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# Employment Effects of Offshoring, Technological Change and Migration in a Group of Western European Economies:

## Impact on Different Occupations

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# Employment Effects of Offshoring, Technological Change and Migration in a Group of Western European Economies:

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# Abstract

This paper estimates conditional demand models to examine the impact of offshoring, technological change, and migration on the labour demand of native workers differentiated by four different types of occupational groups: managers/professionals, clerical workers, craft (skilled) workers and manual workers. The analysis is conducted for an unbalanced panel of five economies Austria, Belgium, France, Spain, and Switzerland covering the period 2005-2018. Our results point to important and occupation-specific effects: offshoring seems to have beneficial employment effects for native craft workers in this set of economies, while negative effects for native manual workers across a wide set of industries (including manufacturing and services industries) and managers/professionals in manufacturing. Furthermore, there are important distinctions whether offshoring occurs in other advanced economies, in the EU13 or in developing countries. The analysis of the impact of technological change shows the strong positive impact which the additional IT equipment has on most occupational groups of native workers (with the exception of manual workers), while robotisation in manufacturing showed strongly negative impacts on the employment of all groups of workers and especially of craft workers. Increasing immigrant shares in the work forces showed strongly negative impacts on native workers – however, considering only the partial substitution effects and not including the potential for productivity and demand effects – and this is mostly accounted for by immigration from low- to medium-income source countries.

Keywords: Employment, occupational groups, offshoring, technological change, immigration

JEL classification: F16, F22, F66, O33

CONTENTS

## TABLES AND FIGURES

# 1. Introduction

## 1.1. MOTIVATION AND THEORETICAL CONSIDERATIONS

Labour markets are going through turbulent times. This paper deals with three of the longer-term challenges that labour forces in advanced Western European economies are exposed to: the impact of offshoring, of technological change (specifically of information and communication technology and of robotisation) and of inward migration.

There is of course a large literature of the impact of each of these items separately on employment of native workers in advanced economies (see Section 1.2). What this paper attempts to do is to look at the impact of these 'forces' affecting employment simultaneously. We shall use detailed data for five Western European economies (Austria, Belgium, France, Spain and Switzerland) to undertake this exercise.

We know from previous analysis (some going back to the classics, such as David Ricardo, Robert Malthus, Karl Marx and, more recently, to Joseph Schumpeter) that – with respect to all these three forces, there can be negative and positive implications for employment. Furthermore, employment should not be seen as simply an aggregate category, as all these three items induce structural changes in an economy which can have very different implications for different groups of workers. We shall follow this type of analysis by investigating the impact on different occupational groups of the native labour force. First of all, whether it is offshoring, technological change or immigration, all of these can have either 'substitutive' or 'complementarity' effects on different groups of workers: new technologies require new (or more of some existing) skills working with these technologies and make other skills redundant. Offshoring of certain production stages to other locations implies that workers employed in 'tasks' required for such production stages domestically will be less in demand; however, since an adapted new 'task specialisation' might accompany changes in international production integration, other tasks that are either kept or even newly attracted to the home base might require the skills of a different composition of occupational groups. Similarly, the employment of migrant workers who bring with them a skill set somewhat different to those of native workers, will lead to a new allocation of 'tasks' to these two sets of workers: some native workers will gain as their skill set is complementary to that of migrant workers and hence their performance gets enhanced by the hiring of migrant workers, and other native workers will be in direct competition with migrant workers as they possess a similar skill set.

Secondly, apart from the 'substitutability' vs. 'complementarity' aspect, we have – in line with much previous analysis – to consider the other impact which the three 'forces' might have on native employment: employers have an interest in introducing new technologies, embark on offshoring of certain tasks, and hire migrant workers because they expect a cost-advantage from doing it. This could be simply a relative price/wage effect, i.e. they might be able to hire workers abroad at a lower wage than workers at home; the same with migrant workers. Or they change the production structure in the way of reducing domestic labour input coefficients. The effect is likely to be different for different occupational groups: this is likely to be the case when employers adopt new technologies (as these are defined by new production functions), or when a new task specialisation is induced by offshoring or by hiring new workers. All of these can lead to changes in labour input coefficients: if these go in the direction of labour-saving (i.e. a fall in labour input coefficients) these would amount to '*productivity effects*'. However, as mentioned above, if offshoring is instituted, new technologies are introduced or immigrant workers are hired, the compositional effect could lead for some groups of native workers also to an increased demand, even per unit of output (which means an increase in their labour input coefficients). Apart from this 'productivity' effect, there is also – what the literature often calls – a '*scale effect*'. This relates to the fact that all these acts by employers (deciding on offshoring, introducing new technologies and hiring of migrant labour) are done in order to reduce unit costs (and/or improve 'quality') that can generate an advantage vis-a-vis consumers unto whom this cost advantage can be passed on (at least to some degree) in the form of lower prices (or they are attracted by better quality) and hence sales will expand. And this expansion of sales and thus output, generates in turn more demand for inputs, including native labour, in the new composition which the changed task specialisation or change in production function demands. There are, furthermore, secondary effects such that this effect on employment can generate a further increase in demand and thus – through a multiplier – in employment, contributing thereby further to the 'scale effect'.

Hence, the overall conclusion from this short discussion is that offshoring, technological change, and migration can have complex (multi-directional) impacts on the employment of native workers, especially when one considers different occupational groups.

In this paper, we shall contribute to the existing research on the impact of offshoring, technological change, and migration in the following way: firstly, as mentioned above, it is possibly the first study which simultaneously estimates the impact of all these three 'forces', Secondly, it looks at a set of technological changes (robotisation, and various dimensions of information and communication technology) which have rarely been looked at together in their impact on employment. Thirdly, we shall distinguish a number of types of 'offshoring'; by destination/sourcing regions (other developed, NMS13, developing), by 'narrow' and 'broad' measures (i.e. whether sourcing of intermediate inputs takes place within the same industry or from other industries), and whether intermediate inputs are of the manufacturing or services types. Similarly, fourthly, we look at the differentiated impact of immigrant workers on native employees by differentiating between whether migrants come from high-income or from low-/medium-income regions. Fifthly, and this is an important aspect which characterises our study, we shall differentiate the impact on native employment not by educational attainment groups – as is done in most studies so far – but by differentiating native employees in terms of occupational groupings (managers/professionals, clerical staff, craft workers and manual workers). This has a number of advantages, in particular that it captures more directly the compositional impacts on 'jobs'/'occupations' which changes in production structures generate. Lastly, we undertake the analysis throughout by distinguishing two sets of estimates: one, across a wide range of industries (including manufacturing and services) and, the other, just focussing on manufacturing. This also contributes to the literature in that, a lot of research on offshoring in the past has focussed on manufacturing industries, while for a number of reasons (partly due a changing trade policy environment, but more importantly due to technological developments i.e. digitalisation) offshoring of services activities has become an increasingly important feature of offshoring with – given the predominance of jobs in services – strong implications for employment.

## 1.2. RELATED LITERATURE

As mentioned earlier, the literature on the effects of offshoring, technological change and migration on employment is vast, and we shall limit ourselves to cover only a small sub-set of contributions.

The literature on offshoring has developed rapidly since the early contribution by Feenstra and Hanson (1996; for a comprehensive survey, see Hummels *et al.*, 2016). Research on the relationship between offshoring and employment has looked at the issue both from the angle of production location and sourcing decisions by international companies (Antras & Yeaple, 2014; Bernard *et al.*, 2007) as well as simply looking at the growth and structure of trade in intermediate inputs (Johnson & Noguera, 2012; Hummels *et al.*, 2001); consequently the analysis was conducted using trade and industry level data as well as firm level data (Ornaghi *et al.*, 2017; Görg & Hanley, 2005; Hijzen *et al.*, 2011) and individual worker-level data (Liu & Trefler, 2011; Geishecker, 2008; Egger *et al.*, 2007). While the early literature was mainly focussed on offshoring of production stages of manufacturing industries, research on offshoring of service activities also gained strong momentum (Amiti & Wei, 2006; Crinò, 2010; Liu & Trefler, 2011). There was a concern for overall employment effects of offshoring, but - in line with the theoretical literature on trade and production location (Grossman & Rossi-Hansberg, 2008; Antras & Chor, 2013; Baldwin & Robert-Nicoud, 2010; Costinot *et al.*, 2013) - the analysis quickly proceeded to study the impact on different ('skill') groups of workers – mostly differentiated by educational attainment levels – especially in advanced economies on which the literature predominantly concentrated (Autor *et al.*, 2013; Blinder, 2007; Davis & Harrigen, 2011; Goos *et al.*, 2014; Hijzen *et al.*, 2005; Hijzen & Swaim, 2010; Geishecker, 2008; Foster-McGregor *et al.*, 2013). This line of literature suggests that offshoring has particularly hurt medium and low-skilled workers (see, e.g., Hijzen *et al.*, 2005; Foster-McGregor *et al.*, 2013; Crinò, 2012 for evidence on Europe). By contrast, there is very limited literature and empirical evidence on the impact of offshoring on different occupational groups of workers. One notable exception is Crinò (2010) who shows for the US for 1997-2002 that services offshoring has a negative effect on less skilled occupations but a positive effect on more skilled occupations.

Coming next to the issue of technology and employment, there is also a vast literature by now, motivated particularly by the wave of digitalisation, robotisation and artificial intelligence (AI) (see also the research undertaken within the UNTANGLED research project: Stehrer, 2022; Bachmann *et al.*, 2022; Albinowski & Lewandowski, 2022). The literature ranges from analysing the impact of technology on different groups of workers defined by their educational attainment levels to relatively detailed assessments which 'tasks' (e.g. 'routine' vs. 'non-routine') are affected by technological change. The literature considers both the regional (within country) dimension (Acemoglu & Restrepo, 2018 and 2020; Autor *et al.*, 2013) as well as explores differences across industries (manufacturing vs. services industries; see Bessen, 2019). Attention has received particularly the 'polarisation' hypothesis which indicates that medium-skilled occupations might be particularly in danger of being displaced by automation and digitalisation which can take over routine cognitive and routine manual tasks (Autor *et al.*, 2003; Autor & Dorn, 2013; Goos *et al.*, 2014). The Albinowski and Lewandowski (2022) paper shows a differentiated impact on occupation types (non-routine cognitive, routine cognitive, routine manual, and non-routine manual) and differentiated impacts on employees differentiated by gender and age: ICT capital adoption complements cognitive skills – for younger workers, especially women; robotisation substitutes routine cognitive skills – for older workers, especially women – for younger workers, especially men. Baldwin (2020) furthermore shows that with artificial intelligence a wide range of occupations might be affected. For us particularly interesting is the recent study by Jestl (2022), as it uses a similar dataset as ours in terms of ICT components (IT, CT, DB) as well as robotisation to study the employment effects of technological change in EU labour markets. It shows for manufacturing industries that both robotisation and software and database (DB) are associated with negative employment effects while information technology (IT) is associated with positive employment effects (communication technology (CT) is unrelated). Moreover, our study in this respect is strongly related to the earlier study by Landesmann and Leitner (2022) but goes beyond it by also including the three components of ICT and robotisation as well as demographic change.

The impact of migration on labour market outcomes, specifically for native workers, is another well-researched area, given also the political and social sensitivity of the topic. There are classic studies such as Altonji and Card (1991), Card (2001), Borjas (2003), Ottaviano and Peri (2012), Dustmann *et al.* (2012), as well as surveys, such as Kerr and Kerr (2011), Dustmann *et al.* (2016), Longhi *et al.* (2010). As the literature developed, attention focussed increasingly on analysing the degree to which migrants compete with natives in particular jobs or might be complementary with regard to their contribution in production and thus to the work executed by natives. Furthermore, it turned out to be important to integrate into the analysis of how native workers and employers respond to the influx of migrant workers: native workers might respond through inter-regional and across jobs-mobility, at times also involving the acquisition of additional skills and thus improve their position on the labour market. Employers, on the other hand, might change the way they organise production to take advantage of the scope for complementarities between migrant and native workers or they might simply take on migrant workers that are willing to work with lower wages or under inferior working conditions. The studies showed important differences in wage and employment effects depending on these reactions. In many studies, the research yields information of the net effects of all these responses. This will also be the case in our study. Furthermore, as already indicated, the literature usually analyses the impact on two variables: on the wages of native workers and on employment. Our study focusses on the latter, but wage responses to the inflow of migrant workers also have an impact on employment in a typical supply-demand model of the labour market. As regards our study, we want to mention two studies which seem to be particularly relevant regarding the thrust of our approach. One is the emphasis on occupational categories of workers rather than the more traditional decomposition of the work force in terms of educational attainment categories: here the study by Sharp and Bollinger (2020) is interesting as it compares the differential employment effects when employment categories are differentiated by educational attainment or in terms of occupational categories (as we do): they find (also in line with other studies, such as Steinhardt, 2011) that the impact of immigration on native wages is substantially higher if the categories of the labour force are differentiated by occupations than by educational attainment. They also show that the negative effect on wages is concentrated on the least-skilled of the native labour force where the substitution effect is very strong, while at the upper end of the occupational ladder the wage effect is positive, indicating complementarity between migrants and natives. The other study by Cattaneo *et al.* (2015) undertakes a longitudinal analysis of reactions of native workers to migrant inflows involving changing occupational structures.

As to the interlinkages between offshoring, technological change and migration, there are indeed also contributions in the literature: in particular how offshoring affects productivity or generates productivity responses (Burstein & Vogel, 2010; Kasahara & Rodgigue, 2008; Verhoogen, 2008; Boler *et al.*, 2015), or how offshoring and migration jointly impact on labour market outcomes (Ottaviano *et al.*, 2013 and 2016).

The remainder of the paper is structured as follows: Section 2 discusses the methodological approach and the different data sources used in the analysis. Section 3 provides, for each country and industry included in the analysis, a brief overview of changes in offshoring and migration patterns between 2008 and 2017. Section 4 reports the main results from the analysis, and Section 5 provides a summary and conclusion.

# 2. Methodological approach and data

## 2.1. THE MODEL

In our analysis, we follow Hamermesh (1993) and employ the log-linear model of labour demand but focus on the *conditional* labour demand model, where the profit-maximising level of labour demand is determined by minimising the costs of production conditional on output. Hence, we identify the employment effect of offshoring, technological change and migration by keeping output constant. We therefore expect to find a negative effect on native employment if offshoring, technological change or immigration has any productivity-enhancing effects, since fewer inputs are needed to produce the same level of output. However, we also allow for the possibility that the introduction of various forms of technology (such as ICT) can have employment-enhancing effects if such technological inputs lead to the employment of complementary occupational groups of employees. Similarly, there is in principle the possibility also that offshoring and migration have positive employment effects for specific occupational groups of native workers, again resulting from complementarity rather than substitutability. The conditional labour demand equation is represented by:

$$lnL_{ict}^{N} = \alpha_0 + \alpha_w lnw_{ict} + \alpha_p lnp_{ict} + \beta_y lny_{ict} + \sum_{l=1}^{L} \gamma_l lnz_{ilct} + \sum_{d=1}^{D} \delta_d lnLF_{dct} + \pi_{ic} + \varepsilon_{ict} \qquad (1)$$

where $L_{ict}^{N}$ is the labour demand of native workers, $w_{ict}$ and $p_{ict}$ are the average gross annual wage of native workers and the price of materials, respectively, $y_{ict}$ is the real gross output (in 2015 prices) and $z_{ilct}$ is a set of $l$ different demand shifters for native workers, including our measures of offshoring, different measures of technological change (ICT capital types and robot density) and the share of immigrants (as discussed in detail in Section 2.2 below). Furthermore, we also include $LF_{dct}$ which refers to the labour force of native workers in its prime-age (18-45 years old) by highest level of educational attainment level (Low=ISCED-11, levels 0-2, Medium=ISCED-11, levels 3-4, and High=ISCED-11, levels 5-8). It represents the supply-push effect and captures the responsiveness of native employment to changes in the native labour force, differentiated by educational attainment. The subscripts $i$, $c$ and $t$ denote industry, country and time, respectively. Typically, the overall stock of capital is also included in standard labour demand equations. However, since we already use as proxies for technological change different types of capital stocks that are part and parcel of the total capital stock, we exclude the total capital stock in our estimations.[1] Furthermore, we follow Hijzen and Swaim (2010) and also include import penetration (IP), defined as $Imports/(GDP + Imports - Exports)$ as a measure of general trade openness. Finally, $\pi_{ic}$ refers to country-industry fixed effects and $\varepsilon_{ict}$ to a random normally distributed disturbance term with zero mean and constant variance.

Furthermore, we difference all data to account for any time-invariant fixed effects that affect the level of labour demand. Typically, in this literature, longer differences are used which not only accounts for lagged responses of native labour demand to shocks, but also helps to decrease measurement errors.

1 Nonetheless, as a sensitivity check, we also ran estimations including the overall capital stock indicator, together with the different proxies for technological change. The results are qualitatively similar and are available from the authors upon request.

However, since our data cover a rather short time horizon, we take shorter differences to increase degrees of freedom and the variation in our data. Specifically, we use five different differencing periods – 1 year, 2 years, 3 years, 4 years and 5 years. This allows us to determine the robustness of our results to the chosen differencing period and to produce more appropriate results, if measurement error is not an issue in our data. The conditional labour demand equation then becomes:

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

where Δ refers to the difference of a variable.

Moreover, we also estimate the model for four *different types of occupation*. In particular, based on the ISCO-08 one-digit classification, we define four types of occupation: (1) *managers/professionals* (ISCO-08: 1-3),[2] (2) *clerks* (ISCO-08: 4-5), (3) *craft workers* (ISCO-08: 6-7) and (iv) *manual workers* (ISCO-08: 8-9) (for further details see Table 1 below).

**Table 1 / Occupational groups according to one-digit ISCO-08 classification**

| Group | ISCO-08 classification |
|---|---|
| Managers/professionals | Managers (ISCO-08: 1), professionals (ISCO-08: 2) and technicians and associate professionals (ISCO-08: 3) |
| Clerks | Clerical support workers (ISCO-08: 4) and services and sales workers (ISCO-08: 5) |
| Craft workers | Skilled agricultural, forestry and fishery workers (ISCO-08: 6) and craft and related trades workers (ISCO-08: 7) |
| Manual workers | Plant and machine operators and assemblers (ISCO-08: 8) and elementary occupations (ISCO-08: 9) |

This further differentiation by occupation is important as it allows us to draw a clearer picture of any substitution or complementarity effects at the *job-level*. Specifically, with respect to offshoring and technological change, it helps us to identify which jobs are more likely to be offshored or replaced (or complemented) by new technologies. With respect to immigration, it allows us to identify the effect when migrants and natives compete for the *same jobs*. In contrast, given the substantial job-skills mismatch among migrants often found in the literature, a skills-based analysis tends to give a wrong picture, since natives and migrants with comparable skills do not compete for the same jobs. In this regard, we expect to find stronger substitution effects than often found in the empirical literature based on skills, which, however, need not automatically translate into higher unemployment but may lead to stronger occupational upward mobility of native workers (see, e.g., Cattaneo *et al.*, 2015 for empirical evidence on Europe). In the occupation-based estimations, the dependent variable is then the industry-level labour demand for native workers of one of the four occupational groups (see Table 1 above), the wage variable is the average annual gross wage of native workers of the same occupational group, and the migration indicator is the share of immigrants in that particular occupational group. We need to highlight here, however, that the focus on occupations instead of skills has some potential drawbacks, as endogeneity issues may arise much more strongly (see the discussion in Altonji & Card, 1991; Card, 2001; and Sharpe & Bollinger, 2020). Specifically, occupational structures could be endogenous since migrant inflows could initiate a shift of activities in line with the skill composition of migrants and could

[2] In this rather broad group managers represent the minority, only accounting for between 30% and 40%, on average.

thereby have an additional negative impact on native employments should their skill composition be different. On the other hand, migrant inflows might provide room for occupational task specialisation which can positively affect natives' employment possibilities.

Methodologically, we estimate the total labour demand equation by ordinary least squares (OLS) and the four occupation-specific labour demand equations by seemingly unrelated regression (SUR). SUR is more efficient than separate estimation by OLS since it allows for the contemporaneous correlation of error terms across all four regression equations. Furthermore, standard errors are clustered at the country-industry level to account for the serial correlation in the residuals within groups.

Although we interpret the equation we estimate as principally a labour demand equation, capturing the main determinants of labour demand, we also account for labour supply developments (differentiated by educational attainment groups). The inclusion of labour supply as an explanatory variable into our model generates in principle a problem with regard to the exogeneity of the wage variable: ceteris paribus one would expect an increased labour supply to dampen wage developments; hence when we attempt to capture the employment effects of wage movements, we have to control for labour supply 'shocks', which we do. However, labour supply itself is not independent of wage developments (positive wage elasticity of labour supply). Hence it is important to account for such endogeneity and we shall employ an instrumental variable (IV) approach to do that. Specifically, we shall make use of the fact, well established in the literature (see, e.g., Evers *et al.*, 2008 or Bargain & Peichl, 2016) that women have a higher elasticity of labour supply than men. Furthermore, for a dynamic approach like ours it is relevant that women have also greatly increased their labour force participation in recent decades. Hence accounting for this change in composition of the labour force and the impact this might have had on differentiated labour supply reactions to wage developments is important and we shall make use of this fact in our IV estimations. Accordingly, in our IV approach, we shall use as instruments information regarding households which may affect the labour force participation of women directly (but labour demand only indirectly). In particular, we choose from a set of potential instruments comprising the fertility rate, the number of children per household (of three different age categories), the crude marriage rate, the crude divorce rate, the marriage-divorce ratio, expenditure on social protection (total, family and children) or public expenditure on different types of active labour market programmes (real, in per capita terms)[3] those two instruments which produce the best test statistics in terms of instrument relevance (underidentification/rank test) and instrument strength (Kleibergen-Paap Wald rk F statistic). We also test the exogeneity of the instruments (Hansen J-tests) and the wage variables (Wu-Hausmann tests). Since our instruments are only available at the country level, we interact them with industry dummies to generate variations across industries.[4] However, some of our instruments have little variation and only change very slowly across our sample period. Hence, we only apply the IV approach to longer differencing periods (3-, 4- and 5-year differencing periods) to make full use of their longer-term variation. Methodologically, we use a standard IV approach for total labour and a multi-equations GMM

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3 All variables stem from either Eurostat or OECD. Specifically, the marriage-divorce ratio (demo_ndivind), the number of children per household (lfst_hhantych), and expenditure on social protection (spr_exp_sum) stem from Eurostat while the total fertility rate (OECD Family Database: SF2), the crude marriage rate (OECD Family Database: SF3), the crude divorce rate (OECD Family Database: SF3), public expenditure on different types of active labour market pro-grammes (OECD: Public expenditure and participant stocks on LMP) stem from OECD.

4 Alternatively, we also used interactions with the share of female employment in each industry (extracted from the EU-LFS).

approach for the four occupational groups, with standard errors clustered at the country-industry level. Results of the IV approach are discussed in Section 4.4 below.

There are potential additional endogeneity issues in our analysis. For instance, an exogenous (demand and/or productivity) shock may impact on the demand for native workers but also on migration decisions. A similar argument also holds for offshoring (i.e. intermediate input purchases) and technology adoption, which are likely correlated with domestic industry-level demand shocks that in turn also affect the demand for native workers in general as well as for different types of occupation among native workers (as addressed in our analysis) in particular.

Moreover, it is also possible that the three demand shifters considered in our analysis are not independent of each other. For instance, more offshoring may induce a shift in demand which can also affect the inflow of migrants. Conversely, migrant inflows may make it more attractive to keep production at home rather than moving it (in part or entirely) abroad. Similarly, through the positive scale effect, more offshoring my lead to an expansion of output and an increase in the demand for labour which is greater for skilled than unskilled workers (due to the substitution of some of their tasks by imported intermediates). This increase in the demand for skilled workers may be accompanied by investments in skill-complementary capital (i.e. technology adoption). Conversely, technology adoption which tends to substitute for less skilled workers, may make offshoring less attractive. Finally, technology adoption may affect the inflow of migrants who either complement the new technologies or specialise in (service) occupations that support the greater task specialisation of natives (such as housekeeping, baby-sitting, etc.). Conversely, the inflow of migrants may affect technology adoption when firms adopt production technologies which use the more abundant factor more intensely.

We have addressed these potential endogeneity issues through IV estimations, using a variety of instruments. As is common in the migration and offshoring literature, we use shift-share instruments. In the case of migration, the traditional instrument (Altonji & Card, 1991; Card, 2001) takes account of the effects of networks on the costs of migration which independently affect migrants' decisions. Specifically, it considers the composition of migrants from different source countries or regions. In this regard, we follow Ottaviano *et al.* (2013) but, due to data limitations, considered immigrant workers from four different source regions (EU15, EU13, other developed, and rest of the world) instead of individual source countries, as in their case.[5] We then used the share of immigrant workers, by origin-region, in each industry in the base year (i.e. the year prior to the estimation period) and then augmented it by the aggregate growth rate of the respective migrant group in each of the five countries considered relative to the overall population[6] growth rate in the countries.[7] We also applied the same approach to account for the endogeneity at the detailed occupational level. But in this case, instruments were calculated at the industry-occupation level, separately for each occupational group to consider that, within industries, migrants and natives compete for the same occupation. In our specific context (differences instead of levels), we use this instrument in two different forms: first, we took the logarithm and differences of the calculated instrument; second, to make full use of differences in the *change* of the share of migrants in

5 EU-LFS statistics provides information on country of birth at a relatively aggregate level; however, the advantage of LFS statistics was that we could compile the composition of migrants at the industry level and occupational level.

6 Alternatively, we also used the relative growth rate in the working-age population (aged 15-64) and the labour force which may both be more relevant sources of employment-related information and support.

7 The underlying data (for migrants and the overall population/working-age population or labour force) were obtained from the EU-LFS.

total employment by region of origin, we calculated a Paasche-like index where we first took the logarithm and differences of the shares of migrants from the four regions and then summed over the weighted (in the base year) logged and differenced shares.

In the case of offshoring, we also used a compositional variable in the base year. Specifically, following the paper by Wright (2010),[8] we first constructed a variable comprising the composition of intermediate imports from different (EU and non-EU) developing countries at the industry level the year prior to the estimation period and then augmented it with alternatively output growth, aggregate intermediate input growth, and hours worked[9] before summing over all sourcing countries. We also use this instrument in two different forms: first, in logarithmic and differenced form, and second, as a Paasche-like index where we tried to make full use of the change in intermediate input purchases from each individual developing country over the entire observation period by first taking the logs and differences of the intermediate input purchases in each industry from each developing country and then weighting and summing over all countries.

Finally, concerning technological change – as captured by the three ICT asset types and robot density – we follow Acemoglu and Restrepo (2019) and instrument each of them with their average in all available advanced economies. Specifically, for IT, CT and DB, we use the average of each ICT type in all other countries in our sample, excluding the country for which the instrument is calculated. Moreover, since the underlying data source (EU-KLEMS, release 2022) also provides information on other advanced EU and non-EU countries, we alternatively also include other countries (with full information on all three ICT asset types), individually or jointly.[10]

Similarly, for robot density in an industry (i.e. the stock of robots per 1,000 employees), we also use as instrument the average robot density in that industry in all other countries in our sample, again excluding the country for which the instrument is calculated.[11] As far as possible, we use employment in the year prior to the estimation period to guarantee that any changes in robot density solely stem from changes in the stock of robots.[12] In the case of robot density, we however cannot include more countries in the estimation of the instrument as the necessary employment data at the detailed 2-digit NACE level is not available to us. We will discuss the results from these IV estimations in Section 4.5.

