1.001	1.006*	1.000
							(0.008)	(0.011)	(0.004)	(0.006)	(0.003)	(0.004)
D.IT	1.296**	1.054	1.048	1.063	1.053	1.010	1.269	0.877	0.648	1.065	0.860	1.056
	(0.158)	(0.110)	(0.068)	(0.044)	(0.070)	(0.038)	(0.698)	(0.435)	(0.269)	(0.237)	(0.163)	(0.124)
D.IT*L.Union density	0.987***	1.000	0.997	0.999	0.998	1.000	1.004	1.023	1.023	1.012	1.016**	1.007
	(0.005)	(0.004)	(0.003)	(0.002)	(0.003)	(0.002)	(0.022)	(0.019)	(0.016)	(0.009)	(0.008)	(0.006)
D.CT	1.156	0.982	1.062**	0.977	1.040	0.952	2.686	0.710	1.388	0.741*	1.211*	0.944
	(0.132)	(0.123)	(0.025)	(0.020)	(0.043)	(0.034)	(1.762)	(0.302)	(0.375)	(0.127)	(0.140)	(0.103)
D.CT*L.Union density	0.994	0.997	0.997**	0.997**	0.996	0.998	0.963	1.012	0.985	1.007	0.990**	1.000
	(0.005)	(0.005)	(0.001)	(0.001)	(0.003)	(0.002)	(0.024)	(0.018)	(0.010)	(0.006)	(0.005)	(0.004)
D.DB	0.790	1.169	0.966	1.019	1.018	1.053	0.488	3.108***	1.148	2.193***	0.949	1.042
	(0.226)	(0.183)	(0.045)	(0.026)	(0.043)	(0.037)	(0.284)	(0.845)	(0.383)	(0.482)	(0.290)	(0.195)
D.DB*L.Union density	1.014	0.993	1.012*	0.998	1.007	0.995	1.011	1.023	0.999	1.008	1.005	0.999
	(0.020)	(0.009)	(0.007)	(0.003)	(0.005)	(0.004)	(0.038)	(0.023)	(0.023)	(0.013)	(0.014)	(0.007)
	(0.023)	(0.059)	(0.023)	(0.059)	(0.024)	(0.059)	(0.067)	(0.079)	(0.075)	(0.083)	(0.074)	(0.099)
No of obs.	24,434	24,434	24,431	24,431	24,431	24,431	3,078	3,078	2,990	2,990	2,852	2,852
Log likelihood	-23172	-23172	-23166	-23166	-23168	-23168	-2987	-2987	-2898	-2898	-2818	-2818

Note: Weights are used in estimations. D1, D2 and D3 refer to 1-, 2- and 3-year differences of the industry-level variables. All calculations also include all other control variables. Odds ratios are reported. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

6. Summary and policy implications

6.1. SUMMARY

This paper has analysed the impacts on the quality of workers' jobs of three factors: (i) the different types of technological change – namely, robotisation and the three ICT asset types (IT, CT and DB); (ii) offshoring – in total and further differentiated by narrow and broad offshoring, manufacturing or services offshoring and offshoring by sourcing region (developed countries, developing countries and NMS13); and (iii) the mediating role of trade union representation at the firm level. The latter is captured by atypical employment and its sub-components (i.e. temporary contracts and involuntary part-time work) as well as by self-reported skills mismatch.

It used worker-level data from two waves of the European Working Conditions Survey (2015 and 2021) for 25 EU member states (excluding Croatia, Cyprus and Malta due to missing data) along with various industry-level data, such as the World Input-Output Database (WIOD), the EU-KELMS Growth and Productivity Accounts, the World Robotics Industrial Robots statistics from the International Federation of Robotics (IFR), the EU Structural Business Statistics (SBS) and the Labour Market Reform Database (LABREF) provided by the European Commission's Directorate-General for Employment, Social Affairs and Inclusion. In addition, it used two different data samples: the total economy sample (excluding all public industries) and the smaller manufacturing sample.

Our results show that a worker's probability of being in atypical employment is related to both forces studied (i.e. technological change and offshoring) – but not necessarily by increasing the probability of having an atypical job – with differences existing across types of technological change and offshoring, samples and years. Specifically, while none of the tested forces turned out to be significant in 2021, in 2015, an increase in total offshoring (and manufacturing offshoring) or IT (i.e. computer hardware) is associated with a higher probability of being in atypical employment (only in the manufacturing sample), while an increase in CT (i.e. telecommunications equipment) is associated with a lower probability of being in atypical employment (in both samples).

Moreover, the two types of atypical employment are affected differently and there are strong differences between the two samples, suggesting that workers in manufacturing industries and services industries (which make up the bulk of the non-manufacturing industries in our sample) are affected differently. In manufacturing, total offshoring and IT are associated with a higher probability of having a temporary contract, while CT and robot density are associated with a lower probability of involuntarily working part-time. In the total sample, both IT and DB are associated with a higher probability of involuntarily working part-time, while CT is associated with a lower probability of having a temporary contract.

Both offshoring and technological change play a limited – and, if so, temporary – role for workers' self-reported skills mismatch, and there are again differences between the two samples. The higher probability of over-skilling associated with offshoring in the total sample – as opposed to the lower probability in manufacturing – is mainly related to private services industries in which, starting from a low level, offshoring has expanded strongly more recently. Moreover, since the higher probability of over-skilling in the total sample is only observed for shorter-term changes in total offshoring, the (disruptive) effect only seems to be temporary. Concerning technological change, an increase in CT and DB is associated with a higher probability of being under-skilled in the total sample, while in manufacturing, an increase in DB is associated with a higher probability of being over-skilled. These results point to the different relevance of ‘substitution’ and ‘reinstatement’ effects associated with offshoring and technological change in the two samples: a (temporary) substitution effect stemming from offshoring, a reinstatement effect from technological change in the total sample, mainly related to services industries; and a substitution effect from technological change in manufacturing.