8 This paper was published in a somewhat modified form as Wright (2014).

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

10 That is, all countries but the country for which the instrument is calculated plus DE or DK, plus DE and DK, plus the US and JP, plus the US, JP and DE.

11 Data are taken from the World Robotics Industrial Robots statistics from the International Federation of Robotics (IFR).

12 This is not possible for Switzerland and France, for which we can only use the first year of our observation period, due to the limited time span of the underlying employment data (which come from the detailed national EU-SILC).

## 2.2. OFFSHORING, TECHNOLOGICAL CHANGE, MIGRATION AND LABOUR DEMAND

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 various offshoring measures. Our initial indicator of offshoring is a measure of total imported intermediate purchases by industry $i$ in country $c$:

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

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

First, we differentiate between narrow (N) and broad (B) offshoring (Feenstra & Hanson, 1999). Narrow offshoring only considers imports of intermediates in an industry from the same industry, while broad offshoring considering imports of intermediates from all industries but its own. Narrow and broad offshoring are defined as follows:

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

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

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

with $M$ and $S$ representing the subset of manufacturing and service industries, respectively.

Third, we decompose our total offshoring measure by sourcing country and, following the classification of the 2005 World Development Report (World Bank, 2004), differentiate between developed countries (those classified as high-income countries in 2005), developing countries (those not classified as high-income countries in 2005) and the group of new EU Member States (NMS13) which, with the exception of Malta and Cyprus, are not classified as high-income countries in 2005.[13] From a European perspective, this further differentiation of the group of NMS countries is important since the NMS have become strongly integrated with the EU since the beginning of their economic transition in the early 1990s and EU accession in 2004 and 2007. As a result, they have become important hubs for Western

[13] The group of developed countries comprises Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Island, Italy, Japan, Korea, Luxembourg, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, Taiwan, 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.

European FDI flows and source countries for intermediate inputs[14]. Our measures of offshoring to developed, developing and NMS countries are defined as follows:

$$IIM_{i,c}^{Devd} = \frac{\sum_{x=1}^{X} O_{x,c}}{GO_{i,c}},\ IIM_{i,c}^{Devg} = \frac{\sum_{y=1}^{Y} O_{y,c}}{GO_{i,c}} \text{ and } IIM_{i,c}^{NMS13} = \frac{\sum_{z=1}^{Z} O_{z,c}}{GO_{i,c}} \quad (6)$$

Furthermore, we identify the effect of technological change on the labour demand of native workers, distinguishing two different technology measures, namely Information and Communication Technologies – and its two tangible components information technology (IT) and communication technology (CT) and its intangible component software and database (DB) – and industrial robots (defined as the stock of industrial robots per 1,000 employees). In this respect, new technologies may either complement or substitute skills (following the skill-biased technological change hypothesis – SBTC) or tasks (following the routine biased technological change hypothesis – RBTC – formulated by Autor *et al.*, 2003). Specifically, the SBTC hypothesis typically considers new technologies as being complementary to skilled labour but to substitute for unskilled labour while the RBTC hypothesis predicts that new technologies result in a decline in jobs that are intensive in routine (manual or cognitive) tasks and an increase in jobs that are intensive in cognitive non-routine tasks.

Finally, we also analyse the effect of immigration on the labour demand of native workers. Specifically, depending on the relative skill endowment of native and foreign workers, migrant workers may complement or substitute for native workers. In particular, we expect that migrants from a particular skill group tend to complement natives with different skills, but substitute for natives with similar skills. The migrant share ($MS_{ict}$) is specified as follows:

$$MS_{ict} = \frac{migrant\ workers_{ict}}{total\ workers_{ict}}, \quad (7)$$

where $migrant\ workers_{ict}$ refers to the total number of migrant workers and $total\ workers_{ict}$ to the total number of employees in industry $i$ of country $c$ at time $t$. Furthermore, similar to native workers, we also differentiate migrant workers by type of occupation (see Table 1 above) to capture the occupation-specific substitution and complementarity effects of migration on employment of native workers.

[14] We can think of the differentiation of labour market effects of offshoring to other advanced, EU13 and developing countries in the following way: Offshoring from the advanced Western European countries in our sample to other advanced economies (i.e. countries with similar composition of factor endowments) falls into the category of ‘horizontal’ task specialisation and hence very limited labour market effects are to be expected. The opposite is to be expected in relation to offshoring to developing countries (which are assumed to have quite different factor i.e. skill endowments from the countries in our sample) and hence we could expect some significant impacts on the labour market position of different occupational groups due to ‘vertical’ task specialisation. The offshoring effects to EU13 could be expected to fall somewhere in between those to advanced and those to developing countries, as organisational integration of production activities located in EU13 and in the countries of our sample would be very close, the relative endowment/skill composition would not be that different (substantial wage gaps still persist but there is also an historically relatively high level of skill endowment) and hence task specialisation would have features of both ‘horizontal’ and ‘vertical’ specialisation.

## 2.3. DATA SOURCES

We construct our database from four different data sources. First, we use the *EU Statistics on Income and Living Conditions (EU-SILC)* for key labour market-related information such as native and migrant employment (total and by occupational group – see Table 1 above), the labour force (aged 18-45) of natives by broad level of educational attainment (low, medium, high), as well as annual average gross wages (defined as cash or near cash income per employee). We use information on country of birth to differentiate native workers from migrant workers. The EU-SILC is a standardised annual survey on income, poverty, social exclusion and living conditions in the EU that has been conducted since 2003/2004 in an ever-increasing number of EU countries and EU candidate countries (plus Iceland, Norway and Switzerland). The EU-SILC is available in cross-sectional and longitudinal form, but we use cross-sectional data since longitudinal data lack the necessary information on workers' industry affiliations. Standardised and anonymised EU-SILC microdata are generally available from Eurostat for all countries that have agreed to their publication. However, these microdata are only available at the very rough one-digit industry level, and some industries are even grouped into more aggregate and larger industry groups: this is particularly the case with manufacturing, which is grouped together with mining and quarrying (NACE-A), electricity, gas, steam and air conditioning supply (NACE-D) and water supply, sewerage, waste management and remediation activities (NACE-E). Particularly for the manufacturing sector – which has borne the brunt of past offshoring activities, plays a key role in the production and adoption of new technologies, and which has absorbed a substantial number of migrant workers – this rough industry classification is a major constraint on the analysis, as it conceals the differentiated and industry-specific effects of offshoring, technological change and migration. In view of this, we contacted and acquired from national statistical offices the detailed – but anonymised – national EU-SILC data at the detailed two-digit industry level. We focused on the group of 'old' EU Member States, which are not only closely integrated into international production networks and technologically more advanced but are also major immigration countries (particularly for immigrants from other parts of Europe, especially the new EU Member States).[15] For the same reasons, we also included Switzerland into this group. All in all, we received detailed national EU-SILC data from five countries – Austria (AT), Belgium (BE), France (FR) and Spain (ES) as old EU Member States and Switzerland (CH) as non-EU Member State – and for different time periods. Relative to the other 'old' EU Member States, the five countries in our sample are characterised by relatively high total offshoring (particularly in the smaller economies Belgium and Austria) and a high robot density in manufacturing, which was among the highest in France and Spain in the early 2000s; it was surpassed by Belgium by the late 2010s with France falling relatively far behind. Finally, the share of immigrants (in the total population as well as in employment) is rather heterogeneous and is highest in Switzerland and Austria but lowest in France. From the detailed national EU-SILC data, we constructed an unbalanced sample, taking into account country-specific breaks that resulted from statistical changes with large impacts (such as new source data) or missing double-codes. Our unbalanced sample contains data for the period 2005-2018 for Austria and Belgium, for the period 2008-2018 for Spain and Switzerland and for the period 2009-2018 for France. All industry-related data were corrected for the NACE break between 2007 and 2008 by means of two-digit double-coded NACE information available in 2008. Similarly, all occupation-related data were corrected for the ISCO break between 2010 and 2011 by means of double-coded ISCO information in 2011. All relevant data were suitably corrected for all preceding years to follow the NACE Rev.2 industry classification and the ISCO-08 occupational classification.

[15] We did not include Luxembourg, whose migration numbers and patterns are too different from the other 'old' EU Member States.

Secondly, we take trade-related data from the 2020 release of the *World Input-Output Database (WIOD)*[16] which combines detailed information on national production activities and international trade. It provides information on international linkages of production processes and structures of final goods trade across 38 industries (NACE Rev.2, A38) and 51 countries, comprising all 27 EU Member States, 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 (RoW) over the period 2005 to 2018. We use information for both domestic and imported inputs at the one- and two-digit industry level to construct the different offshoring measures (as discussed above) for 2005-2018.

Thirdly, information on input prices, real gross output, and the real capital stock of computer hardware (IT), telecommunications equipment (CT) and computer software and database (DB) is taken from the *EU-KLEMS Growth and Productivity Accounts* 2021 release. It is generally available for all 27 EU Member States (plus Norway, Japan, the US and the United Kingdom) for the period 1995-2019, for 40 detailed industries (plus 23 industry aggregates), according to the NACE Rev.2 industry classification. However, since Switzerland is not included in the EU-KLEMS, we retrieved information on input prices and real gross output from Eurostat's national accounts data. Nonetheless, there is no information for Switzerland on capital stocks, in total and by asset type.

Finally, information on industrial robots is taken from the *World Robotics Industrial Robots statistics* which is compiled and published by the International Federation of Robotics (IFR)[17] and available for the period 1993-2019. The IFR measures 'multipurpose industrial robots' based on ISO 8373: 2012 (§ 2.9) as '*an automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications*' (see IFR, 2018: p. 29). Hence, the IFR dataset refers to a specific kind of industrial automation (Jurkat *et al.*, 2022), nonetheless, it covers more than 90% of the global market for industrial robots (Acemoglu & Restrepo, 2020). The data is collected from nearly all industrial robot suppliers worldwide and supplemented with (secondary) data provided by several national robot associations.[18] The IFR provides data on the number of robots (stocks and flows) delivered to each industry, by country and year.[19] Data are available for 11 broad manufacturing industries (further disaggregated to two- and three-digit industries),[20] six broad non-manufacturing industries (at the section level), and one 'Unspecified' category. Since IFR industry classes partly deviate from ISIC Rev.4, we used a correspondence table between the IFR classification and ISIC Rev.4 and reclassified all industries to follow the ISIC Rev.4 classification.

Because of certain data limitations (i.e. limited information on migrant workers in some detailed two-digit industries), we ultimately used an industry classification scheme that closely follows the EU-KLEMS (2022 release), but is less detailed in a few service industries (see Table A.1 for the list of industries). In our analysis, we use all industries, but exclude all public sector industries (O, P, Q and R-S and T) as well as D-E which is of little relevance in terms of offshoring as well as immigration.

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

17 See https://ifr.org/worldrobotics

18 Such as the national robot associations of North America (RIA), Japan (JARA) Denmark, (DIRA), Germany (VDMA, R+A), Italy (SIRI), Republic of Korea (KAR), Spain (AER), Russian Federation (RAR) and Peoples Republic of China (CRIA).

19 It assumes a 12-year service life of a robot and calculates the operational stocks of robots as the sum of robot installations of the last 12 years.

20 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.

We also use two different data samples: the total economy sample (comprising all industries but NACE O-T and D-E) and 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 different samples: in our estimations for the total economy sample, we use the three ICT asset types while in our estimations for the manufacturing sample we use robot density (in addition to all other indicators mentioned in equation (1)).

# 3. Descriptive analysis

In this section we shall give a short descriptive account of the three ‘forces’ which are the focus of our analysis of labour market effects: offshoring, technological change and migration.

We start with the measure of offshoring used in our analysis i.e. imports of intermediate inputs. For total imports of intermediate inputs (by NACE industries) it is depicted in Figure 1 and further differentiated by regions of origin of these imported intermediate inputs (from other advanced countries, from EU13 countries and from developing countries) in Figure 2. In each case we show the extent of offshoring in a starting year (different for different countries due to data availability) and average p.a. growth rates over the period of observation (up to 2018).

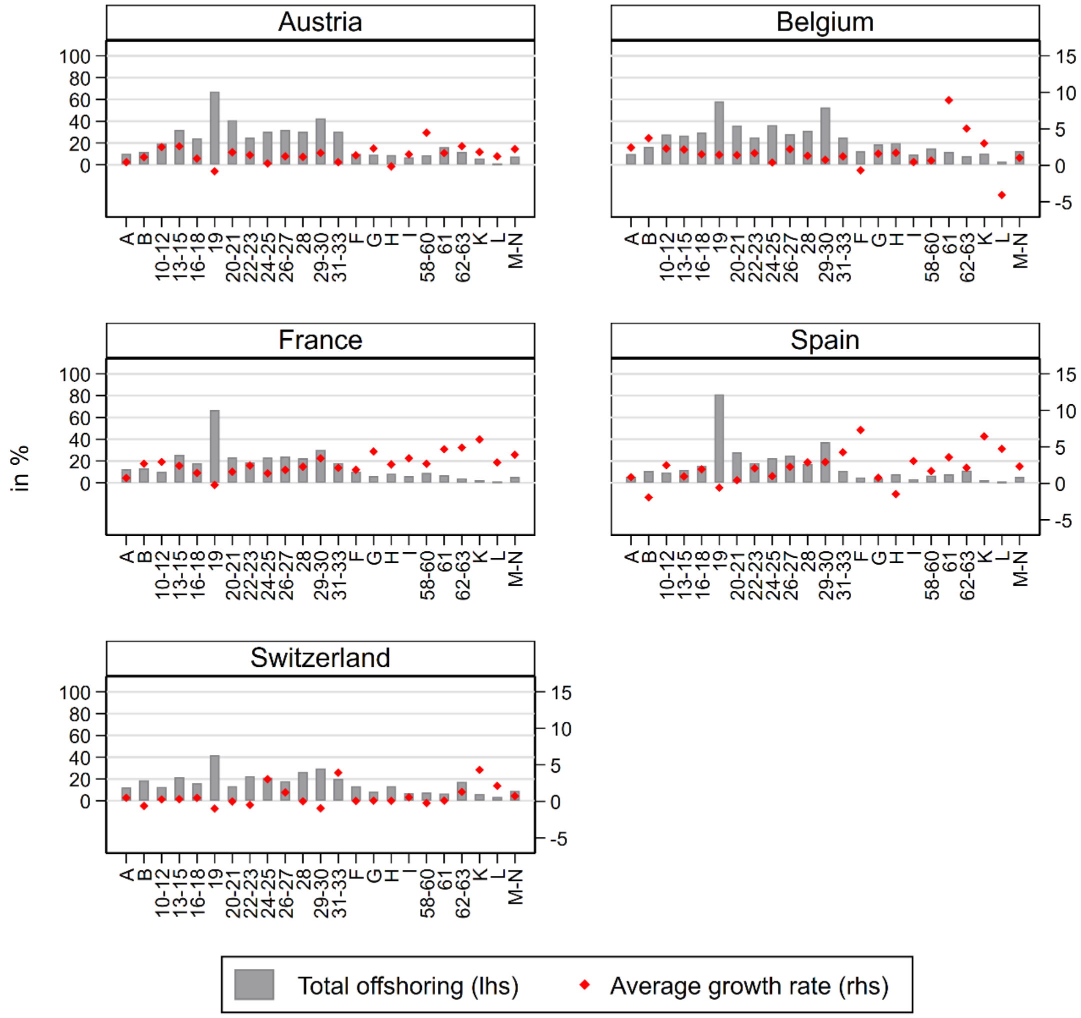
We shall point selectively to a few features which emerge from these figures and which we find worth drawing attention to – as we shall also do with the following figures.

As regards offshoring, we can see from Figure 1 that offshoring was in general more prominent in manufacturing industries than in services industries (the bars refer to the starting years i.e. mid- to end of the first decade of the 2000s). As one would expect the coke and refined petroleum industry (19) was/is particularly dependent on importing intermediates. However, the growth rate figures show a different picture of rather higher growth rates in quite a few of the services industries; they were particularly high in telecommunications (61) and IT and information services (62-63), but also in financial and insurance activities (K) and real estate activities (L) in most of the countries. This shows a catching-up pattern of services industries relative to manufacturing industries in terms of their reliance on imported intermediates over the more recent period.

Coming to the more detailed assessment of offshoring differentiating between the regions of origin of imports of intermediates, i.e. other advanced economies, EU13 and developing countries (see Figure 2), we observe the following interesting pattern: at the starting point (mid- to end of first decade of 2000s) the sourcing of intermediate inputs from other advanced economies was by far greater than from the other two groups of economies. However, the growth rates over the period of observation (until 2018) shows a certain shift of sourcing patterns: further growth of the imports of intermediates from advanced economies (as ratios relative to gross output) was very low (in some cases even negative – see particularly Switzerland), while growth of this indicator of offshoring was high from both the EU13 and from developing countries. Furthermore, these high growth rates showed a high spread across pretty much all industries (manufacturing and services).

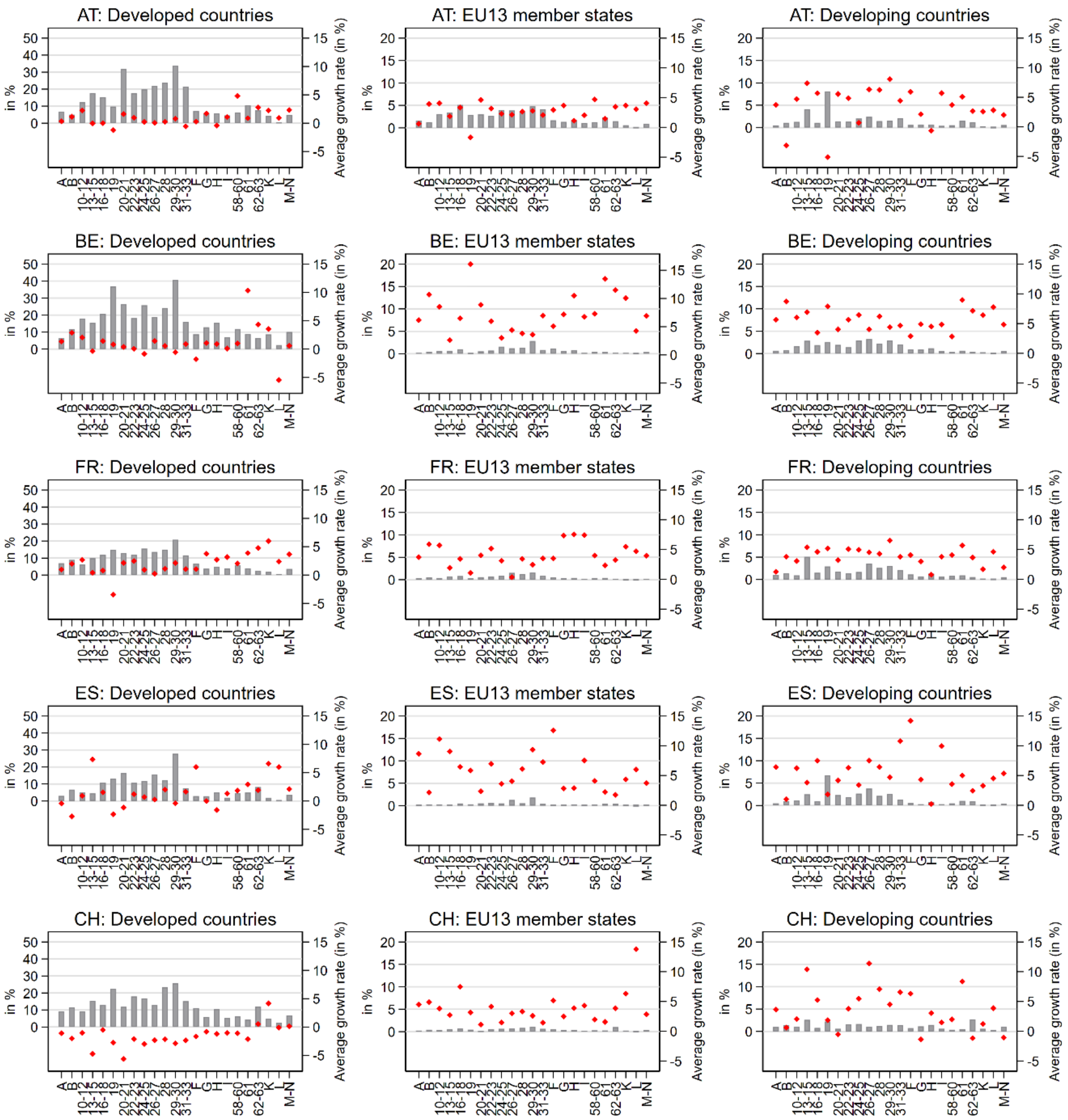
We can take this as an indication that the period over the past two decades saw a shift towards ‘vertical specialisation’ (i.e. offshoring to regions with quite different factor endowments), while offshoring (or – more generally – cross-border production integration) to rather similar economies as regards factor endowments, had already reached high levels over earlier periods and did not progress that much further.

**Figure 1 / Total offshoring by industry in the first year* (lhs) and the average offshoring growth rate between the first year and 2018 (rhs)**




Note: * refers to 2005 for Austria and Belgium, to 2008 for Spain and Switzerland, and to 2009 for France. For the calculation of average growth rates, the outlier for Spain in industry 13-15 in 2013 was removed. A refers to Agriculture, forestry and fishing, B to Mining and quarrying, 10-12 to Food products, beverages and tobacco, 13-15 to Textiles, wearing apparel, leather and related products, 16-18 to Wood and paper products; printing and reproduction of recorded media, 19 to Coke and refined petroleum products, 20-21 to Chemicals and chemical products, 22-23 to Rubber and plastics products, and other non-metallic mineral products, 24-25 to Basic metals and fabricated metal products, except machinery and equipment, 26-27 to Computer, electronic and optical products; electrical equipment, 28 to Machinery and equipment n.e.c., 29-30 to Transport equipment, 31-33 to Other manufacturing; repair and installation of machinery and equipment, D-E to Electricity, gas, steam and air conditioning supply; water supply, sewerage, waste management and remediation activities, F to Construction, G to Wholesale and retail trade; repair of motor vehicles and motorcycles, H to Transportation and storage, I to Accommodation and food service activities, 58-60 to Publishing, audio-visual and broadcasting activities, 61 to Telecommunications, 62-63 to IT and other information services, K to Financial and insurance activities, L to Real estate activities, and M-N to Professional, scientific and technical activities; administrative and support service activities.
Source: WIOD 2022 release, own calculations.

**Figure 2 / Offshoring to developed countries, EU13 Member States and developing countries by industry in the first year* (lhs) and the average offshoring growth rate between the first year and 2018 (rhs)**



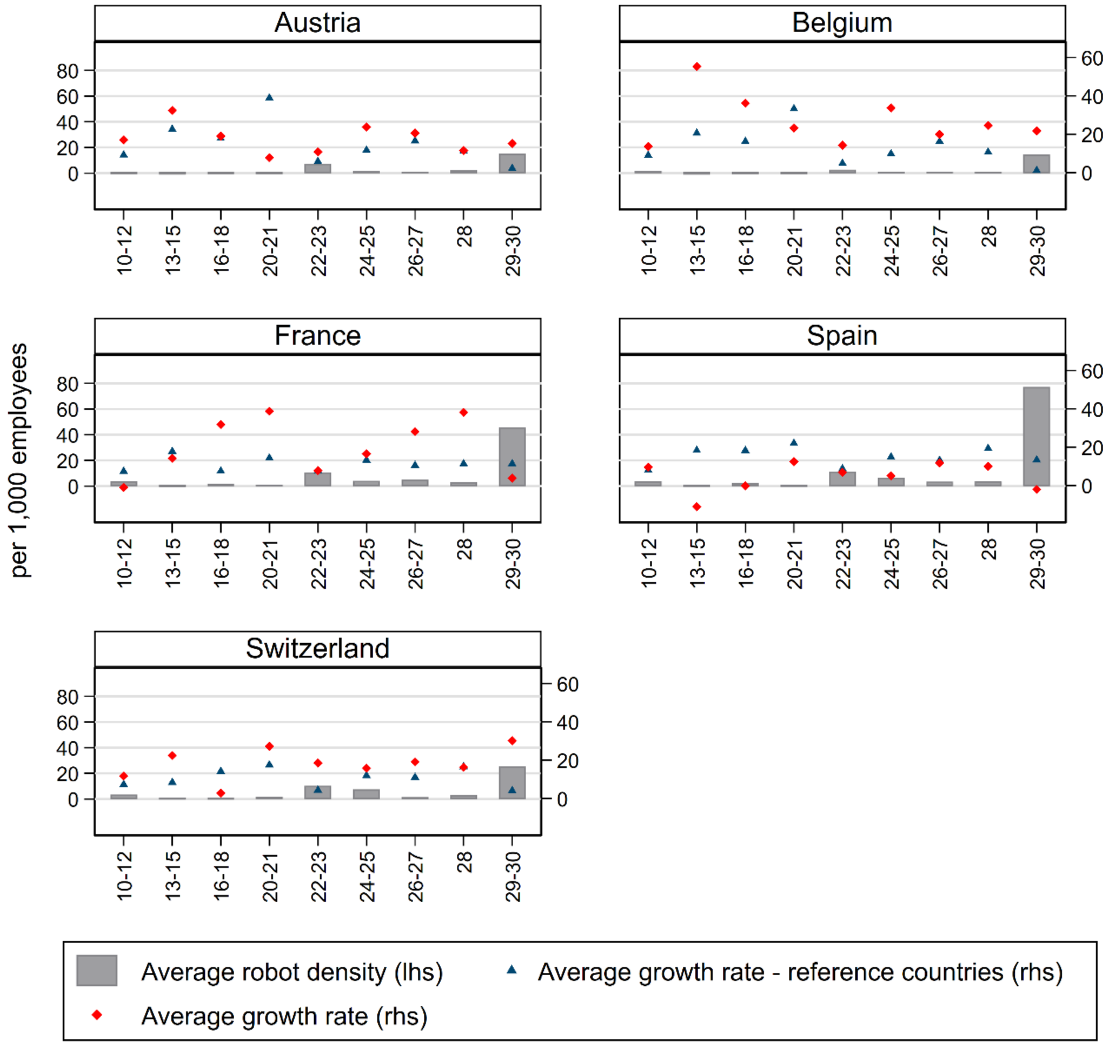

Note: AT refers to Austria, BE to Belgium, FR to France, ES to Spain and CH to Switzerland. The grey bars refer to offshoring in the first year (*2005 for Austria and Belgium, to 2008 for Spain and Switzerland, and to 2009 for France), the diamonds to the average offshoring growth rate between the first year and 2018. For the calculation of average growth rates, two outliers for offshoring to EU13 Member States were removed for Spain: in industry 19 in 2014 and in industry 13-15 in 2013. A refers to Agriculture, forestry and fishing, B to Mining and quarrying, 10-12 to Food products, beverages and tobacco, 13-15 to Textiles, wearing apparel, leather and related products, 16-18 to Wood and paper products; printing and reproduction of recorded media, 19 to Coke and refined petroleum products, 20-21 to Chemicals and chemical products, 22-23 to Rubber and plastics products, and other non-metallic mineral products, 24-25 to Basic metals and fabricated metal products, except machinery and equipment, 26-27 to Computer, electronic and optical products; electrical equipment, 28 to Machinery and equipment n.e.c., 29-30 to Transport equipment, 31-33 to Other manufacturing; repair and installation of machinery and equipment, D-E to Electricity, gas, steam and air conditioning supply; water supply, sewerage, waste management and remediation activities, F to Construction, G to Wholesale and retail trade; repair of motor vehicles and motorcycles, H to Transportation and storage, I to Accommodation and food service activities, 58-60 to Publishing, audio-visual and broadcasting activities, 61 to Telecommunications, 62-63 to IT and other information services, K to Financial and insurance activities, L to Real estate activities, and M-N to Professional, scientific and technical activities; administrative and support service activities.
Source: WIOD 2022 release, own calculations.

We now come to the second ‘force’ which we focus on in this study regarding labour market impacts, i.e. technology. We show in Figures 3 and 4 two different indicators: firstly, robot intensity (Figure 3) which we shall use as an important variable in our econometric investigation as technology indicator across manufacturing industries. Secondly, various ICT indicators (Figure 4) which we shall use when analysing technology impacts on employment across the entire range of industries.

Starting with robotisation (measured by the number of robots per 1,000 employees), we can see in Figure 3 – in the starting year of the observation period – the much higher use of robots in the transport equipment industry (29-30) than in any of the other manufacturing industries. However, depending on country, also other manufacturing industries show a relatively high degree of robot intensity: rubber and plastics (22-23; somewhat linked to transport equipment because of tire manufacturing), metals and fabricated metals (24-25), computer, electronic and optical products (26-27), and machinery and equipment n.e.c. (26). As regards growth rates over the observation period, the transport equipment industry no longer sticks out as exceptional and a wide range of manufacturing industries is increasing the degree of robotisation. In order to ascertain distinct national patterns of robotisation we show in Figure 3 not only the growth rates of robotisation characterising national industries but also those of a reference group (the other countries in our sample). This variable will also be employed as an instrument in our IV analysis later on.

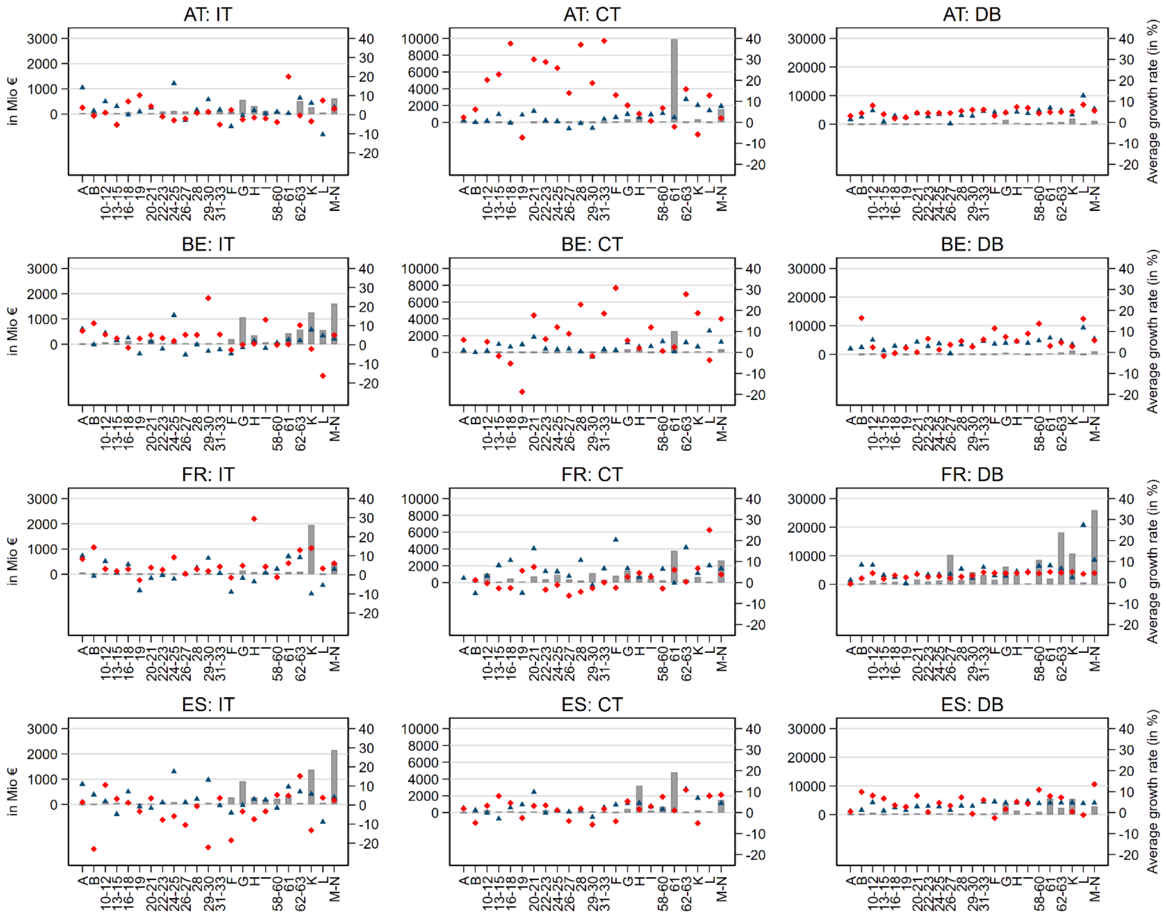
Moving on to ICT indicators (Figure 4), we observe a rather differentiated picture with quite a few service industries sticking out with high ICT use (see bars for ‘starting years’). Depending on country and indicator, ICT intensity is high in industries such as wholesale and retail trade (G), publishing, audio-visual and broadcasting activities (58-60), and, as one would expect, telecommunications (61), and IT and other information services (62-62). ICT is furthermore relatively high in financial and insurance services (K), real estate activities (L) and professional, scientific and technical activities (M-N). As regards growth rates over the observation period, there is again a lot of diversity, although one feature emerges quite strongly: the almost uniformly positive growth rates in the use of database and computer software (DB); we also observe very high growth rates in some countries (specifically AT and BE) in telecom equipment (CT). Growth in the intensity of use of office and computing equipment (IT) over the observation period, on the other hand, is rather more muted. Also in these figures, we present national growth rates as well as growth rates in the reference group of countries; the latter will again be used as an instrument in the econometric analysis, but it also shows the specific characteristics of national vs. reference group patterns of growth.

**Figure 3 / Average robot density of the first three years (lhs) and the average robot density growth rates between the first year and 2018 (rhs) (manufacturing only)**



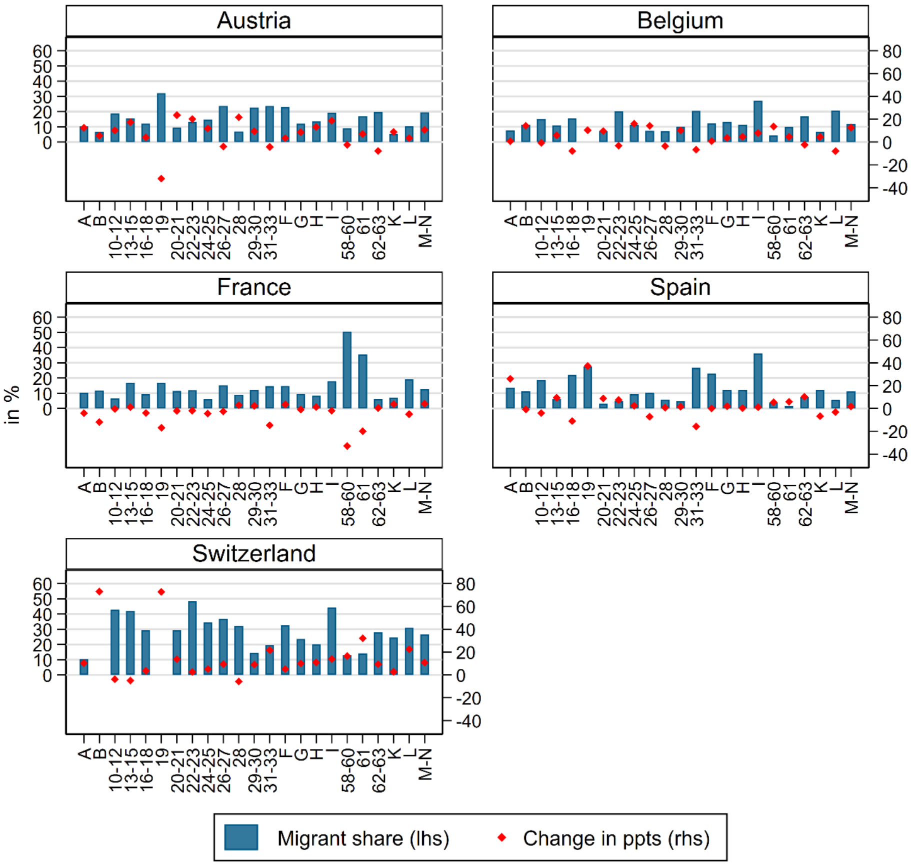

Note: Robot density is defined as the number of robots per 1,000 employees. The bars refer to the average of the earliest three years (2005-2007 for Austria and Belgium; 2008-2010 for Spain and Switzerland; 2009 2011 for France); the reference refers are all countries used in the calculation of the instrument, that is, all other countries in the sample, excluding the reporting country. The diamond and triangle refer to the average growth rate for the industry and its reference, respectively. 10-12 refers to Food products, beverages and tobacco, 13-15 to Textiles, wearing apparel, leather and related products, 16-18 to Wood and paper products; printing and reproduction of recorded media, 19 to Coke and refined petroleum products, 20-21 to Chemicals and chemical products, 22-23 to Rubber and plastics products, and other non-metallic mineral products, 24-25 to Basic metals and fabricated metal products, except machinery and equipment, 26-27 to Computer, electronic and optical products; electrical equipment, 28 to Machinery and equipment n.e.c., 29-30 to Transport equipment.
Source: World Robotics Industrial Robots statistics and national EU-SILC, own calculations.

**Figure 4 / Information technology (IT), communication technology (CT) and database and computer software (DB) by industry in the first year* (lhs) and the average growth rate between the first year and 2018 (rhs)**




Note: AT refers to Austria, BE to Belgium, FR to France, ES to Spain and CH to Switzerland. * refers to 2005 for Austria and Belgium, to 2008 for Spain and Switzerland, and to 2009 for France. For the calculation of average growth rates, several outliers were removed: for IT – in industry 24-25 for 2017 in France; for CT–- in industries 20-21, 26-27 and 29-30 in Austria and in industry 28 in 2015 in Belgium; for DB – in industry B in 2007 and 2016 in Belgium and industry L in 2014 in Spain. The diamond and triangle refer to the average growth rate for the industry and its reference (i.e. all other countries in the sample, excluding the reporting country), respectively. A refers to Agriculture, forestry and fishing, B to Mining and quarrying, 10-12 to Food products, beverages and tobacco, 13-15 to Textiles, wearing apparel, leather and related products, 16-18 to Wood and paper products; printing and reproduction of recorded media, 19 to Coke and refined petroleum products, 20-21 to Chemicals and chemical products, 22-23 to Rubber and plastics products, and other non-metallic mineral products, 24-25 to Basic metals and fabricated metal products, except machinery and equipment, 26-27 to Computer, electronic and optical products; electrical equipment, 28 to Machinery and equipment n.e.c., 29-30 to Transport equipment, 31-33 to Other manufacturing; repair and installation of machinery and equipment, D-E to Electricity, gas, steam and air conditioning supply; water supply, sewerage, waste management and remediation activities, F to Construction, G to Wholesale and retail trade; repair of motor vehicles and motorcycles, H to Transportation and storage, I to Accommodation and food service activities, 58-60 to Publishing, audio-visual and broadcasting activities, 61 to Telecommunications, 62-63 to IT and other information services, K to Financial and insurance activities, L to Real estate activities, and M-N to Professional, scientific and technical activities; administrative and support service activities.
Source: EU-KLEMS, own calculations.

**Figure 5 / Migrant share in the first year* (lhs) and absolute change (in percentage points) between the first year and 2018 (rhs)**



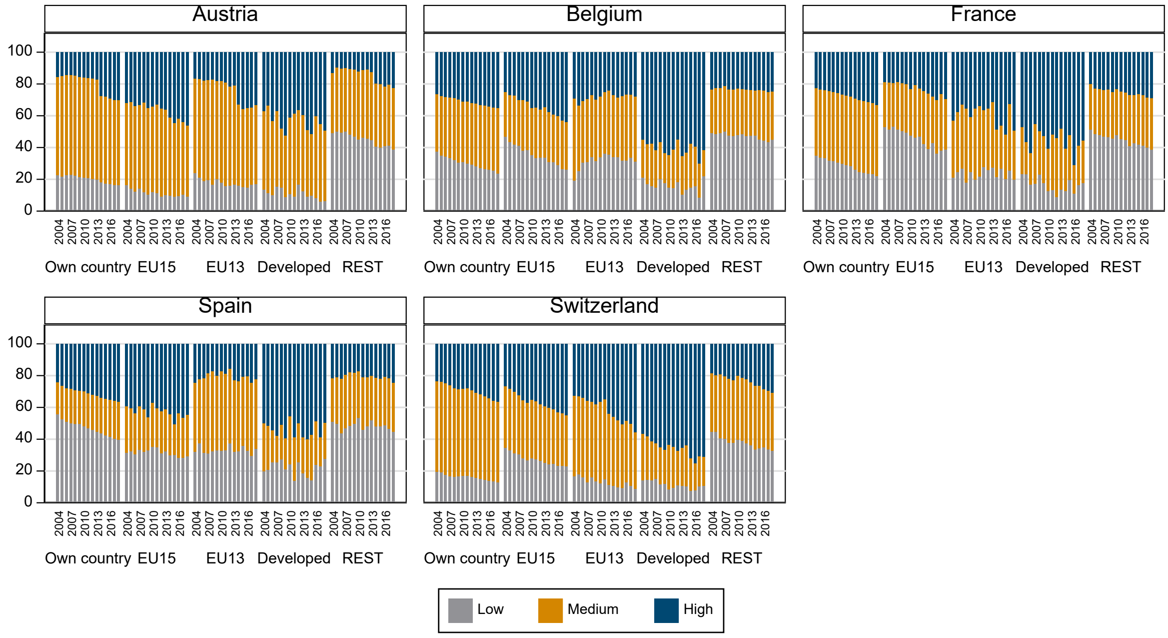

Note: * refers to 2005 for Austria and Belgium, to 2008 for Spain and Switzerland, and to 2009 for France. The relatively high growth rates for industries B and 19 in Switzerland are the result of comparatively high values in the last two years (i.e. 2017 and 2018). A refers to Agriculture, forestry and fishing, B to Mining and quarrying, 10-12 to Food products, beverages and tobacco, 13-15 to Textiles, wearing apparel, leather and related products, 16-18 to Wood and paper products; printing and reproduction of recorded media, 19 to Coke and refined petroleum products, 20-21 to Chemicals and chemical products, 22-23 to Rubber and plastics products, and other non-metallic mineral products, 24-25 to Basic metals and fabricated metal products, except machinery and equipment, 26-27 to Computer, electronic and optical products; electrical equipment, 28 to Machinery and equipment n.e.c., 29-30 to Transport equipment, 31-33 to Other manufacturing; repair and installation of machinery and equipment, D-E to Electricity, gas, steam and air conditioning supply; water supply, sewerage, waste management and remediation activities, F to Construction, G to Wholesale and retail trade; repair of motor vehicles and motorcycles, H to Transportation and storage, I to Accommodation and food service activities, 58-60 to Publishing, audio-visual and broadcasting activities, 61 to Telecommunications, 62-63 to IT and other information services, K to Financial and insurance activities, L to Real estate activities, and M-N to Professional, scientific and technical activities; administrative and support service activities.
Source: National EU-SILC, own calculations.

Finally, we come to our third ‘force’ on which we focus in this study of labour market impacts, i.e. migration. Here we present first migrant shares and growth in migrant shares (percentage point change between first and last year of the observation period) across industries/sectors in Figure 5 and, in Figure 6, information regarding the characteristics of migrant stocks coming from different source regions – EU15, EU13, other developed countries and other (mostly developing) countries. These characteristics extend to educational attainment levels (low, medium, high by ISCED categories) –

Figure 6a – and to the occupational composition of employment of migrants coming from these different regions of origin – Figure 6b.

As regards migrant shares (in the starting year), we observe quite a bit of diversity across countries and industries and we point to just a few: thus, e.g. in France migrant shares are particularly high in publishing, audio-visual and broadcasting activities (I) and telecommunications (61) i.e. areas which attract more highly skilled migrants, while in Spain we observe high migrant shares in industries such as construction (I), transportation (H), accommodation and food service industries (I) and also in repairs and installation (31-33) i.e. industries which are usually classified as requiring employees with lower educational attainment levels.

**Figure 6a / Stock of migrants (working-age population 15-64) by region of origin and educational attainment level, 2004-2018**



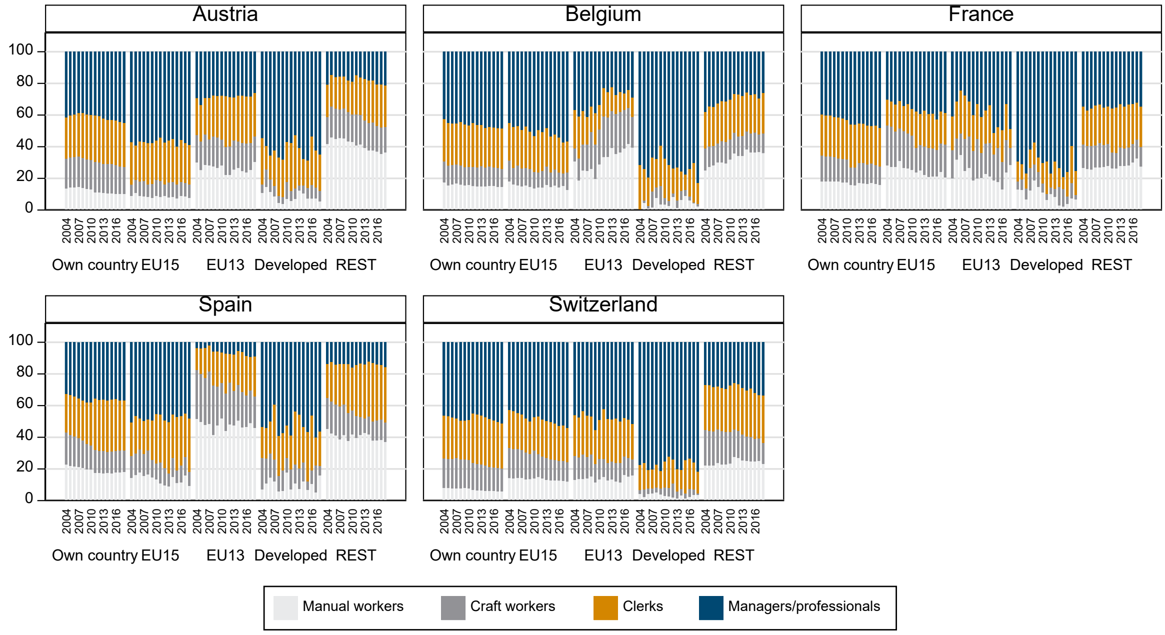

Note: The country of birth aggregations are based on the groupings available in the anonymised LFS microdata. Own country refers to natives; EU15 to persons who were born in one of the EU15 Member States, EU13 to those who were born in one of the EU13 Member States, Developed to those who were born in a developed country (i.e. EFTA, North America, Australia and Oceania), and REST to those who were born in any other country, mainly developing countries (i.e. Other Europe, North Africa, Other Africa, Near Middle East, East Asia, South and South East Asia, Central America (and Caribbean), South America). The three educational attainment levels are based on the ISCED-2011 classification: Low refers to levels 0-2, Medium to levels 3-4, and High to levels 5-8. The ISCED-break between 2014 and 2015 is visible in the figure.
Source: EU-LFS, own calculations.

As regards the last two graphs on educational attainment (Figure 6.a) and occupational composition of migrants coming from different regions of origin (Figure 6.b), we can see very distinct characteristics. For comparative purposes, the composition of the native population resp. native employees is also shown. As expected, migrants from other developed countries and – in most countries – also migrants from EU15 countries have higher educational attainment levels, and those from REST (mostly developing countries) significantly lower educational attainment. However, there are also inter-country differences regarding the migrants they attract from the same regions of origin: to give an example, Austria and

Spain attract migrants from EU13 with mostly ‘medium’ educational attainment, while France and Switzerland attract quite a lot of migrants from EU13 with ‘high’ educational attainment. Similarly, the migrants from EU15 have quite a different profile e.g. in France (rather high share of persons with ‘low’ educational attainment) as compared to most of the other countries where migrants from EU15 countries show relatively high educational attainment. This could reflect the more dominant migration pattern in France from EU South, as compared to the other countries in our sample.

Overall, one can discern that the educational attainment profile (Figure 6.a) also shows up in the occupational composition of migrants coming from the different source regions (Figure 6.b). Thus, many migrants from developed countries get employed in managerial and professional positions, while migrants from REST (i.e. mostly developing countries) get employed as manual workers. Again, we see quite interesting differences regarding migrants from EU13: in Austria, Belgium and Spain quite a high share of these get employed as manual workers, while in France and Switzerland a high share gets employed in managerial and professional positions. These are just selective examples for intercountry differences and occupational and educational characteristics of migrants coming from different source countries; some of these features will also show up in some of our econometric results.

**Figure 6b / Stock of employed migrants by region of origin and occupational group, 2004-2018**




Note: The country of birth aggregations are based on the groupings available in the anonymised LFS microdata. Own country refers to natives; EU15 to persons who were born in one of the EU15 Member States, EU13 to those who were born in one of the EU13 Member States, Developed to those who were born in a developed country (i.e. EFTA, North America, Australia and Oceania), and REST to those who were born in any other country, mainly developing countries (i.e. Other Europe, North Africa, Other Africa, Near Middle East, East Asia, South and South East Asia, Central America (and Caribbean), South America). The four occupational groups are defined (as in Table 1) as follows: manual workers include plant and machine operators and assemblers (ISCO-08: 8) and elementary occupations (ISCO-08: 9); craft workers include skilled agricultural, forestry and fishery workers (ISCO-08: 6) and craft and related trades workers (ISCO-08: 7); clerks include clerical support workers (ISCO-08: 4), and service and sales workers (ISCO-08: 5); managers/professionals include managers (ISCO-08: 1), professionals (ISCO-08: 2), and technicians and associate professionals (ISCO-08: 3); clerks include clerical support workers (ISCO-08: 4), and service and sales workers (ISCO-08: 5).
Source: EU-LFS, own calculations.

# 4. Results

In the following we shall discuss the results of our estimations, initially without taking account of endogeneity issues and then (in Sections 4.4 and 4.5) we shall report on IV estimations which attempt to address endogeneity issues. For reasons discussed in the Data section, we shall always present two sets of results: one including the entire set of industries covered in the analysis, which include both manufacturing and services industries, and, the other one, which focusses just on manufacturing industries. Apart from the fact that it is interesting to look at manufacturing industries separately, we also faced the problem that, so far, the variable 'robot density' was only available for manufacturing industries, while the other variables covering 'information and communication technology' (IT, CT and DB) were available for all industries. We made the choice that in estimations on the first set – including all industries – we included the ICT variables but excluded the robot density variable, while in the estimations covering the manufacturing industries alone, we included the robot density variable but dropped the ICT variables, as there would have been too much correlation between the robot density and ICT variables. In discussing our results, we focus on the medium to longer term – i.e. 3-, 4-, and 5-year differences – which is particularly instructive in terms of longer term labour demand effects of offshoring, technical change and migration, as opposed to the more volatile and erratic short-term effects. For the sake of comparison, results for the short run (1- and 2- year differences) are provided in the annex.

In the following we shall report in Section 4.1 on the estimates covering the effects of total offshoring, technological change and overall migration on the demand for native employees differentiated by occupational categories. In Section 4.2 we further differentiate between various offshoring measures (offshoring to different regions; offshoring in a 'narrow', i.e. within industry, or 'broad', i.e. sourcing imported inputs from other industries, sense; and offshoring of manufactured products or of services). In Section 4.3 we differentiate between two different source regions from which migrants originate (other developed, high-income regions; or lower- to medium-income regions, the latter including migrants from the NMS13). In Sections 4.4 and 4.5 we report on our attempts to deal with endogeneity issues.

## 4.1. TOTAL OFFSHORING, TECHNOLOGICAL CHANGE, IMMIGRATION AND LABOUR DEMAND

Tables 2 (for all industries) and 3 (for manufacturing industries alone) report the results for the impact of total offshoring, technological change and immigration on the labour demand for total native employment, and for the four types of occupation, respectively. Results are reported for the three longer year differences: 3 years, 4 years and 5 years.[21]

Let us first turn to the variables which are the focus of our analysis, indicators of offshoring, technology (IT, CT, DB and robot density) and immigration. We should remind the reader that we are estimating a conditional labour demand equation in which the impact of the three 'forces' (offshoring, technology, migration) on the native labour force is analysed, in the first instance, under the assumption of a given level

[21] Results for 1-year and 2-year differences are reported in Tables A.2 and A.3 in the annex.

of output. In this 'partial' assessment of the impact of these three forces, the focus is on the 'structural' impact on different occupational groups of native workers and this is separately identified for the three forces. The 'scale' effect, on the other hand (i.e. to which extent cost reductions induces demand and further employment effects) is captured through the output term which however does not allow us to differentially attribute such induced demand effects to the three forces separately. However, since the dependent variable refers to changes in (logs of) employment levels of different occupational groups of native workers, we do capture 'total' employment changes, i.e. including 'structural' and 'scale' effects, even though only the former can – in our framework – differentially be attributed to the three forces individually. We should keep this in mind when discussing the results of our estimations below which refer mostly to the 'partial' (i.e. structural') impacts of the three forces on native occupational groups.

With regard to the impact of offshoring we observe an important difference whether we look at the industry sample as a whole (Table 2) or only at manufacturing industries (Table 3). In the first case, we obtain a positive (significant) sign only for craft workers, i.e. increased offshoring increases the demand for skilled native craft workers. Specifically, our results suggest that a 1% increase in total offshoring over a period of 3 to 5 years is associated with around a 0.4% increase in the growth of labour demand for craft workers. In the case of manufacturing industries alone, on the other hand, increased offshoring leads to reduced demand specifically for native managers and, to a lesser degree, native manual workers. This contrasts with what is typically found in the literature[22] and suggests that tasks of managers have become increasingly offshorable. More specifically, the estimated coefficients suggest that the demand for native managers falls by between 0.2 and 0.5% in response to an increase of total offshoring by 1% over a period of 3 to 5 years.

Amongst the technology variables, i.e. IT, CT, and DB in the case of the full industry sample, and robot density in the case of manufacturing industries alone, we obtain again quite interesting diverse results: for the ICT variables in the full industry sample (Table 2) we find strongly positive effects for IT (information technology equipment) for the employment of all categories of workers except for manual workers, with the strongest impact on craft workers and then managers/professionals and clerks. Hence IT is complementary to the employment of these skilled and white-collar categories of employees. Overall, the quantitative effect is, however, limited: the demand for the respective categories of workers increases only by between 0.1 and 0.2% as a result of an increase in the IT capital stock by 1% over a period of 3 to 5 years. For manufacturing industries alone (Table 3) where we included the robot density variable, we find uniformly and strong negative effects of the introduction of robots on the employment of all categories of workers, with the strongest negative effects this time on craft workers. Specifically, our results suggest that a 1% increase in the robot density over a period of 3 to 5 years is associated with a decrease in labour demand of about 0.5% for all types of workers. Overall, our results are in line with Jestl (2022) who also finds a positive employment effect from IT but a negative employment effect from robotisation.