While trade union representation is associated with a lower probability of being in atypical employment (only in the total sample but in both waves), it is unrelated to self-reported skills mismatch. However, trade unions play a limited mediating role for the quality of workers’ jobs. When a significant effect is observed at all, it is often positive, suggesting that trade unions in industries characterised by increases in offshoring or ICT are associated with a higher probability of workers’ being in atypical work or reporting a skills mismatch. However, this result needs to be interpreted with caution, as causality can run both ways and it more likely indicates that trade unions are more strongly present in industries in which the quality of jobs is deteriorating due to offshoring and/or technological change. The results hardly change when endogeneity is taken into account through the higher-level union density indicator.

6.2. POLICY IMPLICATIONS

At first sight, the evidence is uneven. Depending on the types of technology being used and the sectors analysed, we find (i) that there are both substitution and reinstatement effects that affect atypical employment, and (ii) that impacts of offshoring and technology use on skill mismatch vary between manufacturing and (private) service sectors. Trade unions have so far had only limited influence on job quality in these dimensions. To explore the policy implications of these findings, we need to widen the lens beyond the immediate evidence of this paper.

In a policy context, it is **precarious rather than atypical employment** that is drawing some attention. Definitions of precarious work combine indicators of (involuntarily) atypical employment with indicators of negative outcomes for workers in terms of pay, working hours, working conditions, social security, and access to labour rights.[34] Jobs with these negative characteristics may also occur under some “normal” employment contracts and may involve a wide range of low-wage work, atypical employment, and some forms of self-employment, such as self-employment depending on one client. For example, in the European Parliament’s 2017 resolution on the subject, the EP “understands precarious employment to mean employment which does not comply with EU, international and national standards and laws and/or does not provide sufficient resources for a decent life or adequate social protection” (European Parliament, 2017, p. 5).

Recently, precarious employment has attracted political attention again in various contexts: (i) those of the **platform economy**, where the EU’s platform directive made some inroads into clarifying the boundaries between employment and self-employment, (ii) the ‘discovery’ that some groups of workers deemed “essential” during the COVID-19 pandemic in sectors such as health and social care, cleaning, logistics or

[34] See, for example, www.eurofound.europa.eu/en/european-industrial-relations-dictionary/precarious-work, last visited July 17, 2024; (Matilla-Santander et al., 2019; Olsthoorn, 2014).

the food industry actually had low wages and poor job quality , and (iii) as a **key risk factor for poor mental health** of workers. In the context of the European Commission's initiatives to improve mental health in Europe at large after the COVID-19 pandemic, the European Economic and Social Committee (EESC) has drawn up an opinion dedicated to mental health and precarious work (EESC, 2023) upon the request of the Spanish Council Presidency. This document reiterates the robustly political definition of precarious work found in the European Parliament's 2017 resolution in addition to presenting evidence that precarious employment is a key risk factor for poor mental health and, thus, a public health issue as well as an issue of labour rights. The EESC opinion aims to implement "prevention of occupational psychosocial risks at the source, and [change] the way work is designed, managed and organised" (EESC, 2023, p. 2). It insists that "neither generating or increasing corporate profits, nor reducing labour costs or ensuring flexibility for employers can come at the cost of health and safety at work" (p. 1).

Arguments in favour of precarious work refer to job creation and labour market access, especially for low-skilled workers, the long-term unemployed, recent immigrants, and those with needs for flexible work and extra income. Employers in sectors with precarious employment point out competitive pressures, the need for cost efficiency, flexible deployment of workers, and customer demand for flexible real-time delivery of products and services. Indeed, enlisting consumers to support business models that rely on precarious employment or self-employment is a feature of the platform economy (Thelen, 2019), but it is also observed in other sectors and often in personal services, such as elderly care or domestic services (Aulenbacher et al., 2021).

As outlined above, arguments against precarious work point out that it creates below-standard forms of working that exacerbate inequalities in the labour market. This undermines labour standards achieved for "regular" employment, as companies have incentives to move work between labour market segments. Various forms of atypical employment enshrined in national labour law and labour market policies (e.g. zero-hours contracts, marginal employment, hybrids between work and services contracts, etc.) foresee exemptions from social security contributions or taxes and, accordingly, may limit workers' access to social benefits. Uncertainty over incomes and job security then adds to the mental and physical health challenges that precarious workers face. Labour flexibility is thus achieved by shifting market uncertainties onto workers, and often onto those who can ill afford to take such risks.

However, precarious jobs – with below-standard outcomes for workers, with or without platform intermediation – rely on a labour reserve with limited options in the labour market. Indeed, groups disproportionately affected by precarious work are recent immigrants, young people (including in some highly-skilled occupations, such as the media or creative industries), women, or those in low-wage occupations, sometimes in combination with health problems or discontinuous careers (Tobsch & Eichhorst, 2017; Kreshpaj et al., 2020). Since employers in many sectors and countries, at both the higher- and the low-skilled ends of the labour market, complain of staffing shortages, there may be some market pressure to improve job quality in precarious labour market segments, as shortages should increase workers' negotiating power on wages as well as working conditions. They should also encourage companies to make the best possible use of their employees' human capital and skills as well as to make efforts to reduce labour turnover and absences due to ill health.

However, evidence that workloads and pressure at work are consistently increasing (Warhurst et al., 2019) and qualitative insights from various sectors (Holtgrewe et al., 2024) suggest that staffing shortages have immediate negative impacts on work intensity and pressure at work. This may also reduce workers' and work teams' time and capacity for learning and making improvements in work organisation, which, again, exacerbates skills mismatches and possibly also labour turnover. For employers to rely on more precarious and atypical employment to fill gaps may be tempting in the short run, but it may result in additional HR headaches and costs as well as distract from investing in more sustainable employment.

For all these reasons, job quality in the dimensions of precarious employment and skills mismatches remains a salient policy issue, especially in the context of recent crises, reconfigurations of global value chains, technological and demographic changes, and the challenges of climate change and the transition to a more sustainable economy. For European economies and societies, addressing these challenges clearly requires effective, high-quality, and sustainable uses of labour and human capital and knowledge on all skill levels. To overcome the short-termism of markets and economic cycles, in addition to individual company initiatives, dedicated efforts by social partners and policymakers will be needed.

Since social partners have and aggregate expertise on sector- and company-specific needs and challenges around flexible employment, their contributions remain essential to successful policies. However, organised interest representation in many countries is unevenly distributed among sectors and companies and, in addition, it often has gaps, especially in those sectors relying on precarious or atypical employment. This may require some joint policy efforts to build the capacities of social partnership, especially in the more precarious sectors and contexts, in order to benefit from social partners' contributions.

Given their expertise in sector- and company-specific needs and challenges, the social partners should also monitor the new and emerging developments in new and growing jobs and sectors, such as “green” ones, as well as in the new technologies that will influence the future of work by affecting business models, staff deployment, and work organisation. With regards to the future of work, a new concern has recently emerged in the literature. According to Acemoglu and Restrepo (2019, p. 5) “the future of work depends on the mixture of new technologies and how these change the task content of production”. These authors reveal that some automation technologies, which they call “so-so technologies”, actually bring significant job losses but only modest productivity gains, especially if the workers who were replaced were cheap in the first place and the automation technology is only marginally more productive than they were. In this context, social partners must take on an essential role in opposing harmful automation technologies (Traverso et al., 2023). At the opposite end, they should support technologies that create new tasks and new jobs or technologies that are highly productive and for which the number of replaceable skills is low (Restrepo, 2023).

On the worker side, it is important to note that the relationship of worker voice and union presence, on the one hand, and atypical employment, on the other, is bidirectional. Generally speaking, limited access to interest representation, voice and discretion over one's own work is one of the characteristics of precarious employment. Union presence may limit the use of atypical and especially precarious work arrangements, but it may also be an incentive for employers to outsource and shift work to less organised sectors or labour market segments. Outsourced services, especially in the context of postal and logistics services (Haidinger, 2015), customer service centres (Doellgast, 2023), or other business services (Kowalik et al., 2024) provide ample examples. Conversely, atypically employed workers often have less of a tendency or opportunity to join unions, exert their voice, and be represented in works councils or other representative bodies – or their experience of poor job quality or skills mismatch becomes an incentive to join unions and/or install interest representation in the company. Indeed, there are recent examples of successful organising initiatives of platform workers and other precariously employed groups (Doellgast et al., 2018; Herr et al., 2021; Tassinari & Maccarrone, 2017).

Hence, limiting precarious work, improving its quality, and strengthening worker voice, trade unions and social partnerships are interrelated policy objectives, as well. Indeed, in a recent meta-analysis of some 56 qualitative studies on **trade union strategies** for countering precarious employment, Carver and Doellgast (2021) find two ways for trade unions to mitigate gaps between regular and precarious labour market segments: either through conflict-based strategies in countries such as the UK and Germany, where unions' institutional power was lacking or in decline, or through social partnership strategies where they were institutionally stronger and able to "leverage existing institutions to widen their jurisdiction and codify new institutional protections for peripheral workers" (Carver und Doellgast, 2021, p. 375). Along both trajectories, they managed (and needed) to secure state support to achieve more solidaristic arrangements.

Whereas flexible working can be designed to take both workers' and employers' interests into account, the impacts of precarious employment appear to be largely disadvantageous to workers. Ways to mitigate them need interrelated and coherent policies that combine:

› legal clarification of employment statuses;

› efforts to address current and emerging challenges to good-quality employment and work in a systemic and coherent way that aligns the various existing and future bodies of EU labour regulations in the direction of ensuring good-quality employment and work for all as well as the sustainable use of human capital, knowledge and capabilities in a way that will lead to both productive economies and good quality of life for Europeans;

› enforcement of existing legislation on minimum wages, working hours, OSH and labour rights through well-coordinated bodies that are able to pool multiple areas of expertise;

› monitoring of new and emerging developments in newly growing jobs and sectors (e.g. "green" ones) as well as of new technologies that affect business models, staff deployment, and work organisation;

› improved access for precarious workers to social security and more "regular" jobs through recognition and upgrading of their skills;

› policy and public support for capacity-building of social partners enabling them to engage in proactive initiatives (on national and regional levels) that shape technological, environmental, and skill-based developments in favourable ways while also including and supporting SMEs and other "atypical" employers;

› exploration of more ambitious ways for policy to improve job quality by integrating social standards, including interest representation, into public procurement; and

› ensuring decent employment on all skill levels, including in the sectors of health, social and educational services, which in many countries are publicly funded but delivered by various private and/or civil society-based, for-profit and non-profit providers.

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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	Professional, scientific and technical activities
N	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
U	Activities of extraterritorial organisation and bodies

Table A.2 / Summary statistics

	EWCS 2015				EWCTS 2021			
	Mean	Std. dev.	Min	Max	Mean	Std. dev	Min	Max
Trade union	0.499	0.500	0	1	0.600	0.490	0	1
Atypical employment	0.228	0.420	0	1	0.181	0.385	0	1
Temporary contract	0.198	0.399	0	1	0.151	0.358	0	1
Involuntary part-time	0.059	0.235	0	1	0.046	0.210	0	1
Skills mismatch: well matched	0.574	0.494	0	1	N/A	N/A	N/A	N/A
Skills mismatch: under-skilled	0.146	0.354	0	1	N/A	N/A	N/A	N/A
Skills mismatch: over-skilled	0.279	0.449	0	1	N/A	N/A	N/A	N/A
Female	0.501	0.500	0	1	0.473	0.499	0	1
Migrant	0.139	0.346	0	1	N/A	N/A	N/A	N/A
15-24 yrs old	0.081	0.273	0	1	0.090	0.286	0	1
25-49 yrs old	0.620	0.485	0	1	0.589	0.492	0	1
ISCED: medium	0.495	0.500	0	1	0.416	0.493	0	1
ISCED: high	0.348	0.476	0	1	0.461	0.498	0	1
Tenure (ln)	1.736	1.454	-0.693	6.908	2.568	1.947	0	6.908
ISCO: med	0.422	0.494	0	1	0.389	0.488	0	1
ISCO: high	0.388	0.487	0	1	0.442	0.497	0	1
Firm size: medium	0.118	0.322	0	1	0.240	0.427	0	1
Firm size: large	0.089	0.285	0	1	0.213	0.409	0	1
Firm type: private	0.653	0.476	0	1	0.608	0.488	0	1
Firm type: other	0.066	0.248	0	1	0.097	0.297	0	1