The effect of increases in migrant shares turns out to be also strongly and significantly negative for all categories of native workers both in the full industry sample as well as for manufacturing industries alone. However, we also see that this negative effect is less strong for managers/professionals than it is for the other categories of workers: only around -0.2% in response to a 1% increase in the share of migrant managers/professionals as opposed to between -0.3 and -0.4% in response to a 1% increase in the share of each of the other migrant shares.

22 See, e.g., Hijzen *et al.* (2005), Foster-McGregor *et al.* (2013), Crinò (2010 and 2012).

Let us now also refer to the impact of control variables: Here our estimates show that there is not much evidence of employment reacting to input price developments, i.e. to either wages or to the price of materials. The unexpected positive sign on wages in the manufacturing sector seems to be fully accounted for by managers/professionals and there it could indeed be that hiring this category of employees is not negatively affected by an increase in their wage bill, i.e. improvements in productivity through the hiring of such workers might justify the additional hiring of such workers. As regards employment decisions reacting to output movements, we see in the full industry sample (Table 2) that the strongest positive relationship is with regard to craft (i.e. skilled) workers, followed by clerks (i.e. white-collar) workers. We can interpret this as the direction of compositional changes in occupations which are linked to output movements. Focussing just on manufacturing industries (Table 3) we find little evidence that output movements go along with compositional changes in occupational structures; it could be that such compositional changes are not ‘scale’-dependent as such but much more linked to trend changes in technology, as we have seen above with the strong impact of robot intensity in occupational employment changes in manufacturing industries.

The import penetration variable is defined only at the aggregate economy-wide level and would therefore not reflect cross-industry variations; the reason for including such a variable only at the aggregate level is that we did not want it to correlate with our proxy for offshoring which is in the focus of our analysis. Hence, given the aggregate nature of the variable, we did not expect much explanatory power. Furthermore, as we control for output movements (which already captures amongst others also the impact of imports on reduced sales in the domestic market), we would expect the import penetration variable to only impact on employment decisions if an intensified import competition does affect the labour intensity of production (i.e. the labour input coefficients). In this respect the results are interesting: the (at first sight unexpected) positive sign on total employment seems to be accounted for by the reaction to increased imports (a proxy for aggregate ‘openness’ of an economy) leading to the hiring of especially more craft workers and, in second place, of clerks and managers.

Finally, we should mention rather idiosyncratic effects of the demographic (labour supply ‘push’) variables, which refer to changes in available labour forces of age categories 18-45 with different educational attainment levels (low, medium and high). The results for the full sample of industries (Table 2) indicate that an increased supply of tertiary-educated (H) persons on the labour market has a significantly positive impact on the employment of managers/professionals, but reduces the employment of craft workers. We can interpret this in the way that a change in the educational attainment structure of the available labour force towards tertiary educated workers favours the availability of a labour force that can take up managerial and professional posts and reduces the availability of craft workers. The latter result is also, although to a weaker extent, replicated for the case of manufacturing industries alone (Table 3). For manufacturing industries, we, furthermore, obtain the – plausible – result that a positive labour supply ‘shock’ of low-educated (L) workers increases the employment of manual and craft workers. In manufacturing we can interpret this as an important complementarity between manual and craft workers as the latter might be needed as foremen and trainers/ supervisors of workers with lower levels of education. We shall return to discussing the robustness of these results in Section 4.4 when we deal with endogeneity issues.

## Table 2 / Employment effect (total economy): Total offshoring

| | 3-year differences (D3) | | | | | 4-year differences (D4) | | | | | 5-year differences (D5) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** | **(7)** | **(8)** | **(9)** | **(10)** | **(11)** | **(12)** | **(13)** | **(14)** | **(15)** |
| | **total** | **manag** | **clerk** | **craft** | **manual** | **total** | **manag** | **clerk** | **craft** | **manual** | **total** | **manag** | **clerk** | **craft** | **manual** |
| w | 0.257* | 0.083 | 0.001 | -0.078 | -0.025 | 0.315** | 0.085 | 0.047 | -0.067 | 0.014 | 0.197 | 0.049 | 0.114 | -0.054 | 0.045 |
| | (1.886) | (0.969) | (0.010) | (-0.707) | (-0.288) | (2.540) | (0.829) | (0.372) | (-0.561) | (0.217) | (1.479) | (0.451) | (1.087) | (-0.381) | (0.555) |
| p | 0.102 | 0.344** | 0.197 | 0.009 | 0.364 | 0.169 | 0.247 | -0.057 | 0.007 | 0.298 | 0.228** | 0.314 | 0.066 | -0.010 | 0.025 |
| | (0.749) | (1.998) | (0.742) | (0.052) | (0.999) | (1.494) | (1.478) | (-0.224) | (0.046) | (0.958) | (1.990) | (1.555) | (0.289) | (-0.061) | (0.086) |
| GO | 0.646*** | 0.169 | 0.340 | 0.847*** | 0.542 | 0.558*** | 0.332* | 0.591** | 0.931*** | 0.504 | 0.491*** | 0.317 | 0.491* | 0.900*** | 0.620* |
| | (4.711) | (0.804) | (0.934) | (4.608) | (1.376) | (4.941) | (1.653) | (2.064) | (5.016) | (1.359) | (4.841) | (1.433) | (1.787) | (7.172) | (1.839) |
| IP | 0.523** | 0.107 | 0.999** | 1.512*** | -0.016 | 0.341 | 0.041 | 0.623 | 1.640*** | -0.116 | -0.040 | 0.661** | -0.399 | -0.517 | -0.099 |
| | (2.200) | (0.320) | (2.551) | (3.995) | (-0.027) | (1.544) | (0.115) | (1.484) | (3.881) | (-0.222) | (-0.192) | (2.318) | (-1.154) | (-1.271) | (-0.207) |
| $IIM^T$ | 0.051 | -0.073 | -0.014 | 0.391** | -0.214 | 0.049 | 0.001 | -0.017 | 0.411** | -0.347* | 0.068 | -0.022 | 0.009 | 0.431** | -0.186 |
| | (0.568) | (-0.665) | (-0.103) | (2.398) | (-1.583) | (0.512) | (0.004) | (-0.133) | (2.361) | (-1.813) | (0.730) | (-0.173) | (0.065) | (2.039) | (-1.114) |
| IT | 0.112*** | 0.113** | 0.151*** | 0.195*** | 0.122* | 0.135*** | 0.163*** | 0.145*** | 0.233*** | 0.114* | 0.131*** | 0.186*** | 0.125** | 0.219*** | 0.075 |
| | (3.276) | (2.067) | (3.449) | (4.042) | (1.726) | (4.192) | (2.877) | (3.143) | (5.706) | (1.954) | (3.951) | (3.364) | (2.330) | (3.860) | (1.303) |
| CT | -0.025 | -0.024 | -0.039 | -0.013 | 0.018 | -0.023 | -0.037 | -0.040 | 0.015 | 0.025 | -0.020 | -0.047 | -0.054 | 0.018 | 0.030 |
| | (-0.876) | (-0.577) | (-0.890) | (-0.259) | (0.508) | (-0.787) | (-0.942) | (-0.911) | (0.322) | (0.697) | (-0.734) | (-1.221) | (-1.136) | (0.461) | (0.753) |
| DB | 0.124* | 0.020 | 0.227* | -0.119 | 0.045 | 0.087 | -0.004 | 0.226* | -0.157 | 0.023 | 0.094 | 0.018 | 0.242* | -0.152 | 0.078 |
| | (1.756) | (0.157) | (1.763) | (-0.847) | (0.275) | (1.283) | (-0.031) | (1.684) | (-1.142) | (0.152) | (1.346) | (0.141) | (1.848) | (-1.309) | (0.523) |
| MS | -0.291*** | -0.190*** | -0.374*** | -0.265*** | -0.407*** | -0.237*** | -0.192*** | -0.380*** | -0.270*** | -0.365*** | -0.229*** | -0.181*** | -0.324*** | -0.300*** | -0.313*** |
| | (-6.526) | (-6.956) | (-5.967) | (-6.411) | (-6.241) | (-5.498) | (-6.325) | (-6.725) | (-6.646) | (-5.807) | (-4.256) | (-5.562) | (-6.071) | (-7.126) | (-5.302) |
| $LF_L$ | 0.090 | -0.059 | 0.261 | 0.305 | 0.222 | 0.159 | 0.107 | -0.080 | 0.241 | 0.554** | 0.081 | 0.015 | -0.459* | 0.213 | 0.517* |
| | (0.842) | (-0.390) | (1.142) | (1.345) | (0.843) | (1.420) | (0.648) | (-0.351) | (1.072) | (2.266) | (0.610) | (0.077) | (-1.908) | (0.811) | (1.854) |
| $LF_M$ | -0.756* | -0.719 | 1.524* | -0.235 | -0.684 | -0.158 | -0.225 | 1.459* | -0.194 | 1.000 | -0.271 | -0.273 | 0.350 | 0.043 | 0.490 |
| | (-1.731) | (-1.122) | (1.858) | (-0.274) | (-0.784) | (-0.380) | (-0.332) | (1.799) | (-0.223) | (1.108) | (-0.656) | (-0.416) | (0.407) | (0.054) | (0.631) |
| $LF_H$ | 0.029 | 0.245 | 0.256 | -0.490 | 0.175 | 0.275 | 0.622*** | 0.161 | -0.753** | 0.792* | 0.208 | 0.884*** | -0.123 | -0.808** | 0.597 |
| | (0.185) | (1.127) | (0.914) | (-1.603) | (0.445) | (1.616) | (2.736) | (0.583) | (-2.186) | (1.686) | (1.279) | (3.200) | (-0.425) | (-2.113) | (1.349) |
| Constant | -0.077** | -0.056 | -0.006 | -0.217** | -0.141 | -0.048 | -0.169** | -0.081 | -0.204* | -0.167 | -0.066 | -0.238* | -0.070 | 0.015 | -0.252* |
| | (-2.205) | (-0.943) | (-0.089) | (-1.985) | (-1.596) | (-1.113) | (-1.991) | (-0.966) | (-1.819) | (-1.428) | (-1.077) | (-1.798) | (-0.656) | (0.096) | (-1.765) |
| Obs. | 779 | 777 | 777 | 777 | 777 | 692 | 690 | 690 | 690 | 690 | 606 | 604 | 604 | 604 | 604 |
| $R^2$ | 0.245 | 0.179 | 0.316 | 0.244 | 0.240 | 0.253 | 0.202 | 0.345 | 0.297 | 0.244 | 0.245 | 0.223 | 0.328 | 0.333 | 0.209 |

Note: All variables are in logs. Standard errors clustered at the country-industry level. Robust t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1. w refers to average gross annual wages, p to the price of materials, GO to gross output, IP to import penetration, $IIM^T$ to total offshoring, IT to information technology, CT to communication technology, DB software and database, MS to the migrant share and $LF_L$, $LF_M$ and $LF_H$ to the native labour force (aged 18-45) with low, medium and high level of educational attainment, respectively.

## Table 3 / Employment effect (manufacturing): Total offshoring

| | 3-year differences (D3) | | | | | 4-year differences (D4) | | | | | 5-year differences (D5) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
| | total | manag | clerk | craft | manual | total | manag | clerk | craft | manual | total | manag | clerk | craft | manual |
| w | 0.406** | 0.256* | -0.033 | 0.124 | -0.401 | 0.412*** | 0.157 | -0.101 | -0.002 | -0.293 | 0.307* | 0.286*** | -0.083 | -0.058 | -0.221 |
| | (2.589) | (1.844) | (-0.319) | (0.779) | (-1.384) | (2.796) | (1.135) | (-0.596) | (-0.010) | (-0.957) | (1.801) | (2.760) | (-0.979) | (-0.303) | (-0.967) |
| p | 0.469** | 0.306 | 0.946* | 0.241 | 1.035** | 0.195 | 0.153 | 0.405 | 0.091 | 0.588 | 0.220 | 0.435 | 0.485 | -0.146 | 0.435 |
| | (2.535) | (1.083) | (1.917) | (0.667) | (2.451) | (1.044) | (0.451) | (0.767) | (0.296) | (1.579) | (1.200) | (1.296) | (0.988) | (-0.393) | (1.306) |
| GO | 0.108 | -0.026 | -0.042 | 0.139 | -0.367 | 0.348* | 0.256 | 0.532 | 0.503 | -0.218 | 0.367* | 0.081 | 0.444 | 0.707** | -0.164 |
| | (0.589) | (-0.088) | (-0.072) | (0.388) | (-0.836) | (1.838) | (0.776) | (1.092) | (1.590) | (-0.556) | (1.951) | (0.254) | (0.862) | (2.036) | (-0.418) |
| IP | 0.695*** | 0.226 | -0.041 | 2.191*** | -0.223 | 0.662** | 0.015 | -0.781 | 1.847*** | 0.042 | 0.151 | 0.218 | -1.826*** | 0.707 | -0.240 |
| | (2.836) | (0.668) | (-0.065) | (3.659) | (-0.246) | (2.428) | (0.039) | (-1.285) | (3.169) | (0.047) | (0.673) | (0.782) | (-3.002) | (1.103) | (-0.371) |
| $IIM^T$ | -0.164* | -0.183* | -0.013 | 0.174 | -0.372 | -0.286*** | -0.363*** | 0.010 | 0.033 | -0.442* | -0.375*** | -0.526*** | -0.201 | -0.078 | -0.342* |
| | (-1.903) | (-1.810) | (-0.037) | (1.111) | (-1.540) | (-2.889) | (-3.145) | (0.026) | (0.210) | (-1.790) | (-3.520) | (-4.106) | (-0.667) | (-0.363) | (-1.854) |
| RD | -0.516*** | -0.387*** | -0.401*** | -0.594*** | -0.524*** | -0.504*** | -0.411*** | -0.390*** | -0.546*** | -0.509*** | -0.451*** | -0.401*** | -0.430*** | -0.479*** | -0.392*** |
| | (-10.574) | (-5.900) | (-5.164) | (-9.285) | (-7.626) | (-10.763) | (-6.200) | (-3.587) | (-7.322) | (-7.586) | (-10.662) | (-7.319) | (-4.108) | (-6.514) | (-5.445) |
| MS | -0.225*** | -0.185*** | -0.345*** | -0.304*** | -0.297*** | -0.209*** | -0.181*** | -0.367*** | -0.267*** | -0.269*** | -0.160*** | -0.133*** | -0.366*** | -0.279*** | -0.238*** |
| | (-5.091) | (-5.926) | (-4.361) | (-5.670) | (-5.023) | (-4.514) | (-4.570) | (-5.100) | (-5.618) | (-4.721) | (-3.339) | (-3.569) | (-5.223) | (-5.440) | (-5.019) |
| $LF_L$ | 0.391*** | 0.071 | 0.396 | 0.507** | 0.494 | 0.524*** | 0.172 | 0.147 | 0.642*** | 1.011*** | 0.480*** | 0.081 | -0.009 | 0.490 | 1.123*** |
| | (2.844) | (0.351) | (1.587) | (2.030) | (1.378) | (3.304) | (0.738) | (0.633) | (2.873) | (2.864) | (2.968) | (0.342) | (-0.028) | (1.631) | (3.980) |
| $LF_M$ | -0.032 | -0.825 | 1.438 | 0.717 | -0.253 | 0.100 | -1.043 | 1.436 | 1.000 | 0.837 | 0.475 | -0.355 | 0.580 | 0.751 | 1.114 |
| | (-0.087) | (-1.184) | (1.263) | (0.878) | (-0.244) | (0.261) | (-1.403) | (1.387) | (1.310) | (0.844) | (1.119) | (-0.473) | (0.434) | (0.932) | (1.278) |
| $LF_H$ | -0.099 | -0.250 | 0.498 | -0.419 | 0.166 | -0.104 | -0.083 | 0.355 | -0.589 | 0.853* | -0.410** | -0.399 | -0.527 | -0.864** | 0.604 |
| | (-0.661) | (-1.190) | (1.472) | (-1.359) | (0.415) | (-0.668) | (-0.412) | (0.884) | (-1.608) | (1.749) | (-2.073) | (-1.350) | (-1.229) | (-2.101) | (1.427) |
| Constant | 0.176*** | 0.069 | 0.191* | -0.066 | 0.047 | 0.260*** | -0.073 | 0.217* | 0.026 | 0.238 | 0.282*** | 0.077 | 0.319 | -0.127 | 0.283 |
| | (4.404) | (1.032) | (1.817) | (-0.508) | (0.318) | (5.348) | (-0.437) | (1.649) | (0.244) | (1.161) | (4.356) | (0.503) | (1.237) | (-0.490) | (1.194) |
| Obs. | 403 | 403 | 403 | 403 | 403 | 358 | 358 | 358 | 358 | 358 | 313 | 313 | 313 | 313 | 313 |
| $R^2$ | 0.689 | 0.396 | 0.389 | 0.468 | 0.352 | 0.683 | 0.396 | 0.438 | 0.498 | 0.364 | 0.680 | 0.407 | 0.492 | 0.484 | 0.340 |

Note: All variables are in logs. Standard errors clustered at the country-industry level. Robust t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1. w refers to average gross annual wages, p to the price of materials, GO to gross output, IP to import penetration, $IIM^T$ to total offshoring, RD to robot density, MS to the migrant share and $LF_L$, $LF_M$ and $LF_H$ to the native labour force (aged 18-45) with low, medium and high level of educational attainment, respectively.

## 4.2. OTHER OFFSHORING MEASURES AND LABOUR DEMAND

Tables 4 and 5 below report the results when total offshoring is further split into (1) offshoring by source country (developed countries, NMS13 and developing countries), (2) narrow and broad offshoring, and (3) manufacturing and services offshoring (as defined in Section 2.2). The results are again reported for total employment, as well as for the four types of occupation, and for the three longer year differences: 3, 4 and 5 years.[23] Since the coefficients for the other control variables are similar to what we observed above (see Tables 2 and 3), we concentrate on the different offshoring indicators.

The decomposition of offshoring by source region of imports of intermediate inputs yields very interesting results regarding the employment effects of offshoring for different occupational groups of natives. Looking first at results across the full set of industries (Table 4) we observe that offshoring to other developed economies has a positive employment impact for native craft workers and no significant negative impacts on other occupational groups. As against this offshoring to developing countries has significant negative employment effects for native workers, in total and this is accounted for by negative employment effects on craft workers and clerks. In principle, these are interesting results: it does seem to indicate that across the entire spectrum of industries, trade integration with other advanced economies (as proxied through our offshoring variable) does put a premium to skilled production (i.e. craft) workers as would be compatible with a view of increased 'horizontal product and production differentiation' in trade amongst countries with similar endowments and high income levels ('love for variety'). Trade integration with less developed economies – and here we might point to a result which does not conform to a classical, static picture of trade and production specialisation between advanced and less advanced economies – seems to show, over our estimation period, already a distinct pressure on skilled (craft) workers and white collar (clerks) segments of the native labour force.

If we focus only on the employment effects of offshoring for workers in the manufacturing industries alone (Table 5), we can see in this more restricted set of industries that offshoring to other developed economies does have a negative employment effect on manual native workers which can be an indication that increased trade integration with advanced economies requires a general 'up-grading' of the domestic labour force. Offshoring to developing countries shows negative employment effects on native clerks specifically and, to a lesser extent, on native managers/professionals, a result which seems at odds with a traditional view that production specialisation with developing countries would mean that production workers (manual and craft workers) would be outsourced to developing countries, while employment of non-production workers (clerks and managers/ professionals) would remain in developed economies; this could be an indication that also tasks associated with 'white-collar' jobs can increasingly be performed in developing economies as these economies are themselves developing capabilities in service activities. Lastly, we come to the special case of offshoring to EU13 where we see some weakly significant positive effects on native managers/professionals, clerical staff and even manual workers. This seems to reveal some special features of production and trade integration of Western with Central and Eastern European (CEE) EU economies which has greatly intensified over the past decades and which seems to have benefited a range of occupational groups in Western European economies; the fact that native craft workers in Western European economies have less benefited from this trade integration could be due to the traditional strength of skilled manufacturing workers in CEE economies. The tenor of the analysis in this section is that differentiating offshoring by source region is important to understand the differential employment effects of offshoring and also to capture more recent developments which reflect changing developmental positions of different source regions and their positions in the international division of labour.

23 Results for 1-year and 2-year differences are reported in Tables A.4 and A.5 in the annex.

## Table 4 / Employment effect (total economy): Other offshoring measures

| | 3-year differences (D3) | | | | | 4-year differences (D4) | | | | | 5-year differences (D5) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
| | total | manag | Clerk | craft | manual | total | manag | clerk | craft | manual | total | manag | clerk | craft | manual |
| **Offshoring to developed countries, NMS13 and developing countries** | | | | | | | | | | | | | | | |
| $IIM^{Devd}$ | 0.164 | -0.059 | 0.153 | 1.233*** | -0.108 | 0.141 | 0.057 | -0.055 | 1.038*** | -0.313 | 0.109 | -0.078 | -0.024 | 1.088*** | -0.225 |
| | (1.100) | (-0.294) | (0.617) | (3.193) | (-0.320) | (0.904) | (0.271) | (-0.239) | (2.776) | (-0.988) | (0.666) | (-0.410) | (-0.112) | (3.139) | (-0.766) |
| $IIM^{NMS13}$ | 0.114 | 0.175 | 0.173 | -0.106 | 0.253 | 0.106 | 0.103 | 0.182 | -0.064 | 0.224 | 0.053 | 0.113 | 0.125 | -0.280 | 0.231 |
| | (1.260) | (1.202) | (0.783) | (-0.508) | (0.839) | (1.040) | (0.683) | (0.963) | (-0.255) | (0.958) | (0.394) | (0.742) | (0.689) | (-1.213) | (1.065) |
| $IIM^{Devg}$ | -0.159* | -0.067 | -0.372*** | -0.558*** | -0.266 | -0.195** | -0.076 | -0.190* | -0.495*** | -0.229 | -0.123 | -0.027 | -0.141 | -0.362** | -0.150 |
| | (-1.892) | (-0.632) | (-3.011) | (-3.518) | (-1.504) | (-2.404) | (-0.760) | (-1.765) | (-2.996) | (-1.228) | (-1.525) | (-0.246) | (-1.381) | (-2.084) | (-0.833) |
| Obs. | 779 | 777 | 777 | 777 | 777 | 692 | 690 | 690 | 690 | 690 | 606 | 604 | 604 | 604 | 604 |
| $R^2$ | 0.254 | 0.181 | 0.326 | 0.266 | 0.245 | 0.265 | 0.204 | 0.349 | 0.314 | 0.248 | 0.251 | 0.224 | 0.331 | 0.343 | 0.213 |
| **Narrow and broad offshoring** | | | | | | | | | | | | | | | |
| $IIM^{N}$ | 0.071 | 0.022 | 0.088 | 0.292*** | 0.070 | 0.133** | 0.085 | 0.105 | 0.238*** | 0.059 | 0.124** | 0.074 | 0.045 | 0.214*** | 0.035 |
| | (1.520) | (0.293) | (0.950) | (3.126) | (0.590) | (2.451) | (1.033) | (1.072) | (2.676) | (0.576) | (2.094) | (0.901) | (0.483) | (2.767) | (0.376) |
| $IIM^{B}$ | 0.024 | -0.014 | -0.055 | 0.016 | -0.056 | -0.051 | 0.032 | -0.087 | 0.210 | -0.517* | 0.003 | 0.026 | 0.011 | 0.541* | -0.262 |
| | (0.243) | (-0.103) | (-0.276) | (0.047) | (-0.287) | (-0.494) | (0.218) | (-0.466) | (0.707) | (-1.847) | (0.034) | (0.186) | (0.055) | (1.959) | (-1.216) |
| Obs. | 779 | 777 | 777 | 777 | 777 | 692 | 690 | 690 | 690 | 690 | 606 | 604 | 604 | 604 | 604 |
| $R^2$ | 0.247 | 0.179 | 0.317 | 0.249 | 0.240 | 0.260 | 0.203 | 0.346 | 0.298 | 0.248 | 0.252 | 0.225 | 0.328 | 0.337 | 0.210 |
| **Manufacturing and services offshoring** | | | | | | | | | | | | | | | |
| $IIM^{M}$ | 0.017 | 0.022 | 0.147 | 0.074 | -0.165 | 0.033 | 0.103 | 0.087 | -0.171 | -0.412* | 0.064 | 0.067 | 0.139 | -0.219 | -0.180 |
| | (0.229) | (0.265) | (1.213) | (0.269) | (-0.613) | (0.538) | (1.130) | (0.700) | (-0.764) | (-1.874) | (0.910) | (0.647) | (1.342) | (-1.094) | (-0.968) |
| $IIM^{S}$ | -0.064 | -0.108 | 0.050 | -0.035 | -0.051 | -0.036 | -0.029 | 0.055 | 0.368 | -0.246* | 0.013 | 0.018 | 0.066 | 0.651*** | -0.153 |
| | (-1.193) | (-1.339) | (0.434) | (-0.126) | (-0.430) | (-0.620) | (-0.309) | (0.499) | (1.507) | (-1.686) | (0.210) | (0.186) | (0.575) | (2.910) | (-1.250) |
| Obs. | 779 | 777 | 777 | 777 | 777 | 692 | 690 | 690 | 690 | 690 | 606 | 604 | 604 | 604 | 604 |
| $R^2$ | 0.246 | 0.181 | 0.318 | 0.240 | 0.240 | 0.253 | 0.203 | 0.346 | 0.298 | 0.250 | 0.246 | 0.224 | 0.330 | 0.346 | 0.211 |

Note: All variables are in logs. Standard errors clustered at the country-industry level. Robust t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1. $IIM^{Devd}$ refers to offshoring to developed countries, $IIM^{NMS13}$ to offshoring to EU13 Member States, $IIM^{Devg}$ to offshoring to developing countries; $IIM^{N}$ and $IIM^{B}$ refers to narrow and broad offshoring, respectively and $IIM^{M}$ and $IIM^{S}$ to manufacturing and services offshoring, respectively.