Table A.3 / Relevance of union density: 2015 and 2021

	Panel A: Total (2015)			Panel B: Manufacturing (2015)			Panel C: Total (2021)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	D1	D2	D3	D1	D2	D3	D1
L.Union density	1.030***	1.031***	1.030***	1.033***	1.034***	1.034***	1.025***
	(0.005)	(0.005)	(0.005)	(0.009)	(0.009)	(0.010)	(0.004)
D.OFF^{tot}	1.273**	1.015	1.002	0.846	0.808	1.273	5.566
	(0.140)	(0.181)	(0.133)	(0.095)	(0.142)	(0.212)	(5.974)
D.RobDens				0.971	0.966	1.001	
				(0.186)	(0.063)	(0.019)	
D.IT	1.192*	1.094	1.020	1.256	0.935	0.791**	1.012
	(0.126)	(0.088)	(0.070)	(0.275)	(0.233)	(0.091)	(0.245)
D.CT	1.127	0.989	1.034	1.324***	1.183	1.066	1.296
	(0.090)	(0.036)	(0.048)	(0.135)	(0.129)	(0.078)	(0.451)
D.DB	0.627*	0.941	0.929	0.485	0.759	0.978	0.862
	(0.155)	(0.038)	(0.043)	(0.252)	(0.336)	(0.262)	(0.131)
Female	0.830***	0.830***	0.830***	0.728***	0.729***	0.727***	0.904***
	(0.040)	(0.041)	(0.040)	(0.073)	(0.075)	(0.077)	(0.034)
Migrant	1.066	1.065	1.065	1.573**	1.602**	1.591*	N/A
	(0.087)	(0.087)	(0.087)	(0.361)	(0.371)	(0.378)	N/A
15-24 yrs old	1.168	1.168	1.168	0.862	0.810	0.827	1.281**
	(0.113)	(0.113)	(0.113)	(0.237)	(0.231)	(0.248)	(0.155)
25-49 yrs old	1.149***	1.150***	1.150***	0.991	0.994	1.001	1.103*
	(0.051)	(0.051)	(0.050)	(0.126)	(0.130)	(0.143)	(0.061)
ISCED: medium	1.168**	1.169**	1.168**	1.159	1.131	1.138	1.067
	(0.083)	(0.083)	(0.083)	(0.165)	(0.159)	(0.166)	(0.160)
ISCED: high	1.435***	1.436***	1.434***	1.128	1.104	1.112	1.296*
	(0.106)	(0.105)	(0.105)	(0.180)	(0.181)	(0.179)	(0.200)
Tenure (ln)	1.373***	1.373***	1.373***	1.279***	1.274***	1.281***	1.375***
	(0.025)	(0.025)	(0.025)	(0.048)	(0.051)	(0.052)	(0.036)
ISCO: medium	0.822***	0.821***	0.821***	0.535***	0.548***	0.544***	1.113
	(0.035)	(0.035)	(0.035)	(0.043)	(0.047)	(0.042)	(0.110)
ISCO: high	0.948	0.949	0.950	0.958	0.968	0.957	1.089
	(0.055)	(0.055)	(0.055)	(0.187)	(0.197)	(0.198)	(0.088)
Firm size: med-sized	2.326***	2.324***	2.322***	2.634***	2.703***	2.835***	3.023***
	(0.243)	(0.243)	(0.242)	(0.761)	(0.794)	(0.867)	(0.496)
Firm size: large	4.622***	4.635***	4.632***	6.296***	6.101***	6.296***	8.158***
	(0.708)	(0.704)	(0.708)	(1.559)	(1.608)	(1.723)	(1.441)
Firm type: private	0.200***	0.199***	0.199***	0.316***	0.308***	0.311***	0.235***
	(0.030)	(0.030)	(0.030)	(0.108)	(0.115)	(0.117)	(0.031)
Firm type: other	0.559***	0.557***	0.558***	1.631	1.600	1.499	0.529***
	(0.083)	(0.084)	(0.083)	(0.700)	(0.732)	(0.672)	(0.047)
var(country)	1.239***	1.252***	1.259***	1.471***	1.543***	1.524***	1.295***
	(0.074)	(0.077)	(0.081)	(0.174)	(0.203)	(0.225)	(0.121)
var(country>nace)	1.596***	1.602***	1.603***	1.311***	1.331***	1.346***	1.465***
	(0.093)	(0.095)	(0.096)	(0.107)	(0.101)	(0.114)	(0.098)
Constant	0.821	0.802	0.800	0.960	0.952	0.909	0.468***
	(0.188)	(0.187)	(0.188)	(0.552)	(0.608)	(0.583)	(0.137)
No. of obs.	24,653	24,650	24,650	3,096	3,007	2,868	22,451
Log likelihood	-12,930	-12,932	-12,932	-1,835	-1,776	-1,708	-11,375

Note: Weights are used in estimations. D1, D2 and D3 refer to 1-, 2- and 3-year differences of the industry-level variables. All calculations also include all other control variables. Odds ratios are reported. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table A.4 / Atypical employment – in total and by type (total, 2015): Endogeneity – the role of union density