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

| | 3-year differences (D3) | | | | | 4-year differences (D4) | | | | | 5-year differences (D5) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
| | total | manag | clerk | craft | manual | total | manag | clerk | craft | manual | total | manag | clerk | craft | manual |
| **Offshoring to developed countries, NMS13 and developing countries** | | | | | | | | | | | | | | | |
| $IIM^{Devd}$ | -0.226 | -0.096 | 0.442 | -0.083 | -0.835** | -0.090 | -0.035 | 0.478 | 0.271 | -0.678 | -0.248 | -0.204 | 0.463 | 0.349 | -0.934* |
| | (-1.436) | (-0.389) | (0.955) | (-0.246) | (-2.311) | (-0.504) | (-0.123) | (1.204) | (0.764) | (-1.424) | (-1.386) | (-0.666) | (1.391) | (0.908) | (-1.722) |
| $IIM^{NMS13}$ | 0.353*** | 0.377* | 0.120 | 0.539* | 0.590* | 0.158 | 0.137 | 0.020 | 0.293 | 0.363 | 0.176 | 0.179 | -0.190 | 0.008 | 0.552 |
| | (3.053) | (1.816) | (0.283) | (1.649) | (1.881) | (1.274) | (0.617) | (0.057) | (0.912) | (1.014) | (1.152) | (0.704) | (-0.581) | (0.027) | (1.515) |
| $IIM^{Devg}$ | -0.110 | -0.158 | -0.464*** | -0.051 | -0.013 | -0.185** | -0.221** | -0.494*** | -0.236* | -0.073 | -0.171* | -0.274** | -0.454*** | -0.226 | 0.049 |
| | (-1.529) | (-1.487) | (-4.006) | (-0.453) | (-0.065) | (-2.205) | (-1.996) | (-4.019) | (-1.746) | (-0.344) | (-1.925) | (-2.420) | (-3.406) | (-1.279) | (0.251) |
| Obs. | 403 | 403 | 403 | 403 | 403 | 358 | 358 | 358 | 358 | 358 | 313 | 313 | 313 | 313 | 313 |
| $R^2$ | 0.697 | 0.406 | 0.408 | 0.475 | 0.359 | 0.686 | 0.398 | 0.458 | 0.507 | 0.366 | 0.681 | 0.407 | 0.511 | 0.490 | 0.353 |
| **Narrow and broad offshoring** | | | | | | | | | | | | | | | |
| $IIM^{N}$ | -0.093 | -0.102 | 0.168 | 0.144 | -0.239 | -0.173* | -0.241** | 0.215 | 0.057 | -0.254 | -0.246** | -0.387*** | 0.049 | -0.033 | -0.196 |
| | (-1.286) | (-1.076) | (0.597) | (1.085) | (-1.309) | (-1.957) | (-2.355) | (0.753) | (0.452) | (-1.124) | (-2.622) | (-3.640) | (0.185) | (-0.263) | (-1.137) |
| $IIM^{B}$ | 0.076 | 0.110 | 0.867 | 0.705 | 0.247 | 0.037 | -0.071 | 1.156* | 0.761 | -0.159 | 0.072 | -0.328 | 0.670 | 1.121** | -0.018 |
| | (0.313) | (0.372) | (1.226) | (1.310) | (0.715) | (0.140) | (-0.201) | (1.847) | (1.458) | (-0.391) | (0.264) | (-0.960) | (1.153) | (2.040) | (-0.043) |
| Obs. | 403 | 403 | 403 | 403 | 403 | 358 | 358 | 358 | 358 | 358 | 313 | 313 | 313 | 313 | 313 |
| $R^2$ | 0.689 | 0.396 | 0.395 | 0.472 | 0.353 | 0.682 | 0.395 | 0.450 | 0.504 | 0.362 | 0.679 | 0.406 | 0.495 | 0.499 | 0.338 |
| **Manufacturing and services offshoring** | | | | | | | | | | | | | | | |
| $IIM^{M}$ | 0.188 | 0.223 | 0.836* | 0.299 | 0.731** | 0.164 | 0.105 | 0.919** | 0.058 | 0.539 | 0.228 | 0.059 | 0.696* | 0.035 | 0.712** |
| | (1.001) | (1.003) | (1.907) | (0.726) | (2.040) | (0.754) | (0.376) | (2.430) | (0.154) | (1.555) | (0.990) | (0.209) | (1.720) | (0.084) | (2.186) |
| $IIM^{S}$ | -0.075 | -0.161 | 0.513 | 0.123 | -0.249 | 0.007 | -0.107 | 0.706** | 0.450* | -0.306 | 0.066 | -0.117 | 0.646** | 0.694*** | -0.385** |
| | (-0.661) | (-1.064) | (1.635) | (0.513) | (-1.131) | (0.051) | (-0.575) | (2.451) | (1.862) | (-1.396) | (0.486) | (-0.652) | (2.175) | (3.789) | (-2.261) |
| Obs. | 403 | 403 | 403 | 403 | 403 | 358 | 358 | 358 | 358 | 358 | 313 | 313 | 313 | 313 | 313 |
| $R^2$ | 0.689 | 0.398 | 0.406 | 0.469 | 0.360 | 0.677 | 0.389 | 0.465 | 0.504 | 0.368 | 0.668 | 0.385 | 0.514 | 0.500 | 0.358 |

Note: All variables are in logs. Standard errors clustered at the country-industry level. Robust t-statistics in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$. $IIM^{Devd}$ refers to offshoring to developed countries, $IIM^{NMS13}$ to offshoring to EU13 Member States, $IIM^{Devg}$ to offshoring to developing countries; $IIM^{N}$ and $IIM^{B}$ refers to narrow and broad offshoring, respectively and $IIM^{M}$ and $IIM^{S}$ to manufacturing and services offshoring, respectively.

Tables 4 and 5 also show further decompositions of the offshoring variable: into ‘narrow’ and ‘broad’ and, secondly, whether offshoring involves importing intermediate inputs from manufacturing or from services industries.

As regards the first decomposition, there are only scant results: we find in the overall industry sample (Table 4) a significant positive impact of narrow offshoring on the employment of native craft workers – pointing to some vertical specialisation impact of offshoring – while for manufacturing industries alone we find a significant negative impact of narrow offshoring on the employment of native managers.

Finally, as regards the impact of importing intermediate inputs either from manufacturing or from services industries on employment of native workers, there are basically some idiosyncratic results and we shall single out only the results for the manufacturing industries: there native workers in clerical jobs benefit both from increased importing of manufactured and services inputs (greater scope for logistics and coordination tasks, i.e. tasks for ‘white-collar’ workers) while native craft workers in manufacturing industries particularly benefit from increased imports of services inputs which seem to serve as being complementary to their own work.

## 4.3. IMMIGRATION BY COUNTRY OF BIRTH AND LABOUR DEMAND

Table 6 below reports the results when overall migrant shares are further split into migrants from high-income/developed countries ($MS^{Devd}$) and from lower-/medium-income countries ($MS^{Devg}$).[24] The results are again reported for total employment, as well as for the four types of occupation, and for the three longer year differences: 3, 4 and 5 years. Since the coefficients for the other control variables are similar to what we observed above (see Tables 2 and 3), we concentrate only on the differentiated migrant share measures.

The results we obtain are indeed very interesting. There is a distinct difference in the impacts of migrant workers whether they originate from other developed economies or from lower-/medium-income countries: The negative impact of increased migrant shares on employment in all occupation categories of native workers is very pronounced if they originate from low-/medium-income countries than from high income countries. While we find some significant but less consistent negative impacts of increased migrant shares coming from high-income countries on different groups of native workers (including on managers/professionals and clerks which can be interpreted as the strong competition for these ‘white-collar’ jobs coming from migrants originating in other advanced economies; see the high educational attainment levels depicted for this group of migrants in Figure 6.a), the impact of increased migrant shares from low-/medium-income countries is much more persistent and affects all occupational groups of native workers. The impact is somewhat less on native managers/professionals than other occupational groups (again quite consistent with the differentiated educational attainment levels depicted between natives and migrants from low-/medium-income countries in Figure 6.a), and in the

24 These two country groups are specified as follows – following the country of birth aggregation based on the groupings available in the anonymised LFS microdata: Developed comprises all EU15 Member States as well as EFTA, North America, Australia and Oceania; Developing comprises all EU13 Member States, other Europe, North Africa, other Africa, Near Middle East, East Asia, South and South East Asia, Central America (and Caribbean), South America. For the complete (and partly changing) list of countries consult the relevant country coding documents at: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=EU_labour_force_survey_-_documentation#Coding_lists.2C_explanatory_notes_and_classifications_used_over_time. The full tables of results are reported in Tables A.6 and A.7 in the annex.

manufacturing industries somewhat stronger for native manual workers than for other occupational groups. Interestingly, when one compares the two industry samples (all industries including services industries vs. manufacturing industries alone), the negative impacts of increased migrant shares (from low-/medium-income economies) is in general more pronounced when one considers the wider sample of industries than when one only considers manufacturing. This can indicate, firstly, that adjustment of migrant/native task specialisation might already be more advanced in manufacturing industries, while it is still more strongly happening in services industries and, secondly, there might still be a stronger job competition between migrants and natives in occupations in some of the services areas which were formerly less open sectors of the economy (considering qualification recognition etc.)

## Table 6 / Employment effect (Total economy & manufacturing): immigration by country of birth

| | 3-year differences (D3) | | | | | 4-year differences (D4) | | | | | 5-year differences (D5) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
| | total | Manag | clerk | craft | manual | total | manag | clerk | craft | manual | total | manag | clerk | craft | manual |
| **Total economy** | | | | | | | | | | | | | | | |
| $MS^{Devd}$ | -0.001 | -0.046 | -0.107*** | -0.080 | -0.119*** | -0.048 | -0.024 | -0.022 | -0.081** | -0.035 | -0.017 | -0.102*** | -0.055 | -0.065 | -0.080* |
| | (-0.026) | (-1.201) | (-2.678) | (-1.619) | (-3.774) | (-0.890) | (-0.642) | (-0.483) | (-2.352) | (-1.024) | (-0.350) | (-2.764) | (-1.275) | (-1.640) | (-1.671) |
| $MS^{Devg}$ | -0.142*** | -0.129*** | -0.276*** | -0.210*** | -0.168*** | -0.096 | -0.161*** | -0.284*** | -0.225*** | -0.248*** | -0.113** | -0.091** | -0.214*** | -0.270*** | -0.204*** |
| | (-3.605) | (-3.619) | (-7.411) | (-4.828) | (-4.169) | (-1.638) | (-4.371) | (-7.692) | (-4.829) | (-4.560) | (-2.015) | (-2.331) | (-4.731) | (-5.426) | (-4.564) |
| Obs. | 697 | 669 | 669 | 669 | 669 | 613 | 586 | 586 | 586 | 586 | 531 | 506 | 506 | 506 | 506 |
| $R^2$ | 0.196 | 0.182 | 0.449 | 0.321 | 0.272 | 0.234 | 0.215 | 0.430 | 0.433 | 0.248 | 0.217 | 0.258 | 0.371 | 0.411 | 0.270 |
| **Manufacturing** | | | | | | | | | | | | | | | |
| $MS^{Devd}$ | 0.039 | -0.019 | -0.108* | -0.065 | -0.055 | 0.033 | -0.012 | -0.140 | -0.042 | 0.017 | 0.048 | -0.121** | -0.214** | -0.041 | -0.058 |
| | (0.884) | (-0.315) | (-1.815) | (-1.339) | (-0.714) | (0.717) | (-0.230) | (-1.315) | (-0.917) | (0.195) | (1.165) | (-1.986) | (-2.564) | (-0.929) | (-0.675) |
| $MS^{Devg}$ | -0.195*** | -0.129** | -0.165*** | -0.157*** | -0.185* | -0.195*** | -0.103* | -0.134** | -0.142** | -0.263** | -0.193*** | 0.020 | -0.070 | -0.171** | -0.191** |
| | (-3.027) | (-2.319) | (-3.865) | (-2.633) | (-1.920) | (-3.112) | (-1.792) | (-2.048) | (-2.140) | (-2.163) | (-3.780) | (0.370) | (-1.101) | (-2.408) | (-2.285) |
| Obs. | 364 | 355 | 355 | 355 | 355 | 319 | 310 | 310 | 310 | 310 | 275 | 270 | 270 | 270 | 270 |
| $R^2$ | 0.608 | 0.326 | 0.506 | 0.381 | 0.306 | 0.622 | 0.369 | 0.551 | 0.400 | 0.307 | 0.670 | 0.419 | 0.628 | 0.402 | 0.313 |

Note: All variables are in logs. Standard errors clustered at the country-industry level. Robust t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1. $MS^{Devd}$ and $MS^{Devg}$ refer to the share of migrants from developed and developing countries, respectively. All regressions also include the usual controls (i.e. wages, the price of materials, real gross output, import penetration, total offshoring, the three ICT asset types (IT, CT and DB) in the case of the total economy sample and robot density in the case of the manufacturing sample, labour force by educational attainment) as well as a constant.

## 4.4. ENDOGENEITY OF WAGES

As discussed above (see Section 2.1), the wage variable in the model may be endogenous since the industry labour supply curve may not be perfectly elastic (which one would have to assume if the model were a pure labour demand model, where shifts in labour supply allow us to trace the position on the labour demand function without independently affecting labour supply). We address this issue by using an IV approach with information regarding households as instruments. Since some of the instruments change very slowly across our estimation period, we only apply the IV approach to longer differencing periods (3-, 4- and 5-year differencing periods). Methodologically, we use a standard IV approach for total employment and a multi-equations GMM approach for the four occupational groups, which is flexible in terms of occupation-specific instrument specification and allows us to choose for each occupation the instruments which produce the best test statistics. For the latter we identify the relevance and validity of the instruments by means of results from the first-stage IV regression and a Hansen J-like test (for the entire system of equations), respectively. For the sake of brevity, we only report results when the total offshoring measure is used in the regression, separately for the total sample and the manufacturing sample (see Table 7 below).[25]

The test statistics show that according to the underidentification test and results from the first-stage IV regression the instruments are relevant in all regressions with only a few exceptions and regardless of the sample considered. However, the Kleinbergen-Paap rk Wald F statistic suggests that the instruments for total employment tend to be weak in most cases. Furthermore, results of the Wu-Hausman test suggest that endogeneity may be an issue (as the null hypothesis cannot be rejected at conventional levels of statistical significance in several of our regressions). Hence, since weak instruments affect the validity and power of the Wu-Hausman test (and often lead to a failure to reject the null), the results mainly reflect the weakness of the instruments and should therefore be considered inconclusive.

There is, however, one notable exception worth mentioning: total employment in the total economy sample for which the instruments are both relevant and strong, and the Wu-Hausman test is rejected. In this case, the initially positive (and significant) wage effects (reported in Table 2 above) turn negative (but not significant).

## 4.5. OTHER ENDOGENEITY ISSUES

We discussed in Section 2.1 several endogeneity issues – either related to the correlation of our key variables of interest (offshoring, technological change, migration) with exogenous industry-level demand (and/or productivity) shocks or to their potential interrelation. We addressed these by separate IV estimations. Similar to above, we use a standard IV approach for total employment and a multi-equations GMM approach for the four occupational groups and evaluate the instruments' relevance by means of results from the first-stage IV regression. Since our IV models are perfectly identified, the instruments' validity cannot be identified.Bi

25 For the sake of brevity, we only report the most relevant information here (wages & test statistics). The full results are reported in Tables A.8 and A.9 in the annex.

## Table 7 / Instrumental variable results for endogenous wages: total economy and manufacturing

| | 3-year differences (D3) | | | | | 4-year differences (D4) | | | | | 5-year differences (D5) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
| | **total** | **manag** | **clerk** | **craft** | **manual** | **total** | **manag** | **clerk** | **craft** | **manual** | **total** | **manag** | **clerk** | **craft** | **manual** |
| **Total economy** | | | | | | | | | | | | | | | |
| w | -0.413 | -0.649** | 1.618 | -0.953 | -1.653 | -0.395 | -0.475 | 0.971* | -0.003 | -0.368 | -0.434 | -0.734* | 0.158 | -0.057 | 1.141 |
| | (-1.609) | (-2.308) | (1.246) | (-1.423) | (-0.854) | (-1.392) | (-1.190) | (1.921) | (-0.005) | (-0.315) | (-1.539) | (-1.648) | (0.269) | (-0.087) | (0.660) |
| Obs. | 779 | 777 | 777 | 777 | 777 | 692 | 690 | 690 | 690 | 690 | 606 | 604 | 604 | 604 | 604 |
| R² | 0.167 | | | | | 0.161 | | | | | 0.175 | | | | |
| Underid. | 29.730*** | | | | | 26.340*** | | | | | 24.420*** | | | | |
| K-P | 28.620 | | | | | 32.150 | | | | | 33.800 | | | | |
| Hansen | 0.520 | | 1.818 | | | 1.743 | | 0.852 | | | 1.456 | | 3.881 | | |
| W-H | 6.327** | | | | | 4.927** | | | | | 4.587** | | | | |
| I-w | | ***, *** | **, * | **, *** | **, ** | | ***, *** | **, ** | ***, *** | x, *** | | ***, *** | *, * | ***, *** | x, ** |
| **Manufacturing** | | | | | | | | | | | | | | | |
| w | 0.816 | 0.881 | 0.459 | -2.005** | 3.018 | 0.583 | 0.430 | 0.791 | -2.004*** | 1.472 | -0.181 | 0.103 | 0.892 | -2.431*** | 3.704 |
| | (1.361) | (1.027) | (1.099) | (-2.106) | (1.058) | (0.879) | (0.443) | (0.939) | (-3.082) | (0.726) | (-0.193) | (0.152) | (0.888) | (-3.664) | (1.044) |
| Obs. | 403 | 403 | 403 | 403 | 403 | 358 | 358 | 358 | 358 | 358 | 313 | 313 | 313 | 313 | 313 |
| R² | 0.672 | | | | | 0.681 | | | | | 0.659 | | | | |
| Underid. | 17.880*** | | | | | 13.410*** | | | | | 7.899** | | | | |
| K-P | 9.230 | | | | | 7.845 | | | | | 4.750 | | | | |
| Hansen | 1.101 | | 3.737 | | | 0.798 | | 6.311 | | | 0.132 | | 3.860 | | |
| W-H | 0.411 | | | | | 0.091 | | | | | 0.225 | | | | |
| I-w | | x, *** | **, * | ***, *** | **, ** | | x, *** | *, * | ***, *** | ***, * | | x, * | x, ** | ***, *** | x, * |

Note: All variables are in logs. Standard errors clustered at the country-industry level. Robust t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1. All regressions also include the usual controls (i.e. the price of materials, real gross output, import penetration, total offshoring, IT, CT and DB for the total economy sample, robot density for the manufacturing sample, the migrant share and the native labour force, by highest level of educational attainment) as well as a constant. w refers to average gross annual wages. Underid. refers to the underidentification test, K-P to the Kleinbergen-Paap rk Wald F statistic, Hansen to the Hansen J-test and W-H to the Wu-Hausman test. As outlined in section 2.1, we use as instruments information from the household and use those two instruments which produce the best test statistics. I-w refers to these instruments and reports the level of significance of the two instruments used in the first stage regression: *** p<0.01, ** p<0.05, * p<0.1, x p≥0.1 The different instruments and data sources are detailed in footnote 3. Information on which particular instruments are used in the respective estimations are available from the authors upon request.

**Table 8 / Instrumental variable results for endogenous offshoring: total economy and manufacturing**

| | 3-year differences (D3) | | | | | 4-year differences (D4) | | | | | 5-year differences (D5) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** | **(7)** | **(8)** | **(9)** | **(10)** | **(11)** | **(12)** | **(13)** | **(14)** | **(15)** |
| | **total** | **manag** | **clerk** | **craft** | **manual** | **total** | **manag** | **clerk** | **craft** | **manual** | **total** | **manag** | **clerk** | **craft** | **manual** |
| **Total economy** | | | | | | | | | | | | | | | |
| $IIM^T$ | 1.928 | 0.418 | 8.935 | 13.128* | -2.147 | 9.640 | 6.109 | 15.462 | 25.218 | -0.848 | -66.778 | -0.697 | -14.250 | -15.243 | 1.797 |
| | (1.062) | (0.144) | (1.306) | (1.785) | (-0.528) | (0.728) | (0.398) | (0.714) | (0.794) | (-0.071) | (-0.106) | (-0.244) | (-0.674) | (-0.716) | (0.521) |
| Obs | 779 | 777 | 777 | 777 | 777 | 692 | 690 | 690 | 690 | 690 | 606 | 604 | 604 | 604 | 604 |
| $R^2$ | 0.101 | | | | | 0.044 | | | | | 0.246 | | | | |
| Underid. | 3.234* | | | | | 0.554 | | | | | 0.011 | | | | |
| K-P | 3.160 | | | | | 0.535 | | | | | 0.011 | | | | |
| W-H | 1.479 | | | | | 8.622*** | | | | | 7.264*** | | | | |
| $I\text{-}IIM^T$ | | -0.055* | -0.056* | -0.061* | -0.046 | | -0.023 | -0.033 | -0.037 | -0.017 | | 0.078 | 0.058 | 0.061 | 0.073 |
| **Manufacturing** | | | | | | | | | | | | | | | |
| $IIM^T$ | -2.185 | -1.830 | 5.545 | 1.248 | -5.102 | 0.287 | -0.501 | 4.200 | 2.589 | -1.415 | 2.318 | 0.299 | -1.857 | -9.968 | 0.669 |
| | (-1.467) | (-0.774) | (1.306) | (0.554) | (-0.720) | (0.128) | (-0.092) | (0.529) | (0.538) | (-0.066) | (0.113) | (0.086) | (-0.446) | (-0.413) | (0.215) |
| Obs. | 403 | 285 | 285 | 285 | 285 | 358 | 244 | 244 | 244 | 244 | 313 | 206 | 206 | 206 | 206 |
| $R^2$ | 0.392 | | | | | 0.655 | | | | | 0.184 | | | | |
| Underid. | 6.784*** | | | | | 1.551 | | | | | 0.013 | | | | |
| K-P | 7.844 | | | | | 1.683 | | | | | 0.012 | | | | |
| W-H | 3.292* | | | | | 0.061 | | | | | 2.152 | | | | |
| $I\text{-}IIM^T$ | | -0.100 | -0.104* | -0.105* | -0.085 | | -0.044 | -0.047 | -0.053 | -0.019 | | 0.087 | 0.081 | 0.069 | 0.092 |

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

## Table 9 / Instrumental variable results for endogenous capital asset types (total economy)

| | 3-year differences (D3) | | | | | 4-year differences (D4) | | | | | 5-year differences (D5) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** | **(7)** | **(8)** | **(9)** | **(10)** | **(11)** | **(12)** | **(13)** | **(14)** | **(15)** |
| | **total** | **manag** | **clerk** | **craft** | **manual** | **total** | **manag** | **clerk** | **craft** | **manual** | **total** | **manag** | **clerk** | **craft** | **manual** |
| **Total economy** | | | | | | | | | | | | | | | |
| IT | -3.864 | -0.206 | 1.117 | 0.412 | 0.093 | 0.298 | 0.275 | 0.849 | 0.562 | 0.455 | -4.026 | -1.802 | 0.147 | 0.813 | -2.016 |
| | (-0.021) | (-0.068) | (1.134) | (0.194) | (0.043) | (0.032) | (0.192) | (0.859) | (0.631) | (0.280) | (-0.061) | (-0.170) | (0.033) | (0.642) | (-0.120) |
| CT | -0.205 | -2.883 | -0.419 | 1.637 | -1.264 | -4.466 | -0.914 | -0.235 | 0.375 | -0.249 | -8.860 | -0.348 | -0.189 | 0.272 | 0.084 |
| | (-0.004) | (-0.448) | (-0.203) | (0.416) | (-0.250) | (-0.118) | (-1.136) | (-0.406) | (0.956) | (-0.266) | (-0.054) | (-0.150) | (-0.162) | (1.412) | (0.035) |
| DB | 6.111 | -4.094 | -0.788 | 4.613 | -5.366 | -0.919 | -3.315 | -2.599 | 0.742 | -5.134 | -0.453 | 7.492 | 10.946 | -0.784 | 9.931 |
| | (0.024) | (-0.273) | (-0.161) | (0.397) | (-0.400) | (-0.019) | (-0.312) | (-0.327) | (0.161) | (-0.413) | (-0.006) | (0.141) | (0.196) | (-0.104) | (0.121) |
| Obs | 779 | 777 | 777 | 777 | 777 | 692 | 690 | 690 | 690 | 690 | 606 | 604 | 604 | 604 | 604 |
| $R^2$ | 0.573 | | | | | 0.730 | | | | | 0.680 | | | | |
| Underid. | 0.001 | | | | | 0.012 | | | | | 0.003 | | | | |
| K-P | 0.001 | | | | | 0.004 | | | | | 0.001 | | | | |
| W-H | 6.083 | | | | | 7.626* | | | | | 9.148** | | | | |
| I-IT | | -0.206 | 1.117 | 0.412 | 0.093 | | 0.275 | 0.849 | 0.562 | 0.455 | | -1.802 | 0.147 | 0.813 | -2.016 |
| I-CT | | -2.883 | -0.419 | 1.637 | -1.264 | | -0.914 | -0.235 | 0.375 | -0.249 | | -0.348 | -0.189 | 0.272 | 0.084 |
| I-DB | | -4.094 | -0.788 | 4.613 | -5.366 | | -3.315 | -2.599 | 0.742 | -5.134 | | 17.492 | 10.946 | -0.784 | 19.931 |

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

## Table 10 / Instrumental variable results for endogenous robot density (manufacturing)

| | 3-year differences (D3) | | | | | 4-year differences (D4) | | | | | 5-year differences (D5) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** | **(7)** | **(8)** | **(9)** | **(10)** | **(11)** | **(12)** | **(13)** | **(14)** | **(15)** |
| | **total** | **manag** | **clerk** | **craft** | **manual** | **total** | **manag** | **clerk** | **craft** | **manual** | **total** | **manag** | **clerk** | **craft** | **manual** |
| **Manufacturing** | | | | | | | | | | | | | | | |
| RD | -0.289*** | -0.087 | -0.328 | -0.159 | -0.152 | -0.256** | -0.189 | -0.079 | -0.097 | -0.099 | -0.162 | 0.076 | -0.113 | -0.171 | 0.092 |
| | (-3.324) | (-0.666) | (-1.634) | (-0.609) | (-0.941) | (-2.396) | (-1.017) | (-0.312) | (-0.323) | (-0.392) | (-1.075) | (0.176) | (-0.240) | (-0.434) | (0.197) |
| Obs | 403 | 285 | 285 | 285 | 285 | 358 | 244 | 244 | 244 | 244 | 313 | 206 | 206 | 206 | 206 |
| $R^2$ | 0.604 | | | | | 0.580 | | | | | 0.516 | | | | |
| Underid. | 12.910*** | | | | | 12.510*** | | | | | 9.922*** | | | | |
| K-P | 16.080 | | | | | 15.111 | | | | | 10.572 | | | | |
| W-H | 9.256*** | | | | | 9.695*** | | | | | 6.597** | | | | |
| I-RD | | 0.725*** | 0.701*** | 0.712*** | 0.709*** | | 0.553** | 0.544** | 0.539** | 0.552** | | 0.447* | 0.440* | 0.452** | 0.429* |

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

## Table 11 / Instrumental variable results for endogenous migration: total economy and manufacturing

| | 3-year differences (D3) | | | | | 4-year differences (D4) | | | | | 5-year differences (D5) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
| | total | manag | clerk | craft | manual | total | manag | clerk | craft | manual | total | manag | clerk | craft | manual |
| **Total economy** | | | | | | | | | | | | | | | |
| IT | -0.443 | 0.845 | 0.648 | -0.335 | -0.969 | -0.191 | 0.488 | 1.684 | -0.312 | -1.571 | 0.332 | 1.789 | 1.303 | -0.795* | 0.255 |
| | (-1.581) | (0.589) | (0.155) | (-1.267) | (-1.113) | (-0.910) | (0.642) | (0.127) | (-1.456) | (-0.646) | (0.699) | (0.370) | (0.454) | (-1.818) | (0.429) |
| Obs. | 779 | 777 | 777 | 777 | 777 | 692 | 690 | 690 | 690 | 690 | 606 | 604 | 604 | 604 | 604 |
| R² | 0.209 | | | | | 0.249 | | | | | -0.231 | | | | |
| Underid. | 4.389** | | | | | 7.066*** | | | | | 2.818* | | | | |
| K-P | 4.401 | | | | | 7.023 | | | | | 2.504 | | | | |
| W-H | 0.278 | | | | | 0.048 | | | | | 1.918 | | | | |
| I-MS | | 1.139 | -0.434 | 1.399 | -0.869 | | 1.573 | -0.527 | 1.393 | -0.485 | | 1.098 | -1.292 | 0.491 | 0.976 |
| **Manufacturing** | | | | | | | | | | | | | | | |
| MS | -0.486 | 1.195 | -0.189 | -0.642*** | 0.510 | 0.145 | 2.087 | -0.087 | -0.628** | -0.566 | 0.273 | -65.959 | -0.128 | -0.655 | -0.709** |
| | (-1.128) | (0.567) | (-0.438) | (-2.596) | (0.302) | (0.314) | (0.481) | (-0.184) | (-2.067) | (-0.212) | (0.716) | (-0.018) | (-0.276) | (-1.586) | (-2.018) |
| Obs. | 403 | 285 | 285 | 285 | 285 | 358 | 244 | 244 | 244 | 244 | 313 | 206 | 206 | 206 | 206 |
| R² | 0.593 | | | | | 0.513 | | | | | 0.401 | | | | |
| Underid. | 1.671 | | | | | 1.187 | | | | | 2.244 | | | | |
| K-P | 1.552 | | | | | 1.102 | | | | | 2.175 | | | | |
| W-H | 0.551 | | | | | 0.862 | | | | | 2.471 | | | | |
| I-MS | | 0.762 | -1.628 | 3.746*** | -0.696 | | 0.764 | -1.561 | 3.028*** | 0.331 | | -0.021 | -1.631 | 2.162* | 2.257* |

Note: All variables are in logs. Standard errors clustered at the country-industry level. Robust t-statistics in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$. All regressions also include the usual controls (i.e. the wage rate, the price of materials, real gross output, import penetration, total offshoring, the migrant share and the native labour force, by highest level of educational attainment) as well as a constant. MS refers to the migrant share. Underid. refers to the underidentification test, K-P to the Kleinbergen-Paap rk Wald F statistic and W-H to the Wu-Hausman test. In the first stage regression, a shift-share instrument based on the augmented composition of migrants from four different regions of origin (EU15, EU13, other developed, and rest of the world) are used (see section 2.1 for details). I-MS refers to this instrument.