	(1) Atypical D1	(2) Atypical D2	(3) Atypical D3	(4) Temp. contract D1	(5) Temp. contract D2	(6) Temp. contract D3	(7) Invol. part-time D1	(8) Invol. part-time D2	(9) Invol. part-time D3
L.Union density	0.999	0.998	0.998	0.997	0.997	0.996	1.003	1.003	1.003
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
D.OFF^{tot}	1.036	1.354*	1.056	1.026	1.284	1.007	1.121	1.384	1.026
	(0.169)	(0.226)	(0.121)	(0.173)	(0.237)	(0.132)	(0.159)	(0.285)	(0.126)
D.IT	1.143*	1.008	0.970	1.108	1.003	0.965	1.307**	1.104	1.072
	(0.088)	(0.117)	(0.111)	(0.084)	(0.116)	(0.121)	(0.147)	(0.141)	(0.112)
D.CT	0.878**	1.006	1.035	0.880**	1.013	1.057	0.908	0.961	0.903
	(0.049)	(0.025)	(0.077)	(0.052)	(0.024)	(0.088)	(0.087)	(0.035)	(0.061)
D.DB	1.274	1.018	1.004	1.299	0.982	0.961	0.929	1.048**	1.042
	(0.257)	(0.020)	(0.048)	(0.303)	(0.026)	(0.048)	(0.277)	(0.022)	(0.061)
Female	1.246***	1.245***	1.246***	1.027	1.027	1.028	1.890***	1.883***	1.886***
	(0.066)	(0.066)	(0.066)	(0.054)	(0.054)	(0.054)	(0.164)	(0.163)	(0.163)
Migrant	1.231***	1.231***	1.231***	1.182**	1.182**	1.183**	1.291**	1.289**	1.289**
	(0.075)	(0.074)	(0.075)	(0.087)	(0.085)	(0.086)	(0.140)	(0.140)	(0.139)
15-24 yrs old	1.110	1.110	1.109	1.027	1.027	1.026	1.236	1.235	1.233
	(0.142)	(0.142)	(0.141)	(0.117)	(0.117)	(0.116)	(0.215)	(0.214)	(0.213)
25-49 yrs old	0.696***	0.696***	0.696***	0.680***	0.680***	0.680***	0.836**	0.837**	0.836**
	(0.037)	(0.037)	(0.037)	(0.049)	(0.049)	(0.049)	(0.073)	(0.073)	(0.073)
ISCED: medium	0.799***	0.799***	0.799***	0.806**	0.806**	0.805**	0.755**	0.754**	0.755**
	(0.064)	(0.064)	(0.064)	(0.073)	(0.073)	(0.073)	(0.100)	(0.100)	(0.100)
ISCED: high	0.654***	0.654***	0.654***	0.667***	0.667***	0.667***	0.660***	0.659***	0.660***
	(0.064)	(0.064)	(0.064)	(0.085)	(0.085)	(0.085)	(0.089)	(0.089)	(0.089)
Tenure (ln)	0.401***	0.400***	0.400***	0.359***	0.359***	0.359***	0.652***	0.652***	0.652***
	(0.021)	(0.021)	(0.021)	(0.020)	(0.020)	(0.020)	(0.023)	(0.023)	(0.023)
ISCO: medium	0.812***	0.811***	0.812***	0.858**	0.858**	0.860**	0.749**	0.745**	0.745**
	(0.046)	(0.046)	(0.046)	(0.056)	(0.056)	(0.057)	(0.100)	(0.100)	(0.100)
ISCO: high	0.655***	0.654***	0.657***	0.719***	0.718***	0.723***	0.574***	0.567***	0.571***
	(0.061)	(0.062)	(0.062)	(0.077)	(0.078)	(0.078)	(0.077)	(0.077)	(0.077)
Firm size: med-sized	0.884**	0.883**	0.883**	0.935	0.934	0.933	0.757**	0.757**	0.759**
	(0.048)	(0.049)	(0.049)	(0.078)	(0.078)	(0.078)	(0.084)	(0.084)	(0.085)
Firm size: large	0.911	0.910	0.910	1.075	1.072	1.071	0.470***	0.472***	0.473***
	(0.076)	(0.076)	(0.075)	(0.100)	(0.099)	(0.099)	(0.069)	(0.069)	(0.069)
Firm type: private	0.772***	0.774***	0.771***	0.733***	0.733***	0.730***	0.847**	0.850*	0.847**
	(0.052)	(0.053)	(0.053)	(0.063)	(0.063)	(0.063)	(0.072)	(0.071)	(0.070)
Firm type: other	1.150	1.153	1.149	1.131	1.132	1.128	1.124	1.129	1.125
	(0.122)	(0.123)	(0.122)	(0.124)	(0.124)	(0.123)	(0.168)	(0.168)	(0.167)
var(country)	1.392***	1.375***	1.397***	1.562***	1.538***	1.560***	1.203***	1.190***	1.208***
	(0.094)	(0.095)	(0.091)	(0.151)	(0.153)	(0.152)	(0.077)	(0.074)	(0.078)
var(country>nace)	1.440***	1.442***	1.438***	1.562***	1.564***	1.554***	1.435***	1.440***	1.448***
	(0.077)	(0.077)	(0.075)	(0.103)	(0.102)	(0.096)	(0.096)	(0.094)	(0.094)
Constant	1.333	1.336	1.364	1.224	1.242	1.274	0.094***	0.091***	0.093***
	(0.339)	(0.330)	(0.344)	(0.330)	(0.326)	(0.339)	(0.023)	(0.021)	(0.022)
No of obs.	24,653	24,650	24,650	24,614	24,611	24,611	24,234	24,231	24,231
Log likelihood	-9,467	-9,467	-9,468	-8,225	-8,225	-8,225	-4,597	-4,596	-4,597