### 4.5.1. Correlation with exogenous shocks

As concerns offshoring (Table 8), for which we used a shift-share instrument based on the augmented composition of intermediate imports from different developing countries a year prior to our estimation period, we found for both samples (total and manufacturing) that most of the instruments are not relevant, particularly in the longer run.[26]

Concerning technological change (Tables 9 and 10), which we instrumented by averaging the respective variable in other advanced countries (excluding the reporting country), our results were again mixed. We did not find any statistically significant results at the first stage for either of the three ICT asset types, both for total employment and the for the four occupational groups.[27] Conversely, our instrument for robot density turned up highly significant at the first stage. And while it has proven strong in the shorter run (1- to 3-year differences), it turned out weaker in the longer run.[28]

Concerning migration, we also applied a shift-share instrument which was based on the augmented composition of migrants from four different regions of origin (to account for network effects on the decision to migrate) and found mixed results (Table 11):[29] for the total economy, we found relevant instruments at the first stage for total employment, but they were rather weak. However, the occupation-specific instruments were not relevant for the four different occupational groups. For manufacturing, on the other hand, although the instrument was irrelevant for total employment, we found some significant first-stage results for the four different occupational groups, especially for craft workers.

### 4.5.2. Interrelationships

As concerns the potential interactions of all three variables of interest, we use results from the first-stage IV regressions for offshoring, technological change and immigration to draw our inferences. These results are particularly suited as they show the relationship (respective coefficient and its level of significance) between the three key variables (when one endogenous variable is regressed on its instrument(s) plus all other variables), in addition to testing the relevance of the instruments.[30]

Our results show that offshoring and migration were generally unrelated, at conventional levels of statistical relevance, irrespective of sample considered. As for technological change, the results depend on which measure of technological change was used. In the case of the three ICT asset types (IT, CT and DB) which we used for the total sample, we also did not detect any significant relationships with both offshoring and migration. However, there were some issues with offshoring and robot density in the manufacturing sample that we found to be interrelated (while robot density was unrelated to migration). In particular, in the manufacturing sector, robot density and offshoring were negatively related which

[26] We only report the most relevant information here (total offshoring & test statistics). The full results are reported in Table A.10 (total economy) and Table A.11 (manufacturing) in the annex.

[27] For the sake of brevity, we only report the most relevant information here (the three capital asset types & test statistics). The full results are reported in Tables A.12 in the annex.

[28] We only report the most relevant information here (robot density & test statistics). The full results are reported in Tables A.13 in the annex.

[29] We only report the most relevant information here (migration share & test statistics). The full results are reported in Tables A.14 (total economy) and A.15 (manufacturing) in the annex.

[30] Results are not reported here but are available from the authors upon request.

suggests that, possibly in response to increasing labour costs in offshoring destination countries or the need for shorter/more flexible supply chains, firms find it cheaper to automate particular production processes instead of moving and running part of their production abroad (Carbonero *et al.*, 2018).

# 5. Summary and conclusions

This paper analyses, for the period 2005-2018, the impact of different measures of offshoring, of technological change (specifically digitalisation and robotisation), and of migration on the labour demand of native workers differentiated by occupation groups in a set of five West European economies (Austria, Belgium, France, Spain and Switzerland).

It contributes to the existing literature in different and important ways. First, it analyses the effects of offshoring, technological change and immigration in a joint approach, which allows an assessment of their relative and differentiated impact on employment of native workers. Secondly, it deviates from most of the existing literature and looks at occupational, rather than educational, categories. In particular, it distinguishes four occupation groups: managers/professionals, clerks, craft workers and manual workers. We feel that this approach is more suitable to study the production/jobs-related aspects of the impact of the three 'forces' of structural change on the employment situation of different groups of workers. It allows to identify more directly to which extent offshoring, technological change and migration lead to substitution (i.e. job losses) or to complementarity (i.e. positive employment prospects) for different occupational groups of the native labour force through changing task compositions, task allocations and task specialisation. Thirdly, while the focus of much research in the past has been on manufacturing which was the classic 'open-economy' sector, our analysis widened the range of industries included in the analysis (adding especially a set of services industries); it was thereby important to us to check whether there are important differences in employment impacts in manufacturing industries as compared to this wider set of industries. This is particularly important as services industries are somewhat 'late-comers' in the degree of offshoring but were catching-up fast, and also the characteristics of technological change and its impact on employment might be quite different between these two sets of industries. Fourthly, we checked on different types of 'decompositions': one was to differentiate between offshoring to different regions of destination (other advanced economies, EU13, and developing countries), as well as between 'narrow' and 'broad' offshoring; the other decomposition refers to looking at migrant share effects differentiated by whether migrants come from high-income countries or from low- to medium-income countries (the second group of countries including the EU13).

Before summarising some of the main findings of this study, we want to refer the reader back to the methodological section 2.1 and also the discussion at the beginning of section 4.1 that our approach distinguishes between 'structural' impacts (i.e. taking the level of output as given) and 'scale' effects on the employment levels of different occupational groups of native workers. Given the analytical framework we have chosen for this analysis (that of estimating a conditional labour demand equation) we are only able to attribute the 'structural' impacts differentially to the three forces we focus on in this paper (offshoring, technological change and migration) while the 'scale' effect – which is taken into account through our output term – cannot be differentially identified in relation to the three forces. We should keep this in mind in the following discussion of some of our main results.

On offshoring effects: Here we found – for total offshoring and the full range of industries – a significant positive (conditional) employment effect on native craft workers implying a benefit of adjusted task specialisation for this skilled group of the native labour force. For manufacturing industries alone our estimates suggested a negative impact on native managers/professionals and – to a lesser degree – on native manual workers which could be seen as the direct substitutive effect of offshoring of parts of the production on these segments of the native labour force.

On the impact of technological change: here we tested for the significance of various parts of ICT technologies across the wider set of industries and found significant positive impacts on employment when equipping workers with additional computer hardware (IT) across all segments of the native labour force except for manual workers, with the strongest effect on craft workers which reveals the complementarity effect of investing in IT. This contrasts strongly with the impact of robotisation in manufacturing industries which turned out to have strongly negative employment implications for all groups of workers and these are strongest for craft workers. Hence robots do substitute this more skilled segment of the work force in manufacturing industries.

On the impact of immigration: Increasing the share of migrants in employment does have significant negative employment implications for the native labour force and this is true across all occupational groups and both across the wider set of industries and in manufacturing industries more narrowly. Hence, we found clear evidence for substitutive effects from hiring migrant workers; the impact was weaker for the group of managers/professionals, the group with the highest level of educational attainment. We should, however, keep in mind that the estimates of migrant share effects – as indeed is also true for the estimations of the impact on offshoring and technological change – track only substitution (or complementarity) effects, i.e. movements along the isoquants, while the productivity and demand effects are controlled for by the additional output variable included in the econometric estimations. The ways how the three different ‘forces’ impact demand are not separately identified by our specification.

The decomposition of the offshoring and migrant share variables revealed also some interesting results. There is an important differentiation regarding offshoring to different destination regions: offshoring to other advanced economies has a significantly positive impact on native craft workers’ employment across the full sample of industries, and – if we consider only manufacturing industries – a significantly negative impact on manual workers, indicating an up-grading process of employment opportunities for native work forces. On the other hand, offshoring to developing countries shows significant negative impacts for specific occupational segments of the native work force (for craft workers and clerks across the wider industry sample, and for clerks and managers/professionals across manufacturing industries). This is evidence of substitutive effects across a range of both blue- and white-collar jobs of offshoring to developing countries. Interesting is also the evidence of some weakly positive (and no negative) employment effects of offshoring to the EU13 (the new Member States of Central-Eastern Europe) for a range of native occupational groups (managers/professionals, clerical staff, manual workers) in manufacturing industries where cross-border production integration was particularly high over the past decades (see e.g. Stehrer & Stoellinger, 2015)

Amongst some of the additional control variable we might want to single out the significant positive impact of our general ‘openness’ variable (IM) on the employment of native craft workers; this is an additional effect after taking account of the industry- (and occupation-) specific offshoring variable. This supports again our hypothesis of a positive impact of increased trade integration especially for the group of craft workers who benefit from task-/job-upgrading across our sample of West European economies. Another interesting result is the impact of one of our 'labour supply' (demographic) variables which shows that an increased supply of a tertiary educated labour force goes along with reduced employment of native craft workers which indicates that such an upgrading of the educational attainment characteristics of the available labour force might generate shortages of craft workers which – given some of the other results obtained in this study – might be of special importance in an age of increased international economic integration.

In our exercise we attempted to deal with manifold issues of endogeneity which we discussed in detail; however, despite our extensive attempts to employ IV estimation procedures we had only very limited success. Our 'successful' IV results suggest that once wage endogeneity is accounted for, the sometimes positive – and unexpected – wage effects found in our analysis (mainly for total employment) may disappear. Furthermore, in the case of robot density, the generally negative employment effects remain. Finally, we detect few interrelationships between the three key forces analysed in our study. The only exception refers to offshoring and robot density in the smaller set of manufacturing industries which are negatively related and suggest that firms may opt for automating particular production processes instead of moving and operating part of their production abroad.

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# Annex

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

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

## Table A.2 / Employment effect (total economy): Total offshoring

| | 1-year differences (D1) | | | | | 2-year differences (D2) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| | total | manag | clerk | craft | manual | total | manag | clerk | craft | manual |
| w | -0.011 | -0.028 | 0.036 | -0.292*** | -0.120 | 0.125 | -0.035 | -0.026 | -0.160 | -0.138 |
| | (-0.106) | (-0.204) | (0.503) | (-2.647) | (-1.111) | (0.862) | (-0.308) | (-0.226) | (-1.290) | (-1.162) |
| p | 0.108 | 0.105 | 0.077 | 0.182 | 0.665** | 0.206 | 0.579*** | 0.142 | 0.122 | 0.666* |
| | (0.542) | (0.310) | (0.219) | (0.747) | (2.274) | (1.144) | (2.936) | (0.574) | (0.702) | (1.949) |
| GO | 0.323** | 0.189 | 0.307 | 0.234 | 0.227 | 0.380*** | -0.241 | 0.343 | 0.561*** | 0.123 |
| | (2.578) | (0.551) | (0.636) | (0.895) | (0.633) | (3.317) | (-1.261) | (0.933) | (2.739) | (0.334) |
| IP | 0.410*** | 0.415 | 0.281 | 0.516* | -0.285 | 0.335 | 0.283 | 0.560* | 0.874** | -0.505 |
| | (2.743) | (1.565) | (1.013) | (1.748) | (-0.780) | (1.519) | (0.871) | (1.740) | (2.293) | (-1.009) |
| $IIM^T$ | 0.154* | 0.378*** | -0.079 | 0.094 | 0.198 | 0.036 | -0.040 | 0.069 | 0.147 | -0.084 |
| | (1.679) | (2.787) | (-0.433) | (0.587) | (0.819) | (0.457) | (-0.369) | (0.489) | (0.904) | (-0.451) |
| IT | 0.100* | 0.005 | 0.093 | 0.229*** | 0.127 | 0.085* | 0.059 | 0.170*** | 0.156*** | 0.130 |
| | (1.723) | (0.077) | (1.318) | (3.591) | (1.453) | (1.849) | (0.947) | (3.768) | (2.636) | (1.577) |
| CT | -0.009 | -0.020 | -0.103** | 0.002 | 0.019 | -0.001 | -0.007 | -0.028 | 0.003 | 0.008 |
| | (-0.454) | (-0.505) | (-2.409) | (0.030) | (0.420) | (-0.033) | (-0.178) | (-0.591) | (0.050) | (0.187) |
| DB | 0.175*** | 0.045 | 0.242 | 0.206 | 0.213 | 0.130* | 0.065 | 0.206 | 0.022 | 0.093 |
| | (2.805) | (0.306) | (1.548) | (1.434) | (1.449) | (1.941) | (0.529) | (1.612) | (0.167) | (0.504) |
| MS | -0.260*** | -0.197*** | -0.505*** | -0.256*** | -0.483*** | -0.264*** | -0.210*** | -0.401*** | -0.275*** | -0.465*** |
| | (-6.612) | (-6.331) | (-6.865) | (-6.446) | (-7.502) | (-7.582) | (-8.019) | (-6.434) | (-7.437) | (-6.848) |
| $LF_L$ | 0.253*** | 0.051 | 0.172 | 0.280 | 0.183 | 0.207** | 0.294** | 0.119 | -0.019 | 0.126 |
| | (2.697) | (0.359) | (0.949) | (1.341) | (1.001) | (2.295) | (2.535) | (0.566) | (-0.105) | (0.575) |
| $LF_M$ | -0.004 | 0.038 | -0.102 | 0.026 | -0.776 | 0.019 | 1.014** | 0.950 | -1.355** | -0.641 |
| | (-0.016) | (0.087) | (-0.183) | (0.054) | (-1.505) | (0.061) | (2.263) | (1.413) | (-2.121) | (-0.862) |
| $LF_H$ | 0.341** | 0.665*** | -0.021 | -0.158 | 0.472 | 0.172 | 0.525** | 0.014 | -0.522* | 0.155 |
| | (2.595) | (2.676) | (-0.073) | (-0.575) | (1.366) | (1.276) | (2.225) | (0.059) | (-1.947) | (0.462) |
| Constant | -0.003 | -0.045* | -0.033 | -0.057* | -0.037 | -0.020 | 0.049 | -0.045 | -0.162*** | -0.080 |
| | (-0.256) | (-1.718) | (-1.183) | (-1.740) | (-1.464) | (-0.824) | (1.450) | (-0.741) | (-3.242) | (-1.327) |
| Obs. | 953 | 953 | 953 | 953 | 953 | 866 | 865 | 865 | 865 | 865 |
| $R^2$ | 0.204 | 0.172 | 0.375 | 0.215 | 0.283 | 0.203 | 0.192 | 0.322 | 0.233 | 0.257 |

Note: All variables are in logs. Standard errors clustered at the country-industry level. Robust t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1. w refers to average gross annual wages, p to the price of materials, GO to gross output, IP to import penetration, $IIM^T$ to total offshoring, IT to information technology, CT to communication technology, DB software and database, MS to the migrant share and $LF_L$, $LF_M$ and $LF_H$ to the native labour force (aged 18-45) with low, medium and high level of educational attainment, respectively.

## Table A.3 / Employment effect (manufacturing): Total offshoring

| | 1-year differences (D1) | | | | | 2-year differences (D2) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| | total | manag | clerk | craft | manual | total | manag | clerk | craft | manual |
| w | 0.172** | 0.083 | -0.028 | -0.116 | -0.315* | 0.289** | 0.171 | -0.166 | -0.095 | -0.402* |
| | (2.331) | (0.646) | (-0.422) | (-0.647) | (-1.771) | (2.094) | (1.143) | (-1.468) | (-0.487) | (-1.860) |
| p | 0.363*** | 0.200 | 0.101 | 0.152 | 0.316 | 0.474*** | 0.397* | 0.862** | 0.193 | 0.883** |
| | (3.068) | (0.922) | (0.186) | (0.265) | (0.897) | (2.944) | (1.664) | (2.224) | (0.552) | (2.191) |
| GO | -0.120 | -0.402* | 0.525 | 0.180 | -0.094 | -0.011 | -0.368 | 0.148 | 0.305 | -0.388 |
| | (-0.896) | (-1.866) | (0.847) | (0.295) | (-0.271) | (-0.067) | (-1.597) | (0.299) | (0.829) | (-0.974) |
| IP | 0.322** | 0.521** | -0.473 | 0.550 | 0.440 | 0.443** | 0.514* | -0.498 | 1.213** | -0.195 |
| | (2.636) | (2.536) | (-1.247) | (1.146) | (1.007) | (2.670) | (1.925) | (-1.076) | (2.286) | (-0.297) |
| $IIM^T$ | -0.063 | 0.158 | -0.087 | 0.055 | -0.139 | -0.147** | -0.072 | 0.170 | 0.102 | -0.339* |
| | (-0.729) | (1.448) | (-0.371) | (0.308) | (-0.506) | (-2.091) | (-0.697) | (0.506) | (0.760) | (-1.809) |
| RD | -0.578*** | -0.524*** | -0.517*** | -0.570*** | -0.601*** | -0.545*** | -0.461*** | -0.426*** | -0.563*** | -0.562*** |
| | (-8.306) | (-7.246) | (-5.681) | (-5.521) | (-8.305) | (-9.161) | (-6.888) | (-4.869) | (-6.604) | (-7.487) |
| MS | -0.227*** | -0.173*** | -0.519*** | -0.301*** | -0.328*** | -0.223*** | -0.194*** | -0.386*** | -0.309*** | -0.303*** |
| | (-6.787) | (-6.823) | (-6.012) | (-5.340) | (-5.969) | (-6.755) | (-7.322) | (-4.717) | (-6.812) | (-6.215) |
| $LF_L$ | 0.120 | -0.076 | 0.257 | 0.309 | 0.387 | 0.245** | 0.225 | 0.180 | 0.124 | 0.384 |
| | (1.235) | (-0.382) | (1.385) | (1.215) | (1.369) | (2.689) | (1.393) | (0.791) | (0.625) | (1.325) |
| $LF_M$ | 0.099 | 0.038 | 1.018* | 1.040* | 0.269 | -0.082 | 0.160 | 0.855 | -0.495 | -0.162 |
| | (0.456) | (0.062) | (1.693) | (1.759) | (0.409) | (-0.390) | (0.309) | (1.240) | (-0.842) | (-0.227) |
| $LF_H$ | 0.160 | 0.189 | 0.322 | 0.117 | 0.701* | -0.056 | -0.129 | 0.247 | -0.367 | 0.327 |
| | (0.886) | (0.556) | (1.176) | (0.378) | (1.921) | (-0.382) | (-0.625) | (0.807) | (-1.256) | (1.025) |
| Constant | 0.083*** | -0.006 | 0.044 | -0.006 | 0.026 | 0.133*** | 0.130*** | 0.060 | -0.092** | 0.039 |
| | (7.172) | (-0.173) | (1.537) | (-0.183) | (0.657) | (5.816) | (2.972) | (0.984) | (-2.102) | (0.551) |
| Obs. | 493 | 493 | 493 | 493 | 493 | 448 | 448 | 448 | 448 | 448 |
| $R^2$ | 0.642 | 0.357 | 0.499 | 0.340 | 0.337 | 0.670 | 0.416 | 0.406 | 0.400 | 0.357 |

Note: All variables are in logs. Standard errors clustered at the country-industry level. Robust t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1. w refers to average gross annual wages, p to the price of materials, GO to gross output, IP to import penetration, $IIM^T$ to total offshoring, IT to information technology, CT to communication technology, DB software and database, MS to the migrant share and $LF_L$, $LF_M$ and $LF_H$ to the native labour force (aged 18-45) with low, medium and high level of educational attainment, respectively.

## Table A.4 / Employment effect (total economy): Other offshoring measures

| | 1-year differences (D1) | | | | | 2-year differences (D2) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| | total | manag | clerk | craft | manual | total | manag | clerk | craft | manual |
| **Offshoring to developed countries, NMS13 and developing countries** | | | | | | | | | | |
| $IIM^{Devd}$ | 0.290** | 0.173 | 0.010 | 0.925*** | 0.648** | 0.245 | -0.029 | 0.044 | 1.456*** | 0.284 |
| | (2.245) | (0.859) | (0.040) | (2.904) | (2.212) | (1.505) | (-0.146) | (0.189) | (4.181) | (0.696) |
| $IIM^{NMS13}$ | -0.140* | -0.045 | 0.149 | -0.258*** | -0.103 | -0.093 | 0.036 | 0.336* | -0.609** | 0.050 |
| | (-1.745) | (-0.345) | (0.952) | (-3.055) | (-0.435) | (-0.596) | (0.291) | (1.676) | (-2.469) | (0.183) |
| $IIM^{Devg}$ | -0.054 | 0.077 | -0.300*** | -0.462*** | -0.183 | -0.086 | 0.038 | -0.281*** | -0.623*** | -0.225 |
| | (-0.796) | (0.617) | (-2.885) | (-3.007) | (-1.028) | (-1.072) | (0.333) | (-2.661) | (-3.825) | (-1.299) |
| Obs. | 953 | 953 | 953 | 953 | 953 | 866 | 865 | 865 | 865 | 865 |
| $R^2$ | 0.209 | 0.170 | 0.378 | 0.229 | 0.287 | 0.207 | 0.192 | 0.329 | 0.266 | 0.260 |
| **Narrow and broad offshoring** | | | | | | | | | | |
| $IIM^{N}$ | 0.015 | 0.051 | 0.128 | 0.014 | 0.099 | 0.038 | 0.006 | 0.082 | 0.146** | 0.034 |
| | (0.353) | (0.587) | (1.328) | (0.187) | (0.941) | (0.907) | (0.084) | (1.066) | (2.128) | (0.317) |
| $IIM^{B}$ | 0.214* | 0.434** | -0.116 | 0.266 | 0.356 | 0.050 | 0.002 | -0.001 | 0.010 | 0.256 |
| | (1.970) | (2.475) | (-0.548) | (0.897) | (1.537) | (0.533) | (0.018) | (-0.003) | (0.035) | (1.049) |
| Obs. | 953 | 953 | 953 | 953 | 953 | 866 | 865 | 865 | 865 | 865 |
| $R^2$ | 0.205 | 0.173 | 0.376 | 0.216 | 0.285 | 0.204 | 0.192 | 0.322 | 0.234 | 0.258 |
| **Manufacturing and services offshoring** | | | | | | | | | | |
| $IIM^{M}$ | 0.074 | 0.156 | -0.067 | 0.400 | 0.192 | 0.044 | 0.074 | 0.165 | 0.196 | 0.059 |
| | (0.933) | (1.464) | (-0.481) | (1.251) | (0.902) | (0.609) | (0.900) | (1.186) | (0.662) | (0.234) |
| $IIM^{S}$ | -0.021 | -0.041 | -0.012 | -0.261 | 0.089 | -0.094* | -0.138* | -0.005 | -0.250 | 0.075 |
| | (-0.349) | (-0.424) | (-0.112) | (-1.090) | (0.700) | (-1.671) | (-1.778) | (-0.041) | (-1.001) | (0.499) |
| Obs. | 953 | 953 | 953 | 953 | 953 | 866 | 865 | 865 | 865 | 865 |
| $R^2$ | 0.203 | 0.169 | 0.375 | 0.219 | 0.283 | 0.206 | 0.195 | 0.323 | 0.235 | 0.257 |

Note: All variables are in logs. Standard errors clustered at the country-industry level. Robust t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1. $IIM^{Devd}$ refers to offshoring to developed countries, $IIM^{NMS13}$ to offshoring to EU13 Member States, $IIM^{Devg}$ to offshoring to developing countries; $IIM^{N}$ and $IIM^{B}$ refers to narrow and broad offshoring, respectively and $IIM^{M}$ and $IIM^{S}$ to manufacturing and services offshoring, respectively.

**Table A.5 / Employment effect (manufacturing): Other offshoring measures**

| | 1-year differences (D1) | | | | | 2-year differences (D2) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| | total | manag | clerk | craft | manual | total | manag | clerk | craft | manual |
| **Offshoring to developed countries, NMS13 and developing countries** | | | | | | | | | | |
| $IIM^{Devd}$ | -0.068 | 0.213 | -0.051 | 0.267 | -0.510 | -0.282** | -0.297 | 0.567 | -0.062 | -0.697** |
| | (-0.685) | (0.962) | (-0.137) | (1.206) | (-1.444) | (-2.242) | (-1.349) | (1.280) | (-0.251) | (-2.173) |
| $IIM^{NMS13}$ | 0.137* | 0.091 | 0.271 | -0.053 | 0.324* | 0.282*** | 0.338* | 0.186 | 0.287 | 0.478* |
| | (1.946) | (0.386) | (1.010) | (-0.254) | (1.681) | (2.928) | (1.752) | (0.486) | (1.020) | (1.883) |
| $IIM^{Devg}$ | -0.043 | 0.022 | -0.260** | -0.102 | 0.134 | -0.047 | 0.021 | -0.342*** | -0.085 | -0.008 |
| | (-0.916) | (0.210) | (-2.011) | (-1.064) | (1.138) | (-0.886) | (0.207) | (-2.773) | (-0.879) | (-0.057) |
| Obs. | 493 | 493 | 493 | 493 | 493 | 448 | 448 | 448 | 448 | 448 |
| $R^2$ | 0.643 | 0.359 | 0.503 | 0.341 | 0.340 | 0.675 | 0.421 | 0.417 | 0.402 | 0.361 |
| **Narrow and broad offshoring** | | | | | | | | | | |
| $IIM^{N}$ | -0.052 | 0.121* | -0.038 | -0.051 | -0.073 | -0.089 | -0.063 | 0.300 | 0.071 | -0.237 |
| | (-0.841) | (1.727) | (-0.215) | (-0.384) | (-0.322) | (-1.489) | (-0.660) | (1.080) | (0.688) | (-1.567) |
| $IIM^{B}$ | 0.059 | 0.307 | 0.201 | 0.626 | -0.616* | 0.043 | 0.395 | 0.722 | 0.478 | -0.055 |
| | (0.504) | (1.221) | (0.390) | (1.577) | (-1.650) | (0.227) | (1.524) | (1.249) | (1.223) | (-0.201) |
| Obs. | 493 | 493 | 493 | 493 | 493 | 448 | 448 | 448 | 448 | 448 |
| $R^2$ | 0.642 | 0.359 | 0.499 | 0.344 | 0.340 | 0.670 | 0.420 | 0.412 | 0.401 | 0.357 |
| **Manufacturing and services offshoring** | | | | | | | | | | |
| $IIM^{M}$ | 0.127 | 0.288 | 0.463 | 0.499 | -0.283 | 0.165 | 0.487** | 0.713 | 0.183 | 0.247 |
| | (1.151) | (1.441) | (1.086) | (1.530) | (-1.084) | (1.060) | (2.394) | (1.562) | (0.528) | (0.833) |
| $IIM^{S}$ | -0.123 | -0.123 | 0.030 | -0.122 | -0.348** | -0.163 | -0.165 | 0.269 | -0.044 | -0.204 |
| | (-1.260) | (-0.739) | (0.119) | (-0.417) | (-2.237) | (-1.498) | (-0.995) | (0.937) | (-0.181) | (-0.939) |
| Obs. | 493 | 493 | 493 | 493 | 493 | 448 | 448 | 448 | 448 | 448 |
| $R^2$ | 0.644 | 0.359 | 0.501 | 0.343 | 0.340 | 0.673 | 0.425 | 0.414 | 0.400 | 0.357 |

Note: All variables are in logs. Standard errors clustered at the country-industry level. Robust t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1. $IIM^{Devd}$ refers to offshoring to developed countries, $IIM^{NMS13}$ to offshoring to EU13 Member States, $IIM^{Devg}$ to offshoring to developing countries; $IIM^{N}$ and $IIM^{B}$ refers to narrow and broad offshoring, respectively and $IIM^{M}$ and $IIM^{S}$ to manufacturing and services offshoring, respectively.