Note: Weights are used in estimations. D1, D2 and D3 refer to 1-, 2- and 3-year differences of the industry-level variables. All calculations also include all other control variables. Odds ratios are reported. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table A.5 / Atypical employment – in total and by type (manufacturing only, 2015): Endogeneity – the role of union density

	(1) Atypical D1	(2) Atypical D2	(3) Atypical D3	(4) Temp. contract D1	(5) Temp. contract D2	(6) Temp. contract D3	(7) Invol. part-time D1	(8) Invol. part-time D2	(9) Invol. part-time D3
L.Union density	0.998	1.000	1.001	0.993	0.996	0.997	1.019***	1.017***	1.015***
	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)	(0.012)	(0.007)	(0.006)	(0.006)
D.OFF^{tot}	1.367**	1.600***	1.356**	1.927***	2.174***	1.114	0.700	0.976	1.300
	(0.217)	(0.280)	(0.170)	(0.371)	(0.406)	(0.244)	(0.423)	(0.719)	(0.355)
D.RobDens	0.853	1.012	0.982	0.909	1.027	0.986	0.758	0.733**	0.712*
	(0.184)	(0.033)	(0.015)	(0.221)	(0.046)	(0.015)	(0.233)	(0.114)	(0.124)
D.IT	2.774***	2.101***	1.688***	2.827***	2.063***	1.698***	1.571	1.291	1.265
	(0.706)	(0.384)	(0.191)	(0.848)	(0.475)	(0.193)	(0.476)	(0.374)	(0.245)
D.CT	0.736**	0.822	0.781**	0.787	0.886	0.824*	0.324	0.358***	0.549***
	(0.107)	(0.132)	(0.091)	(0.118)	(0.145)	(0.093)	(0.292)	(0.139)	(0.126)
D.DB	1.197	1.351	0.828	1.453	1.531	0.869	2.713	2.602	2.192
	(0.628)	(0.502)	(0.229)	(0.842)	(0.643)	(0.238)	(3.136)	(1.696)	(1.294)
Female	1.213	1.209	1.239*	1.085	1.070	1.104	2.256***	2.375***	2.446***
	(0.156)	(0.154)	(0.157)	(0.162)	(0.161)	(0.167)	(0.631)	(0.660)	(0.683)
Migrant	1.283	1.351	1.410	1.284	1.354	1.408	1.164	1.133	1.226
	(0.386)	(0.382)	(0.413)	(0.470)	(0.473)	(0.511)	(0.617)	(0.592)	(0.644)
15-24 yrs old	0.669*	0.625**	0.696	0.680	0.627*	0.697	0.842	0.850	0.887
	(0.146)	(0.139)	(0.160)	(0.164)	(0.156)	(0.177)	(0.345)	(0.348)	(0.381)
25-49 yrs old	0.699***	0.639***	0.652***	0.778	0.701	0.705	0.689*	0.670**	0.750
	(0.095)	(0.093)	(0.106)	(0.162)	(0.162)	(0.174)	(0.136)	(0.135)	(0.156)
ISCED: medium	1.102	1.215	1.217	1.143	1.276*	1.255	0.837	0.900	0.952
	(0.188)	(0.144)	(0.156)	(0.236)	(0.189)	(0.192)	(0.178)	(0.183)	(0.192)
ISCED: high	0.632*	0.701	0.721	0.660	0.741	0.753	0.608	0.637	0.672
	(0.174)	(0.182)	(0.190)	(0.205)	(0.212)	(0.219)	(0.214)	(0.234)	(0.251)
Tenure (ln)	0.295***	0.289***	0.284***	0.264***	0.257***	0.254***	0.699***	0.706**	0.700***
	(0.028)	(0.027)	(0.028)	(0.029)	(0.027)	(0.027)	(0.096)	(0.100)	(0.095)
ISCO: medium	0.800	0.777	0.733*	0.800	0.771	0.729*	1.072	1.099	1.084
	(0.125)	(0.132)	(0.132)	(0.130)	(0.133)	(0.135)	(0.340)	(0.353)	(0.373)
ISCO: high	0.314***	0.311***	0.301***	0.313***	0.311***	0.303***	0.381	0.395	0.391
	(0.056)	(0.053)	(0.054)	(0.052)	(0.048)	(0.049)	(0.233)	(0.245)	(0.249)
Firm size: med-sized	0.623	0.689	0.728	0.750	0.848	0.912	0.222***	0.226***	0.230**
	(0.184)	(0.195)	(0.209)	(0.238)	(0.252)	(0.272)	(0.129)	(0.130)	(0.133)
Firm size: large	0.681	0.717	0.729	0.782	0.835	0.856	0.248***	0.256***	0.248***
	(0.185)	(0.186)	(0.192)	(0.226)	(0.223)	(0.237)	(0.131)	(0.132)	(0.125)
Firm type: private	0.453	0.437	0.450	0.366*	0.351*	0.360*	0.449	0.434	0.400
	(0.234)	(0.227)	(0.251)	(0.204)	(0.198)	(0.218)	(0.388)	(0.370)	(0.339)
Firm type: other	0.294*	0.273*	0.255*	0.231**	0.211**	0.197**	0.354	0.329	0.300
	(0.198)	(0.186)	(0.192)	(0.163)	(0.151)	(0.158)	(0.528)	(0.485)	(0.454)
var(country)	1.836***	1.880***	2.234**	1.984***	2.003***	2.591**	1.328	1.313	1.237
	(0.390)	(0.392)	(0.845)	(0.513)	(0.506)	(1.204)	(0.281)	(0.271)	(0.284)
var(country>nace)	1.363	1.351	1.340	1.486*	1.452*	1.431	1.360	1.230	1.300
	(0.280)	(0.260)	(0.286)	(0.339)	(0.308)	(0.334)	(0.395)	(0.376)	(0.387)
Constant	3.364	2.779	2.821	3.461	2.773	2.850	0.070***	0.074***	0.084***
	(2.588)	(2.101)	(2.400)	(2.978)	(2.377)	(2.700)	(0.062)	(0.070)	(0.080)
No of obs.	3,089	3,000	2,862	3,088	2,999	2,861	3,043	2,955	2,820
Log likelihood	-969.3	-934.2	-889.7	-873.8	-838.4	-799.8	-309.2	-301.7	-288.8