## Table A.6 / Employment effect: immigration by country of birth (total economy)

| | 3-year differences (D3) | | | | | 4-year differences (D4) | | | | | 5-year differences (D5) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
| | total | manag | clerk | craft | manual | total | manag | clerk | craft | manual | total | manag | clerk | craft | manual |
| w | -0.081 | -0.047 | 0.120 | -0.188 | -0.265** | 0.086 | 0.085 | 0.112 | -0.042 | -0.216 | 0.126 | 0.001 | 0.172 | -0.022 | -0.214** |
| | (-0.645) | (-0.482) | (1.004) | (-1.152) | (-2.279) | (0.642) | (0.741) | (1.017) | (-0.297) | (-1.556) | (0.992) | (0.007) | (1.409) | (-0.158) | (-2.146) |
| p | 0.363*** | 0.291* | 0.251 | 0.267 | 0.357 | 0.230 | 0.057 | 0.215 | 0.085 | 0.433 | 0.208 | 0.167 | 0.405 | 0.125 | 0.264 |
| | (2.876) | (1.714) | (1.032) | (0.921) | (1.209) | (1.653) | (0.306) | (0.704) | (0.415) | (1.480) | (1.415) | (0.918) | (1.548) | (0.469) | (0.743) |
| GO | 0.403*** | 0.236 | 0.441 | 0.465 | 0.482 | 0.500*** | 0.677*** | 0.443 | 0.889*** | 0.306 | 0.579*** | 0.546*** | -0.085 | 0.949*** | 0.275 |
| | (2.838) | (0.990) | (1.220) | (1.454) | (1.557) | (3.164) | (3.078) | (1.437) | (3.474) | (1.073) | (3.475) | (2.651) | (-0.323) | (3.058) | (0.852) |
| IP | -0.022 | -0.028 | 0.695* | 0.301 | -0.060 | 0.129 | 0.007 | 1.060*** | 0.517 | -0.136 | -0.174 | 0.382 | -0.198 | -1.006** | -0.694 |
| | (-0.111) | (-0.082) | (1.909) | (0.776) | (-0.128) | (0.726) | (0.018) | (2.610) | (1.426) | (-0.290) | (-0.852) | (1.228) | (-0.418) | (-2.338) | (-1.437) |
| $IIM^T$ | 0.086 | 0.004 | 0.117 | 0.390*** | -0.120 | 0.030 | 0.026 | -0.146 | 0.442*** | -0.269* | -0.004 | -0.114 | 0.010 | 0.350** | -0.285 |
| | (1.020) | (0.027) | (0.482) | (2.996) | (-0.733) | (0.318) | (0.159) | (-1.243) | (4.354) | (-1.898) | (-0.045) | (-0.782) | (0.073) | (2.476) | (-1.226) |
| IT | 0.079** | 0.032 | 0.083 | 0.159** | 0.075 | 0.105*** | 0.052 | 0.180*** | 0.216*** | 0.075 | 0.104*** | 0.091* | 0.106** | 0.195*** | 0.040 |
| | (2.220) | (0.613) | (1.168) | (2.524) | (1.137) | (3.152) | (1.022) | (2.740) | (3.612) | (1.194) | (3.456) | (1.832) | (2.256) | (2.741) | (0.622) |
| CT | -0.013 | -0.016 | -0.039 | 0.026 | 0.001 | -0.020 | -0.035 | -0.038 | 0.058 | 0.003 | -0.023 | -0.053 | -0.056 | 0.023 | 0.007 |
| | (-0.408) | (-0.363) | (-0.597) | (0.549) | (0.043) | (-0.620) | (-0.885) | (-0.775) | (1.451) | (0.082) | (-0.784) | (-1.337) | (-0.829) | (0.702) | (0.150) |
| DB | 0.087 | -0.052 | 0.301 | -0.067 | 0.113 | 0.042 | -0.046 | 0.270** | -0.050 | 0.081 | 0.056 | -0.072 | 0.227* | 0.015 | 0.164 |
| | (1.274) | (-0.647) | (1.556) | (-0.635) | (0.984) | (0.644) | (-0.447) | (2.058) | (-0.473) | (0.596) | (0.862) | (-0.740) | (1.903) | (0.128) | (1.163) |
| $MS^{Devd}$ | -0.001 | -0.046 | -0.107*** | -0.080 | -0.119*** | -0.048 | -0.024 | -0.022 | -0.081** | -0.035 | -0.017 | -0.102*** | -0.055 | -0.065 | -0.080* |
| | (-0.026) | (-1.201) | (-2.678) | (-1.619) | (-3.774) | (-0.890) | (-0.642) | (-0.483) | (-2.352) | (-1.024) | (-0.350) | (-2.764) | (-1.275) | (-1.640) | (-1.671) |
| $MS^{Devg}$ | -0.142*** | -0.129*** | -0.276*** | -0.210*** | -0.168*** | -0.096 | -0.161*** | -0.284*** | -0.225*** | -0.248*** | -0.113** | -0.091** | -0.214*** | -0.270*** | -0.204*** |
| | (-3.605) | (-3.619) | (-7.411) | (-4.828) | (-4.169) | (-1.638) | (-4.371) | (-7.692) | (-4.829) | (-4.560) | (-2.015) | (-2.331) | (-4.731) | (-5.426) | (-4.564) |
| LFL | 0.221*** | -0.016 | 0.236 | 0.476** | 0.189 | 0.161* | -0.038 | -0.089 | 0.326* | 0.368* | 0.023 | -0.016 | -0.408 | 0.201 | 0.480* |
| | (2.723) | (-0.104) | (1.602) | (2.146) | (0.799) | (1.702) | (-0.216) | (-0.451) | (1.681) | (1.683) | (0.195) | (-0.085) | (-1.582) | (0.758) | (1.684) |
| LFM | 0.677* | 0.276 | 1.327** | 1.876*** | 0.823 | 0.597 | -0.007 | 1.119* | 1.191 | 1.356* | 0.297 | 0.020 | 0.401 | 0.237 | 0.902 |
| | (1.881) | (0.464) | (2.160) | (2.638) | (1.228) | (1.648) | (-0.013) | (1.859) | (1.435) | (1.863) | (0.763) | (0.034) | (0.482) | (0.274) | (1.077) |
| LFH | 0.358** | 0.251 | 0.173 | 0.183 | 0.294 | 0.377** | 0.340 | 0.095 | -0.363 | 0.586 | 0.346* | 0.447 | -0.156 | -0.045 | -0.023 |
| | (2.165) | (1.171) | (0.623) | (0.727) | (0.807) | (2.133) | (1.387) | (0.336) | (-1.350) | (1.246) | (1.886) | (1.365) | (-0.430) | (-0.157) | (-0.063) |
| Constant | 0.027 | -0.005 | 0.013 | 0.066 | -0.185** | 0.041 | -0.087 | -0.090 | -0.020 | -0.193 | 0.008 | -0.111 | -0.069 | -0.081 | -0.058 |
| | (0.803) | (-0.081) | (0.161) | (0.852) | (-2.187) | (0.881) | (-1.171) | (-1.073) | (-0.188) | (-1.484) | (0.111) | (-1.114) | (-0.563) | (-0.565) | (-0.343) |
| Obs. | 697 | 669 | 669 | 669 | 669 | 613 | 586 | 586 | 586 | 586 | 531 | 506 | 506 | 506 | 506 |
| $R^2$ | 0.196 | 0.182 | 0.449 | 0.321 | 0.272 | 0.234 | 0.215 | 0.430 | 0.433 | 0.248 | 0.217 | 0.258 | 0.371 | 0.411 | 0.270 |

Note: All variables are in logs. Standard errors clustered at the country-industry level. Robust t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1. w refers to average gross annual wages, p to the price of materials, GO to gross output, IP to import penetration, $IIM^T$ to total offshoring, IT to information technology, CT to communication technology, DB software and database, $MS^{Devd}$ and $MS^{Devg}$ to the share of migrants from either developed or developing countries and $LF_L$, $LF_M$ and $LF_H$ to the native labour force (aged 18-45) with low, medium and high level of educational attainment, respectively.

## Table A.7 / Employment effect: immigration by country of birth (manufacturing)

| | 3-year differences (D3) | | | | | 4-year differences (D4) | | | | | 5-year differences (D5) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) total | (2) manag | (3) clerk | (4) craft | (5) manual | (6) total | (7) manag | (8) clerk | (9) craft | (10) manual | (11) total | (12) manag | (13) clerk | (14) craft | (15) manual |
| w | -0.020 | 0.179 | -0.186 | 0.042 | -0.707** | 0.025 | 0.325** | -0.192 | 0.033 | -0.500 | 0.137 | 0.364*** | -0.147 | -0.159 | -0.335 |
| | (-0.146) | (1.027) | (-1.225) | (0.232) | (-2.235) | (0.211) | (2.081) | (-1.383) | (0.154) | (-1.442) | (0.960) | (2.845) | (-1.256) | (-0.564) | (-1.294) |
| p | 0.343** | 0.374 | 1.073*** | 0.207 | 1.036*** | 0.084 | 0.075 | 0.711 | -0.010 | 0.971*** | 0.204 | 0.635* | 1.083* | 0.274 | 0.739*** |
| | (2.054) | (1.547) | (2.653) | (0.495) | (2.708) | (0.460) | (0.233) | (1.249) | (-0.027) | (3.245) | (1.100) | (1.841) | (1.777) | (0.603) | (2.781) |
| GO | 0.153 | -0.293 | 0.100 | 0.041 | -0.561 | 0.487** | 0.341 | 0.640 | 0.716** | -0.671* | 0.431** | -0.043 | -0.218 | 0.699* | -0.535 |
| | (0.965) | (-0.935) | (0.229) | (0.098) | (-1.430) | (2.625) | (1.074) | (0.968) | (2.265) | (-1.929) | (2.157) | (-0.135) | (-0.366) | (1.879) | (-1.483) |
| IP | 0.454* | 0.264 | 0.272 | 1.164** | 0.198 | 0.387* | 0.044 | -0.564 | 0.793 | 0.151 | 0.046 | -0.116 | -1.502 | -0.278 | -0.398 |
| | (1.937) | (0.686) | (0.338) | (2.405) | (0.201) | (1.882) | (0.103) | (-0.530) | (1.484) | (0.153) | (0.241) | (-0.355) | (-1.253) | (-0.531) | (-0.504) |
| $IIM^T$ | -0.116 | -0.124 | 0.283 | 0.228* | -0.386 | -0.179** | -0.384 | -0.130 | 0.228* | -0.443* | -0.312*** | -0.641*** | -0.456 | -0.021 | -0.330* |
| | (-1.520) | (-0.440) | (0.327) | (1.951) | (-1.348) | (-2.178) | (-1.270) | (-0.294) | (1.796) | (-1.679) | (-3.842) | (-3.049) | (-1.248) | (-0.114) | (-1.864) |
| RD | -0.406*** | -0.377*** | -0.416*** | -0.439*** | -0.414*** | -0.380*** | -0.386*** | -0.470*** | -0.324*** | -0.407*** | -0.365*** | -0.345*** | -0.605*** | -0.338*** | -0.354*** |
| | (-8.722) | (-4.543) | (-3.320) | (-6.610) | (-5.667) | (-9.427) | (-6.143) | (-3.611) | (-4.822) | (-5.006) | (-11.200) | (-6.413) | (-4.536) | (-4.324) | (-3.665) |
| $MS^{Devd}$ | 0.039 | -0.019 | -0.108* | -0.065 | -0.055 | 0.033 | -0.012 | -0.140 | -0.042 | 0.017 | 0.048 | -0.121** | -0.214** | -0.041 | -0.058 |
| | (0.884) | (-0.315) | (-1.815) | (-1.339) | (-0.714) | (0.717) | (-0.230) | (-1.315) | (-0.917) | (0.195) | (1.165) | (-1.986) | (-2.564) | (-0.929) | (-0.675) |
| $MS^{Devg}$ | -0.195*** | -0.129** | -0.165*** | -0.157*** | -0.185* | -0.195*** | -0.103* | -0.134** | -0.142** | -0.263** | -0.193*** | 0.020 | -0.070 | -0.171** | -0.191** |
| | (-3.027) | (-2.319) | (-3.865) | (-2.633) | (-1.920) | (-3.112) | (-1.792) | (-2.048) | (-2.140) | (-2.163) | (-3.780) | (0.370) | (-1.101) | (-2.408) | (-2.285) |
| LFL | 0.325** | 0.050 | 0.679** | 0.584** | 0.468 | 0.303** | 0.104 | 0.093 | 0.475** | 0.738** | 0.212 | -0.040 | 0.348 | 0.356 | 0.876*** |
| | (2.468) | (0.192) | (2.163) | (2.304) | (1.325) | (2.101) | (0.393) | (0.227) | (2.325) | (2.113) | (1.421) | (-0.155) | (0.668) | (0.925) | (2.825) |
| LFM | 0.956** | 0.139 | 1.656* | 1.835** | 0.641 | 0.632 | -0.589 | 1.223 | 1.171 | 0.968 | 0.730* | -0.287 | 1.871 | 0.321 | 0.969 |
| | (2.341) | (0.182) | (1.695) | (2.360) | (0.679) | (1.541) | (-0.801) | (0.952) | (1.436) | (0.960) | (1.716) | (-0.326) | (1.146) | (0.271) | (1.065) |
| LFH | 0.161 | -0.055 | -0.263 | 0.209 | 0.469 | 0.078 | -0.150 | -0.047 | -0.267 | 0.965 | -0.277 | -0.659 | -0.925 | -0.167 | 0.310 |
| | (0.884) | (-0.190) | (-0.531) | (0.636) | (1.035) | (0.426) | (-0.552) | (-0.060) | (-0.741) | (1.606) | (-1.383) | (-1.626) | (-1.070) | (-0.396) | (0.711) |
| Constant | 0.200*** | 0.057 | 0.205 | 0.045 | 0.183* | 0.230*** | -0.043 | 0.077 | 0.021 | 0.298* | 0.213*** | -0.016 | 1.866*** | -0.339 | 0.424** |
| | (5.324) | (0.494) | (0.765) | (0.474) | (1.661) | (4.796) | (-0.285) | (0.497) | (0.183) | (1.871) | (3.306) | (-0.064) | (4.453) | (-0.734) | (2.275) |
| Obs. | 364 | 355 | 355 | 355 | 355 | 319 | 310 | 310 | 310 | 310 | 275 | 270 | 270 | 270 | 270 |
| $R^2$ | 0.608 | 0.326 | 0.506 | 0.381 | 0.306 | 0.622 | 0.369 | 0.551 | 0.400 | 0.307 | 0.670 | 0.419 | 0.628 | 0.402 | 0.313 |

Note: All variables are in logs. Standard errors clustered at the country-industry level. Robust t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1. w refers to average gross annual wages, p to the price of materials, GO to gross output, IP to import penetration, $IIM^T$ to total offshoring, RD to robot density, $MS^{Devd}$ and $MS^{Devg}$ to the share of migrants from either developed or developing countries and $LF_L$, $LF_M$ and $LF_H$ to the native labour force (aged 18-45) with low, medium and high level of educational attainment, respectively.

## Table A.8 / Instrumental variable approach for endogenous wages (total economy)

| | 3-year differences (D3) | | | | | 4-year differences (D4) | | | | | 5-year differences (D5) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) total | (2) manag | (3) clerk | (4) craft | (5) manual | (6) total | (7) manag | (8) clerk | (9) craft | (10) manual | (11) total | (12) manag | (13) clerk | (14) craft | (15) manual |
| w | -0.413 | -0.649** | 1.618 | -0.953 | -1.653 | -0.395 | -0.475 | 0.971* | -0.003 | -0.368 | -0.434 | -0.734* | 0.158 | -0.057 | 1.141 |
| | (-1.609) | (-2.308) | (1.246) | (-1.423) | (-0.854) | (-1.392) | (-1.190) | (1.921) | (-0.005) | (-0.315) | (-1.539) | (-1.648) | (0.269) | (-0.087) | (0.660) |
| p | 0.140 | 0.296 | -0.001 | -0.013 | -0.175 | 0.208 | 0.108 | -0.348 | 0.025 | -0.136 | 0.242** | 0.135 | -0.035 | 0.150 | -0.401 |
| | (0.908) | (1.368) | (-0.001) | (-0.050) | (-0.307) | (1.621) | (0.438) | (-0.876) | (0.092) | (-0.379) | (1.983) | (0.418) | (-0.090) | (0.512) | (-0.699) |
| GO | 0.549*** | 0.006 | 0.720 | 1.032*** | 0.831 | 0.479*** | 0.388 | 1.043** | 1.110*** | 0.962*** | 0.455*** | 0.592 | 0.893* | 0.789** | 1.540* |
| | (3.246) | (0.014) | (1.066) | (2.587) | (1.181) | (3.150) | (0.953) | (2.434) | (3.240) | (3.419) | (3.563) | (1.232) | (1.916) | (2.254) | (1.910) |
| IP | 0.303 | -0.578 | 2.346* | 0.961* | -1.013 | 0.176 | -0.859* | 1.763** | 1.420*** | -0.445 | -0.167 | -0.285 | -0.425 | -0.151 | -0.091 |
| | (1.207) | (-1.522) | (1.853) | (1.739) | (-0.927) | (0.775) | (-1.872) | (2.376) | (2.773) | (-0.674) | (-0.742) | (-0.565) | (-0.835) | (-0.389) | (-0.171) |
| $IIM^T$ | 0.045 | -0.062 | -0.224 | 0.387** | -0.461 | 0.045 | 0.032 | -0.212 | 0.305*** | -0.233 | 0.077 | -0.091 | 0.110 | 0.215* | 0.043 |
| | (0.524) | (-0.425) | (-0.498) | (2.001) | (-1.177) | (0.503) | (0.321) | (-0.702) | (2.637) | (-0.908) | (0.819) | (-0.645) | (0.406) | (1.838) | (0.139) |
| IT | 0.107*** | 0.121** | 0.287*** | 0.159** | 0.117 | 0.131*** | 0.156*** | 0.177*** | 0.226*** | 0.082 | 0.129*** | 0.151*** | 0.120* | 0.221*** | 0.080 |
| | (2.752) | (2.504) | (2.913) | (2.381) | (1.236) | (3.612) | (3.114) | (2.915) | (3.826) | (1.266) | (3.464) | (2.950) | (1.801) | (3.320) | (1.172) |
| CT | -0.026 | -0.011 | -0.022 | 0.056 | 0.063 | -0.026 | -0.026 | -0.032 | 0.033 | 0.052 | -0.023 | -0.030 | -0.057 | 0.037 | 0.000 |
| | (-0.936) | (-0.214) | (-0.370) | (1.223) | (1.191) | (-0.930) | (-0.554) | (-0.642) | (0.665) | (0.979) | (-0.886) | (-0.639) | (-1.190) | (1.016) | (0.003) |
| DB | 0.134* | 0.019 | 0.112 | -0.111 | 0.018 | 0.096 | 0.109 | 0.176 | -0.175 | -0.022 | 0.107 | 0.162 | 0.319* | -0.156 | -0.044 |
| | (1.856) | (0.170) | (0.453) | (-0.756) | (0.092) | (1.291) | (0.831) | (0.986) | (-1.369) | (-0.144) | (1.402) | (1.182) | (1.835) | (-1.528) | (-0.326) |
| MS | -0.282*** | -0.160*** | -0.379*** | -0.199*** | -0.289*** | -0.231*** | -0.166*** | -0.345*** | -0.199*** | -0.324*** | -0.220*** | -0.146*** | -0.296*** | -0.211*** | -0.261*** |
| | (-6.110) | (-5.459) | (-3.531) | (-4.584) | (-4.230) | (-5.066) | (-4.407) | (-4.261) | (-6.530) | (-4.838) | (-3.748) | (-3.881) | (-4.410) | (-5.694) | (-5.615) |
| $LF_L$ | 0.084 | 0.014 | -0.045 | 0.297 | -0.221 | 0.221* | 0.001 | -0.128 | 0.027 | 0.182 | 0.164 | -0.028 | -0.394 | 0.050 | 0.303 |
| | (0.831) | (0.076) | (-0.130) | (1.323) | (-0.612) | (1.882) | (0.003) | (-0.510) | (0.092) | (0.617) | (1.127) | (-0.093) | (-1.376) | (0.178) | (0.751) |
| $LF_M$ | -0.897** | 0.145 | 0.783 | 0.697 | -0.225 | -0.211 | 0.077 | 1.511 | 0.534 | 0.760 | -0.218 | -0.227 | 0.372 | 0.820 | 0.164 |
| | (-2.036) | (0.175) | (0.612) | (0.699) | (-0.277) | (-0.511) | (0.079) | (1.471) | (0.496) | (0.791) | (-0.536) | (-0.244) | (0.350) | (0.895) | (0.198) |
| $LF_H$ | -0.217 | 0.057 | 0.419 | -0.482 | -0.391 | -0.001 | 0.319 | 0.526 | -0.265 | 0.379 | 0.006 | 0.099 | -0.078 | -0.516 | 0.394 |
| | (-1.085) | (0.174) | (1.022) | (-0.872) | (-0.593) | (-0.004) | (0.844) | (1.426) | (-0.483) | (0.529) | (0.027) | (0.236) | (-0.208) | (-0.822) | (0.593) |
| Constant | -0.027 | 0.033 | -0.341 | 0.071 | -0.020 | 0.027 | -0.111 | -0.320* | -0.262 | -0.056 | 0.025 | -0.064 | -0.174 | 0.056 | -0.073 |
| | (-0.754) | (0.368) | (-1.505) | (0.471) | (-0.141) | (0.574) | (-0.749) | (-1.794) | (-0.995) | (-0.408) | (0.335) | (-0.288) | (-0.782) | (0.208) | (-0.443) |
| Obs. | 779 | 777 | 777 | 777 | 777 | 692 | 690 | 690 | 690 | 690 | 606 | 604 | 604 | 604 | 604 |
| $R^2$ | 0.167 | | | | | 0.161 | | | | | 0.175 | | | | |
| Underid. | 29.730*** | | | | | 26.340*** | | | | | 24.420*** | | | | |
| K-P | 28.620 | | | | | 32.150 | | | | | 33.800 | | | | |
| Hansen | 0.520 | 1.818 | | | | 1.743 | 0.852 | | | | 1.456 | 3.881 | | | |
| W-H | 6.327** | | | | | 4.927** | | | | | 4.587** | | | | |

Note: All variables are in logs. Standard errors clustered at the country-industry level. Robust t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1. w refers to average gross annual wages, p to the price of materials, GO to gross output, IP to import penetration, $IIM^T$ to total offshoring, IT to information technology, CT to communication technology, DB to software and database, MS to the share of migrants and $LF_L$, $LF_M$ and $LF_H$ to the native labour force (aged 18-45) with low, medium and high level of educational attainment, respectively. Underid. refers to the underidentification test, K-P to the Kleinbergen-Paap rk Wald F statistic, Hansen to the Hansen J-test and W-H to the Wu-Hausman test.