Note: Weights are used in estimations. D1, D2 and D3 refer to 1-, 2- and 3-year differences of the industry-level variables. All calculations also include all other control variables. Odds ratios are reported. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table A.6 / Atypical employment – in total and by type (total, 2021): Endogeneity – the role of union density

	(1) Atypical D1	(2) Temp. contract D1	(3) Invol. part-time D1
L.Union density	0.999	0.998	1.005
	(0.004)	(0.004)	(0.004)
D.OFF^{tot}	1.444	1.607	2.305
	(1.697)	(2.169)	(3.125)
D.IT	1.012	1.086	0.734
	(0.177)	(0.202)	(0.273)
D.CT	0.891	0.712	1.274
	(0.239)	(0.244)	(0.444)
D.DB	0.942	1.115	0.548
	(0.215)	(0.342)	(0.229)
Female	1.143**	0.945	2.108***
	(0.071)	(0.069)	(0.450)
15-24 yrs old	1.605***	1.605***	1.638**
	(0.203)	(0.185)	(0.361)
25-49 yrs old	0.962	0.933	1.015
	(0.058)	(0.062)	(0.208)
ISCED: medium	0.944	0.834	1.249
	(0.104)	(0.134)	(0.310)
ISCED: high	0.948	0.942	1.007
	(0.161)	(0.162)	(0.335)
Tenure (ln)	0.473***	0.419***	0.708***
	(0.038)	(0.045)	(0.061)
ISCO: medium	0.689**	0.748*	0.584***
	(0.117)	(0.113)	(0.104)
ISCO: high	0.462***	0.511***	0.404***
	(0.070)	(0.063)	(0.083)
Firm size: med-sized	0.775*	0.866	0.489***
	(0.108)	(0.134)	(0.064)
Firm size: large	0.707***	0.824*	0.328***
	(0.085)	(0.090)	(0.059)
Firm type: private	0.593***	0.450***	1.252*
	(0.071)	(0.070)	(0.167)
Firm type: other	0.737***	0.640***	1.209
	(0.073)	(0.080)	(0.187)
var(country)	1.169***	1.207***	1.062
	(0.069)	(0.070)	(0.052)
var(country>nace)	1.508***	1.491***	1.709***
	(0.119)	(0.100)	(0.313)
Constant	0.981	1.108	0.049***
	(0.186)	(0.255)	(0.016)
No. of obs.	22,451	22,342	22,402
Log likelihood	-8114	-6968	-3479

Note: Weights are used in estimations. D1, D2 and D3 refer to 1-, 2- and 3-year differences of the industry-level variables. All calculations also include all other control variables. Odds ratios are reported. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table A.7 / Skills mismatch (total and manufacturing only, 2015): Endogeneity – the role of union density

	Panel A: Total						Panel B: Manufacturing					
	(1) Under-skilled	(2) Over-skilled	(3) Under-skilled	(4) Over-skilled	(5) Under-skilled	(6) Over-skilled	(1) Under-skilled	(2) Over-skilled	(3) Under-skilled	(4) Over-skilled	(5) Under-skilled	(6) Over-skilled
	D1		D2		D3		D1		D2		D3	
L.Union density	0.995	1.000	0.996	1.000	0.996	1.000	1.002	1.006	1.002	1.005	1.002	1.002
	(0.005)	(0.003)	(0.005)	(0.003)	(0.005)	(0.003)	(0.005)	(0.006)	(0.006)	(0.006)	(0.005)	(0.007)
D.OFF^{tot}	1.130	1.221**	1.111	1.399**	1.150	0.938	0.697	1.293	0.584	1.254	0.945	0.785**
	(0.178)	(0.116)	(0.244)	(0.195)	(0.175)	(0.104)	(0.244)	(0.349)	(0.215)	(0.327)	(0.159)	(0.085)
D.RobDens							1.145	0.977	1.021	0.977	0.988	0.973
							(0.134)	(0.139)	(0.024)	(0.040)	(0.032)	(0.026)
D.IT	1.139	1.068	1.032	1.064	1.073	1.034	1.458	1.174	0.883	1.069	0.958	1.055
	(0.145)	(0.059)	(0.075)	(0.043)	(0.070)	(0.037)	(0.386)	(0.263)	(0.264)	(0.165)	(0.169)	(0.101)
D.CT	1.100	0.951	1.054***	1.013	1.023	0.954	0.962	0.878*	0.988	0.816**	1.045	0.917
	(0.081)	(0.067)	(0.018)	(0.024)	(0.032)	(0.033)	(0.074)	(0.065)	(0.083)	(0.084)	(0.079)	(0.062)
D.DB	0.840	1.257	1.038**	1.009	1.062*	1.039	0.882	1.725	1.041	1.752**	0.938	1.035
	(0.223)	(0.202)	(0.017)	(0.011)	(0.037)	(0.037)	(0.393)	(0.597)	(0.288)	(0.441)	(0.325)	(0.205)
Female	0.835***	0.850***	0.834***	0.849***	0.831***	0.851***	0.722	0.889	0.714	0.876	0.681**	0.897
	(0.039)	(0.030)	(0.039)	(0.030)	(0.039)	(0.031)	(0.145)	(0.081)	(0.146)	(0.083)	(0.133)	(0.089)
Migrant	1.186***	1.048	1.179***	1.052	1.182***	1.049	1.192	1.127	1.225	1.086	1.111	1.057
	(0.073)	(0.063)	(0.075)	(0.059)	(0.075)	(0.058)	(0.216)	(0.165)	(0.220)	(0.159)	(0.175)	(0.153)
15-24 yrs old	1.762***	1.062	1.760***	1.063	1.762***	1.060	1.849**	1.016	1.812**	1.027	1.772*	1.036
	(0.294)	(0.120)	(0.291)	(0.120)	(0.289)	(0.119)	(0.501)	(0.290)	(0.504)	(0.285)	(0.517)	(0.293)
25-49 yrs old	1.108	1.101**	1.109	1.102**	1.110*	1.101**	1.021	1.319***	0.990	1.290**	0.973	1.295**
	(0.070)	(0.052)	(0.070)	(0.052)	(0.070)	(0.052)	(0.160)	(0.126)	(0.147)	(0.128)	(0.147)	(0.137)
ISCED: medium	1.089	1.078	1.085	1.079	1.084	1.078	1.100	1.436**	1.070	1.465**	1.162	1.424**
	(0.125)	(0.085)	(0.125)	(0.086)	(0.122)	(0.083)	(0.190)	(0.224)	(0.185)	(0.232)	(0.222)	(0.230)
ISCED: high	1.345**	1.685***	1.340**	1.686***	1.330**	1.695***	1.346	2.186***	1.270	2.232***	1.391	2.155***
	(0.182)	(0.136)	(0.182)	(0.136)	(0.177)	(0.135)	(0.383)	(0.428)	(0.361)	(0.449)	(0.421)	(0.450)
Tenure (ln)	0.890***	0.950**	0.890***	0.949**	0.891***	0.949**	0.841***	0.919	0.836***	0.907	0.815***	0.898*
	(0.026)	(0.023)	(0.026)	(0.023)	(0.026)	(0.023)	(0.047)	(0.056)	(0.048)	(0.056)	(0.045)	(0.057)
ISCO: medium	1.613***	1.036	1.597***	1.035	1.602***	1.039	1.011	0.903	1.081	0.896	1.116	0.897
	(0.119)	(0.059)	(0.120)	(0.059)	(0.121)	(0.059)	(0.117)	(0.128)	(0.121)	(0.128)	(0.127)	(0.131)
ISCO: high	2.718***	0.840***	2.680***	0.839***	2.686***	0.845***	1.986***	0.839	2.069***	0.846	2.031***	0.824
	(0.321)	(0.055)	(0.319)	(0.055)	(0.321)	(0.054)	(0.374)	(0.165)	(0.412)	(0.170)	(0.413)	(0.162)

Contd.

Table A.7 / Continued

	Panel A: Total						Panel B: Manufacturing					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	Under-skilled	**Over-skilled**	**Under-skilled**	**Over-skilled**	**Under-skilled**	**Over-skilled**	**Under-skilled**	**Over-skilled**	**Under-skilled**	**Over-skilled**	**Under-skilled**	**Over-skilled**
	D1		**D2**		**D3**		**D1**		**D2**		**D3**	
Firm size: med-sized	1.019	1.101*	1.021	1.099*	1.017	1.103**	1.054	0.969	1.052	0.952	1.019	0.945
	(0.088)	(0.055)	(0.087)	(0.054)	(0.088)	(0.054)	(0.214)	(0.165)	(0.221)	(0.163)	(0.215)	(0.164)
Firm size: large	1.001	1.042	1.010	1.039	1.003	1.045	1.106	0.900	1.084	0.889	1.087	0.868
	(0.122)	(0.067)	(0.121)	(0.067)	(0.120)	(0.066)	(0.288)	(0.163)	(0.286)	(0.157)	(0.279)	(0.162)
Firm type: private	0.771***	1.091*	0.783***	1.089*	0.773***	1.092*	1.830	1.561*	1.658	1.551*	1.970	1.448
	(0.035)	(0.056)	(0.040)	(0.056)	(0.039)	(0.057)	(0.884)	(0.393)	(0.782)	(0.405)	(1.023)	(0.365)
Firm type: other	1.006	1.003	1.023	0.997	1.020	0.994	3.288*	0.788	2.992*	0.774	3.488*	0.739
	(0.099)	(0.104)	(0.103)	(0.103)	(0.103)	(0.105)	(2.018)	(0.377)	(1.762)	(0.369)	(2.316)	(0.359)
var(country)	1.072***		1.074***		1.073**		1.168*		1.180*		1.159	
	(0.029)		(0.030)		(0.030)		(0.107)		(0.115)		(0.115)	
var(country>nace)	1.078***		1.073***		1.077***		1.077*		1.079*		1.069	
	(0.020)		(0.020)		(0.020)		(0.044)		(0.049)		(0.050)	
Constant	0.191***	0.405***	0.186***	0.407***	0.184***	0.415***	0.114***	0.166***	0.136***	0.176***	0.120***	0.240***
	(0.034)	(0.071)	(0.032)	(0.071)	(0.033)	(0.073)	(0.064)	(0.079)	(0.077)	(0.083)	(0.075)	(0.112)
No of obs.	24,434	24,434	24,431	24,431	24,431	24,431	3,078	3,078	2,990	2,990	2,852	2,852
Log likelihood	-23182	-23182	-23177	-23177	-23179	-23179	-2996	-2996	-2905	-2905	-2823	-2823

Note: Weights are used in estimations. D1, D2 and D3 refer to 1-, 2- and 3-year differences of the industry-level variables. All calculations also include all other control variables. Odds ratios are reported. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0

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Offenlegung nach § 25 Mediengesetz: Medieninhaber (Verleger): Verein "Wiener Institut für Internationale Wirtschaftsvergleiche", A 1060 Wien, Rahlgasse 3. Vereinszweck: Analyse der wirtschaftlichen Entwicklung der zentral- und osteuropäischen Länder sowie anderer Transformationswirtschaften sowohl mittels empirischer als auch theoretischer Studien und ihre Veröffentlichung; Erbringung von Beratungsleistungen für Regierungs- und Verwaltungsstellen, Firmen und Institutionen.