## Table A.9 / Instrumental variable approach for endogenous wages (manufacturing)

| | 3-year differences (D3) | | | | | 4-year differences (D4) | | | | | 5-year differences (D5) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
| | total | manag | clerk | craft | manual | total | manag | clerk | craft | manual | total | manag | clerk | craft | manual |
| w | 0.816 | 0.881 | 0.459 | -2.005** | 3.018 | 0.583 | 0.430 | 0.791 | -2.004*** | 1.472 | -0.181 | 0.103 | 0.892 | -2.431*** | 3.704 |
| | (1.361) | (1.027) | (1.099) | (-2.106) | (1.058) | (0.879) | (0.443) | (0.939) | (-3.082) | (0.726) | (-0.193) | (0.152) | (0.888) | (-3.664) | (1.044) |
| p | 0.471** | 0.820** | 0.558 | 0.991*** | 0.543 | 0.184 | 0.742** | 0.121 | 1.182*** | 0.488 | 0.238 | 1.054*** | 0.572 | 0.842** | -0.636 |
| | (2.446) | (2.269) | (1.141) | (2.983) | (0.736) | (0.900) | (1.984) | (0.234) | (3.029) | (0.787) | (1.301) | (3.160) | (1.224) | (2.101) | (-0.446) |
| GO | 0.157 | -0.321 | 0.138 | -0.078 | 0.360 | 0.374 | -0.416 | 0.680 | -0.268 | 0.179 | 0.325 | -0.492 | 0.292 | 0.171 | 2.059 |
| | (0.760) | (-1.109) | (0.188) | (-0.176) | (0.302) | (1.610) | (-1.219) | (1.257) | (-0.716) | (0.182) | (1.552) | (-1.551) | (0.459) | (0.402) | (0.987) |
| IP | 0.693*** | -1.128** | 1.346* | -0.353 | 1.061 | 0.667** | -1.606*** | 0.849 | -0.629 | 0.145 | 0.118 | -0.863** | -1.047 | -1.695** | 0.859 |
| | (2.782) | (-2.473) | (1.763) | (-0.265) | (0.593) | (2.497) | (-2.728) | (0.649) | (-0.695) | (0.151) | (0.506) | (-2.064) | (-1.031) | (-2.082) | (0.507) |
| $IIM^T$ | -0.148 | -0.101 | -0.073 | 0.284 | 0.366 | -0.276** | -0.216 | -0.188 | 0.175 | -0.085 | -0.391*** | -0.509*** | -0.204 | -0.240* | 0.412 |
| | (-1.520) | (-0.717) | (-0.164) | (1.330) | (0.436) | (-2.556) | (-1.240) | (-0.355) | (1.117) | (-0.159) | (-3.702) | (-3.590) | (-0.407) | (-1.673) | (0.678) |
| RD | -0.505*** | -0.260*** | -0.284*** | -0.228* | -0.386*** | -0.502*** | -0.318*** | -0.207 | -0.231* | -0.287*** | -0.453*** | -0.288*** | -0.274 | -0.259*** | -0.093 |
| | (-10.597) | (-3.660) | (-2.590) | (-1.947) | (-4.241) | (-10.952) | (-3.745) | (-1.267) | (-1.951) | (-5.913) | (-10.473) | (-3.213) | (-1.549) | (-2.921) | (-0.621) |
| MS | -0.228*** | -0.165*** | -0.437*** | -0.191** | -0.323** | -0.212*** | -0.169*** | -0.488*** | -0.156** | -0.307*** | -0.157*** | -0.146*** | -0.481*** | -0.042 | -0.240*** |
| | (-5.325) | (-4.276) | (-4.251) | (-2.447) | (-2.104) | (-4.843) | (-3.699) | (-5.440) | (-2.431) | (-3.218) | (-3.099) | (-3.002) | (-7.087) | (-0.526) | (-2.911) |
| $LF_L$ | 0.397*** | -0.114 | -0.012 | 0.421 | 0.898 | 0.522*** | 0.043 | -0.305 | 0.565** | 0.954* | 0.477*** | -0.295 | -0.811*** | 0.448 | 0.804 |
| | (2.969) | (-0.702) | (-0.046) | (1.177) | (1.118) | (3.380) | (0.210) | (-1.093) | (2.052) | (1.827) | (3.042) | (-1.266) | (-2.839) | (1.069) | (0.798) |
| $LF_M$ | 0.054 | -0.508 | 0.729 | 1.663* | 2.259 | 0.113 | -0.152 | 1.409 | 2.674*** | 1.673 | 0.346 | -0.652 | -0.833 | 1.243 | 0.774 |
| | (0.152) | (-0.499) | (0.472) | (1.703) | (1.099) | (0.297) | (-0.158) | (0.860) | (3.011) | (1.116) | (0.699) | (-0.776) | (-0.527) | (1.170) | (0.455) |
| $LF_H$ | 0.045 | 0.122 | 0.365 | -0.179 | 1.381 | -0.068 | 0.269 | 0.539 | -0.206 | 1.589** | -0.524* | -0.262 | -0.516 | -0.692 | 1.546 |
| | (0.172) | (0.412) | (1.023) | (-0.344) | (1.415) | (-0.333) | (0.927) | (1.074) | (-0.429) | (2.203) | (-1.872) | (-0.744) | (-0.936) | (-0.967) | (1.273) |
| Constant | 0.138** | 0.006 | -0.017 | 0.283*** | 0.113 | 0.239*** | 0.180 | -0.044 | 0.484*** | 0.264 | 0.343*** | 0.116 | -0.273 | 0.670*** | -0.184 |
| | (2.175) | (0.048) | (-0.177) | (3.157) | (0.488) | (2.671) | (0.788) | (-0.198) | (5.469) | (1.052) | (2.703) | (0.608) | (-1.002) | (4.789) | (-0.480) |
| Obs. | 403 | 403 | 403 | 403 | 403 | 358 | 358 | 358 | 358 | 358 | 313 | 313 | 313 | 313 | 313 |
| $R^2$ | 0.672 | | | | | 0.681 | | | | | 0.659 | | | | |
| Underid. | 17.880*** | | | | | 13.410*** | | | | | 7.899** | | | | |
| K-P | 9.230 | | | | | 7.845 | | | | | 4.750 | | | | |
| Hansen | 1.101 | 3.737 | | | | 0.798 | 6.311 | | | | 0.132 | 3.860 | | | |
| W-H | 0.411 | | | | | 0.091 | | | | | 0.225 | | | | |

Note: All variables are in logs. Standard errors clustered at the country-industry level. Robust t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1. w refers to average gross annual wages, p to the price of materials, GO to gross output, IP to import penetration, $IIM^T$ to total offshoring, RD to robot density, MS to the share of migrants and $LF_L$, $LF_M$ and $LF_H$ to the native labour force (aged 18-45) with low, medium and high level of educational attainment, respectively. Underid. refers to the underidentification test, K-P to the Kleinbergen-Paap rk Wald F statistic, Hansen to the Hansen J-test and W-H to the Wu-Hausman test.

**Table A.10 / Instrumental variable approach for endogenous offshoring (total economy)**

| | 3-year differences (D3) | | | | | 4-year differences (D4) | | | | | 5-year differences (D5) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
| | total | manag | clerk | craft | manual | total | manag | clerk | craft | manual | total | manag | clerk | craft | manual |
| w | 0.266 | -0.013 | -0.304 | -0.540* | -0.486** | 0.359 | 0.264 | -0.952 | -0.180 | -0.337 | 1.073 | 0.050 | 0.805 | -0.635 | 0.073 |
| | (1.643) | (-0.101) | (-0.841) | (-1.882) | (-2.016) | (0.717) | (0.393) | (-0.554) | (-0.327) | (-0.576) | (0.125) | (0.247) | (0.852) | (-1.081) | (0.276) |
| p | -0.292 | -0.012 | -1.453 | -2.251 | 0.171 | -1.941 | -0.656 | -2.178 | -2.722 | -0.158 | 16.477 | -0.042 | 0.661 | 0.682 | -0.391 |
| | (-0.662) | (-0.025) | (-1.012) | (-1.325) | (0.231) | (-0.613) | (-0.414) | (-0.698) | (-0.601) | (-0.131) | (0.108) | (-0.109) | (0.201) | (0.208) | (-0.512) |
| GO | 0.950*** | 0.427 | 2.515 | 3.650* | 0.685 | 2.170 | 1.557 | 3.484 | 4.529 | 1.012 | -14.671 | 0.773 | -2.065 | -1.924 | 1.660* |
| | (2.675) | (0.693) | (1.619) | (1.924) | (0.743) | (0.920) | (0.666) | (0.962) | (0.875) | (0.596) | (-0.102) | (0.963) | (-0.387) | (-0.374) | (1.708) |
| IP | -0.178 | -0.466 | -2.702 | -4.080 | 0.296 | -4.449 | -4.436 | -8.983 | -13.826 | -0.016 | 29.906 | 0.525 | 8.094 | 8.495 | -1.347 |
| | (-0.273) | (-0.438) | (-0.906) | (-1.233) | (0.206) | (-0.661) | (-0.470) | (-0.623) | (-0.687) | (-0.002) | (0.106) | (0.329) | (0.707) | (0.759) | (-0.739) |
| $IIM^T$ | 1.928 | 0.418 | 8.935 | 13.128* | -2.147 | 9.640 | 6.109 | 15.462 | 25.218 | -0.848 | -66.778 | -0.697 | -14.250 | -15.243 | 1.797 |
| | (1.062) | (0.144) | (1.306) | (1.785) | (-0.528) | (0.728) | (0.398) | (0.714) | (0.794) | (-0.071) | (-0.106) | (-0.244) | (-0.674) | (-0.716) | (0.521) |
| IT | 0.068 | 0.104 | 0.026 | -0.094 | 0.138 | -0.141 | -0.027 | -0.170 | -0.210 | 0.092 | 1.989 | 0.115 | 0.325 | 0.361 | 0.041 |
| | (1.164) | (1.286) | (0.100) | (-0.299) | (1.195) | (-0.314) | (-0.059) | (-0.254) | (-0.246) | (0.408) | (0.116) | (1.585) | (0.747) | (0.899) | (0.456) |
| CT | -0.021 | -0.012 | 0.015 | 0.129 | 0.024 | 0.003 | 0.028 | 0.096 | 0.265 | 0.042 | 0.071 | -0.052 | -0.138 | -0.024 | 0.044 |
| | (-0.716) | (-0.215) | (0.151) | (0.950) | (0.491) | (0.035) | (0.146) | (0.360) | (0.636) | (0.387) | (0.069) | (-1.167) | (-0.607) | (-0.116) | (0.704) |
| DB | 0.226* | 0.014 | 0.407 | 0.037 | -0.037 | 0.693 | 0.077 | 0.444 | 0.062 | -0.014 | -5.028 | 0.156 | 0.113 | -0.410 | -0.025 |
| | (1.917) | (0.137) | (1.234) | (0.080) | (-0.221) | (0.655) | (0.237) | (0.574) | (0.054) | (-0.081) | (-0.106) | (1.219) | (0.150) | (-0.528) | (-0.135) |
| MS | -0.279*** | -0.145*** | -0.280* | -0.223** | -0.322*** | -0.228 | 0.006 | -0.325 | -0.400 | -0.318** | 0.520 | -0.145** | -0.246 | 0.066 | -0.314*** |
| | (-5.741) | (-2.701) | (-1.830) | (-2.555) | (-5.980) | (-1.563) | (0.013) | (-1.240) | (-0.969) | (-1.979) | (0.076) | (-2.563) | (-1.002) | (0.229) | (-3.041) |
| $LF_L$ | -0.029 | -0.052 | -0.001 | -0.070 | 0.032 | -0.233 | -0.162 | 0.415 | 0.777 | 0.227 | 1.410 | -0.291 | -0.521 | -0.051 | 0.187 |
| | (-0.194) | (-0.408) | (-0.003) | (-0.128) | (0.156) | (-0.222) | (-0.471) | (0.421) | (0.490) | (0.494) | (0.123) | (-1.220) | (-0.563) | (-0.051) | (0.742) |
| $LF_M$ | -1.316** | -0.044 | 0.502 | -0.839 | -0.407 | -2.025 | 0.190 | 3.886 | 3.284 | 0.489 | 19.254 | -0.476 | 2.738 | 3.594 | -0.327 |
| | (-1.994) | (-0.067) | (0.271) | (-0.331) | (-0.585) | (-0.477) | (0.083) | (0.648) | (0.364) | (0.273) | (0.107) | (-0.437) | (0.590) | (0.701) | (-0.291) |
| $LF_H$ | 0.034 | 0.170 | 0.243 | -0.487 | -0.113 | 1.007 | 0.994 | 1.742 | 1.856 | 0.249 | -8.621 | 0.342 | -1.200 | -2.361 | 0.221 |
| | (0.193) | (0.623) | (0.355) | (-0.487) | (-0.294) | (0.964) | (0.693) | (0.884) | (0.630) | (0.158) | (-0.103) | (0.747) | (-0.522) | (-0.884) | (0.344) |
| Constant | -0.167* | -0.016 | -0.520 | -0.582 | 0.101 | -0.540 | -0.516 | -0.848 | -1.463 | 0.103 | 3.886 | -0.140 | 1.481 | 2.313 | -0.167 |
| | (-1.731) | (-0.100) | (-1.221) | (-1.233) | (0.435) | (-0.685) | (-0.517) | (-0.669) | (-0.675) | (0.138) | (0.105) | (-0.334) | (0.577) | (0.818) | (-0.329) |
| Obs | 779 | 777 | 777 | 777 | 777 | 692 | 690 | 690 | 690 | 690 | 606 | 604 | 604 | 604 | 604 |
| $R^2$ | 0.101 | | | | | 0.044 | | | | | 0.246 | | | | |
| Underid. | 3.234* | | | | | 0.554 | | | | | 0.011 | | | | |
| K-P | 3.160 | | | | | 0.535 | | | | | 0.011 | | | | |
| W-H | 1.479 | | | | | 8.622*** | | | | | 7.264*** | | | | |

Note: All variables are in logs. Standard errors clustered at the country-industry level. Robust t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1. w refers to average gross annual wages, p to the price of materials, GO to gross output, IP to import penetration, $IIM^T$ to total offshoring, IT to information technology, CT to communication technology, DB to software and database, MS to the share of migrants and $LF_L$, $LF_M$ and $LF_H$ to the native labour force (aged 18-45) with low, medium and high level of educational attainment, respectively. Underid. refers to the underidentification test, K-P to the Kleinbergen-Paap rk Wald F statistic, Hansen to the Hansen J-test and W-H to the Wu-Hausman test.

## Table A.11 / Instrumental variable approach for endogenous offshoring (manufacturing)

| | 3-year differences (D3) | | | | | 4-year differences (D4) | | | | | 5-year differences (D5) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
| | **total** | **manag** | **clerk** | **craft** | **manual** | **total** | **manag** | **clerk** | **craft** | **manual** | **total** | **manag** | **clerk** | **craft** | **manual** |
| w | 0.349* | 0.085 | -0.180 | -0.116 | -0.809* | 0.446** | 0.025 | -0.769 | -0.080 | -0.574 | 1.237 | 0.151 | 0.253 | -0.272 | -0.221 |
| | (1.897) | (0.586) | (-0.658) | (-0.697) | (-1.663) | (2.473) | (0.091) | (-0.432) | (-0.192) | (-0.376) | (0.160) | (1.048) | (0.451) | (-0.578) | (-0.713) |
| p | 1.047** | 0.352 | -0.361 | 0.239 | 1.634 | -0.017 | -0.064 | -3.908 | -2.599 | 0.719 | -10.480 | 0.018 | 4.281 | 3.035 | 0.383 |
| | (2.537) | (0.719) | (-0.336) | (0.419) | (1.164) | (-0.022) | (-0.053) | (-0.510) | (-0.509) | (0.149) | (-0.111) | (0.014) | (0.444) | (0.381) | (0.360) |
| GO | -0.542 | -0.146 | 1.425 | 0.329 | -1.330 | 0.583 | 0.390 | 5.647 | 4.077 | -0.582 | 12.773 | 0.703 | -5.230 | -4.346 | 0.164 |
| | (-1.194) | (-0.252) | (1.075) | (0.437) | (-0.731) | (0.639) | (0.218) | (0.563) | (0.561) | (-0.084) | (0.116) | (0.367) | (-0.412) | (-0.398) | (0.095) |
| IP | 1.258** | 0.569 | -2.167 | 1.234 | 1.063 | 0.521 | 0.017 | -6.933 | -3.998 | 0.324 | -3.852 | 0.031 | 0.692 | 2.805 | -0.360 |
| | (2.398) | (0.636) | (-1.072) | (1.312) | (0.384) | (0.962) | (0.007) | (-0.489) | (-0.352) | (0.034) | (-0.104) | (0.033) | (0.154) | (0.635) | (-0.414) |
| $IIM^T$ | -2.185 | -1.830 | 5.545 | 1.248 | -5.102 | 0.287 | -0.501 | 4.200 | 2.589 | -1.415 | 2.318 | 0.299 | -1.857 | -9.968 | 0.669 |
| | (-1.467) | (-0.774) | (1.306) | (0.554) | (-0.720) | (0.128) | (-0.092) | (0.529) | (0.538) | (-0.066) | (0.113) | (0.086) | (-0.446) | (-0.413) | (0.215) |
| RD | -0.556*** | -0.344*** | -0.219 | -0.420*** | -0.544** | -0.479*** | -0.333 | 0.472 | 0.344 | -0.484 | 0.880 | -0.278 | -1.205 | -1.052 | -0.303 |
| | (-10.449) | (-4.825) | (-1.005) | (-4.188) | (-2.210) | (-4.039) | (-0.952) | (0.234) | (0.194) | (-0.390) | (0.071) | (-1.126) | (-0.900) | (-0.772) | (-1.540) |
| MS | -0.240*** | -0.205*** | -0.441*** | -0.261*** | -0.344*** | -0.210*** | -0.198 | -0.491* | -0.396 | -0.305 | -0.422 | -0.146* | -0.313 | 0.062 | -0.327** |
| | (-5.473) | (-3.530) | (-3.537) | (-4.972) | (-3.861) | (-4.474) | (-1.130) | (-1.719) | (-0.946) | (-0.591) | (-0.162) | (-1.817) | (-1.438) | (0.117) | (-2.259) |
| $LF_L$ | 0.441*** | 0.023 | 0.197 | 0.434** | 0.338 | 0.510*** | 0.088 | -0.651 | -0.290 | 0.738 | 0.058 | -0.132 | 0.465 | 0.657 | 0.615* |
| | (2.674) | (0.108) | (0.722) | (2.327) | (0.970) | (3.242) | (0.203) | (-0.427) | (-0.202) | (0.962) | (0.015) | (-0.408) | (0.457) | (0.537) | (1.849) |
| $LF_M$ | 0.200 | -0.844 | 2.048 | 1.421* | -0.508 | 0.076 | -0.634 | 4.462 | 3.043 | 0.501 | -3.350 | -0.515 | 0.709 | 1.023 | 0.551 |
| | (0.387) | (-0.818) | (1.351) | (1.802) | (-0.285) | (0.217) | (-0.574) | (0.571) | (0.477) | (0.117) | (-0.100) | (-0.603) | (0.242) | (0.393) | (0.580) |
| $LF_H$ | -0.072 | 0.032 | 0.577 | 0.024 | 0.195 | -0.073 | 0.154 | 2.071 | 1.345 | 0.836 | 2.514 | 0.026 | -2.930 | -2.488 | 1.000 |
| | (-0.319) | (0.133) | (1.019) | (0.071) | (0.307) | (-0.347) | (0.233) | (0.657) | (0.529) | (0.265) | (0.097) | (0.025) | (-0.505) | (-0.516) | (1.115) |
| Constant | 0.271*** | 0.201 | -0.174 | 0.193 | 0.314 | 0.220 | 0.051 | -0.997 | -0.957 | 0.326 | -1.922 | 0.203 | 1.587 | 2.357 | 0.277 |
| | (3.582) | (1.291) | (-0.658) | (0.855) | (0.869) | (1.257) | (0.088) | (-0.445) | (-0.428) | (0.159) | (-0.098) | (0.428) | (0.451) | (0.699) | (0.498) |
| Obs | 403 | 285 | 285 | 285 | 285 | 358 | 244 | 244 | 244 | 244 | 313 | 206 | 206 | 206 | 206 |
| $R^2$ | 0.392 | | | | | 0.655 | | | | | 0.184 | | | | |
| Underid. | 6.784*** | | | | | 1.551 | | | | | 0.013 | | | | |
| K-P | 7.844 | | | | | 1.683 | | | | | 0.012 | | | | |
| W-H | 3.292* | | | | | 0.061 | | | | | 2.152 | | | | |

Note: All variables are in logs. Standard errors clustered at the country-industry level. Robust t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1. w refers to average gross annual wages, p to the price of materials, GO to gross output, IP to import penetration, $IIM^T$ to total offshoring, RD to robot density, MS to the share of migrants and $LF_L$, $LF_M$ and $LF_H$ to the native labour force (aged 18-45) with low, medium and high level of educational attainment, respectively. Underid. refers to the underidentification test, K-P to the Kleinbergen-Paap rk Wald F statistic, Hansen to the Hansen J-test and W-H to the Wu-Hausman test.

## Table A.12 / Instrumental variable approach for endogenous capital asset types (total economy)

| | 3-year differences (D3) | | | | | 4-year differences (D4) | | | | | 5-year differences (D5) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
| | total | manag | clerk | craft | manual | total | manag | clerk | craft | manual | total | manag | clerk | craft | manual |
| w | -0.297 | 0.150 | 0.064 | -0.830 | -0.045 | 0.077 | 0.194 | 0.124 | -0.380 | -0.265 | -0.636 | -0.094 | -0.646 | -0.246 | -0.461 |
| | (-0.013) | (0.214) | (0.413) | (-0.661) | (-0.038) | (0.051) | (0.416) | (0.284) | (-1.309) | (-0.840) | (-0.048) | (-0.029) | (-0.179) | (-1.351) | (-0.125) |
| p | -2.561 | -1.606 | 0.305 | 0.690 | -0.501 | 2.979 | -0.436 | -0.021 | 0.328 | 0.299 | 7.819 | -4.448 | -2.750 | 0.364 | -4.884 |
| | (-0.020) | (-0.318) | (0.193) | (0.209) | (-0.152) | (0.093) | (-0.262) | (-0.020) | (0.326) | (0.143) | (0.051) | (-0.156) | (-0.196) | (0.209) | (-0.126) |
| GO | 0.077 | 3.874 | 0.481 | -1.200 | 2.940 | 1.918 | 2.295 | 1.410 | 0.360 | 1.930 | 4.193 | 0.811 | 0.841 | 0.517 | 0.426 |
| | (0.003) | (0.382) | (0.150) | (-0.184) | (0.387) | (0.147) | (0.808) | (0.708) | (0.250) | (0.633) | (0.061) | (0.091) | (0.220) | (0.670) | (0.048) |
| IP | -2.452 | -4.012 | 0.961 | 3.184 | -2.024 | -4.609 | -1.133 | 1.400 | 1.640** | -0.153 | -12.831 | 6.434 | 3.895 | 0.030 | 7.139 |
| | (-0.034) | (-0.433) | (0.324) | (0.595) | (-0.304) | (-0.152) | (-0.880) | (1.163) | (2.110) | (-0.107) | (-0.055) | (0.134) | (0.182) | (0.011) | (0.115) |
| $IIM^T$ | 3.503 | -0.616 | -0.183 | 0.797 | -0.546 | -0.510 | -0.122 | -0.178 | 0.326 | -0.380 | 1.131 | 0.288 | 0.400 | 0.170 | 0.311 |
| | (0.023) | (-0.406) | (-0.395) | (0.753) | (-0.508) | (-0.037) | (-0.200) | (-0.432) | (1.359) | (-0.552) | (0.134) | (0.100) | (0.180) | (0.400) | (0.071) |
| IT | -3.864 | -0.206 | 1.117 | 0.412 | 0.093 | 0.298 | 0.275 | 0.849 | 0.562 | 0.455 | -4.026 | -1.802 | 0.147 | 0.813 | -2.016 |
| | (-0.021) | (-0.068) | (1.134) | (0.194) | (0.043) | (0.032) | (0.192) | (0.859) | (0.631) | (0.280) | (-0.061) | (-0.170) | (0.033) | (0.642) | (-0.120) |
| CT | -0.205 | -2.883 | -0.419 | 1.637 | -1.264 | -4.466 | -0.914 | -0.235 | 0.375 | -0.249 | -8.860 | -0.348 | -0.189 | 0.272 | 0.084 |
| | (-0.004) | (-0.448) | (-0.203) | (0.416) | (-0.250) | (-0.118) | (-1.136) | (-0.406) | (0.956) | (-0.266) | (-0.054) | (-0.150) | (-0.162) | (1.412) | (0.035) |
| DB | 16.111 | -4.094 | -0.788 | 4.613 | -5.366 | -0.919 | -3.315 | -2.599 | 0.742 | -5.134 | -0.453 | 17.492 | 10.946 | -0.784 | 19.931 |
| | (0.024) | (-0.273) | (-0.161) | (0.397) | (-0.400) | (-0.019) | (-0.312) | (-0.327) | (0.161) | (-0.413) | (-0.006) | (0.141) | (0.196) | (-0.104) | (0.121) |
| MS | -0.775 | -0.132 | -0.272*** | -0.268 | -0.349* | -0.456 | -0.105 | -0.346* | -0.221 | -0.326** | -0.171 | -0.409 | -0.143 | -0.202 | -0.165 |
| | (-0.047) | (-0.398) | (-3.498) | (-1.269) | (-1.806) | (-0.495) | (-0.400) | (-1.782) | (-1.612) | (-2.494) | (-0.033) | (-0.185) | (-0.208) | (-1.037) | (-0.204) |
| $LF_L$ | -3.077 | -1.421 | 0.050 | 0.631 | 0.007 | -1.554 | 0.460 | 0.792 | 0.091 | 1.730 | -1.105 | -5.752 | -3.429 | 0.560 | -6.128 |
| | (-0.032) | (-0.518) | (0.058) | (0.443) | (0.004) | (-0.248) | (0.157) | (0.334) | (0.069) | (0.461) | (-0.093) | (-0.160) | (-0.209) | (0.232) | (-0.120) |
| $LF_M$ | -11.230 | -9.150 | 0.415 | 3.848 | -2.344 | -17.220 | -0.778 | 3.852 | 1.019 | 4.946 | -25.526 | -18.144 | -9.884 | 2.322 | -18.379 |
| | (-0.043) | (-0.484) | (0.069) | (0.375) | (-0.165) | (-0.162) | (-0.079) | (0.484) | (0.215) | (0.395) | (-0.065) | (-0.164) | (-0.190) | (0.329) | (-0.122) |
| $LF_H$ | 2.392 | -0.081 | -0.009 | -0.279 | -0.311 | -0.229 | 0.423 | 0.057 | -0.717 | 0.057 | 11.174 | 4.928 | 2.103 | -1.272 | 4.331 |
| | (0.020) | (-0.055) | (-0.019) | (-0.195) | (-0.250) | (-0.022) | (0.356) | (0.062) | (-1.130) | (0.039) | (0.058) | (0.192) | (0.191) | (-0.782) | (0.128) |
| Constant | -2.570 | 0.403 | -0.139 | -0.489 | 0.621 | 1.829 | 0.457 | 0.299 | -0.230 | 1.084 | 5.882 | -5.416 | -3.722 | 0.351 | -5.812 |
| | (-0.021) | (0.215) | (-0.212) | (-0.341) | (0.393) | (0.073) | (0.217) | (0.178) | (-0.267) | (0.425) | (0.045) | (-0.146) | (-0.211) | (0.164) | (-0.118) |
| Obs | 779 | 777 | 777 | 777 | 777 | 692 | 690 | 690 | 690 | 690 | 606 | 604 | 604 | 604 | 604 |
| $R^2$ | 0.573 | | | | | 0.730 | | | | | 0.680 | | | | |
| Underid. | 0.001 | | | | | 0.012 | | | | | 0.003 | | | | |
| K-P | 0.001 | | | | | 0.004 | | | | | 0.001 | | | | |
| W-H | 6.083 | | | | | 7.626* | | | | | 9.148** | | | | |

Note: All variables are in logs. Standard errors clustered at the country-industry level. Robust t-statistics in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$. w refers to average gross annual wages, p to the price of materials, GO to gross output, IP to import penetration, $IIM^T$ to total offshoring, IT to information technology, CT to communication technology, DB to software and database, MS to the share of migrants and $LF_L$, $LF_M$ and $LF_H$ to the native labour force (aged 18-45) with low, medium and high level of educational attainment, respectively. Underid. refers to the underidentification test, K-P to the Kleinbergen-Paap rk Wald F statistic, Hansen to the Hansen J-test and W-H to the Wu-Hausman test.

## Table A.13 / Instrumental variable approach for endogenous robot density (manufacturing)

| | 3-year differences (D3) | | | | | 4-year differences (D4) | | | | | 5-year differences (D5) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
| | total | manag | clerk | craft | manual | total | manag | clerk | craft | manual | total | manag | clerk | craft | manual |
| w | 0.506*** | 0.125 | -0.067 | -0.168 | -0.666** | 0.478*** | 0.040 | -0.174 | -0.272 | -0.525 | 0.326 | 0.044 | -0.078 | -0.168 | -0.287 |
| | (2.719) | (0.943) | (-0.738) | (-0.914) | (-2.260) | (2.665) | (0.286) | (-1.190) | (-1.022) | (-1.567) | (1.635) | (0.217) | (-0.722) | (-0.839) | (-0.946) |
| p | 0.350 | -0.128 | 0.761 | 0.170 | 0.549 | 0.029 | -0.281 | -0.269 | 0.008 | 0.101 | -0.096 | -0.329 | -0.114 | -0.194 | 0.035 |
| | (1.448) | (-0.443) | (1.413) | (0.417) | (1.386) | (0.108) | (-0.772) | (-0.540) | (0.018) | (0.223) | (-0.300) | (-0.486) | (-0.197) | (-0.275) | (0.044) |
| GO | 0.417** | 0.497 | 0.118 | 0.479 | 0.065 | 0.726*** | 0.714 | 1.275** | 0.855 | 0.323 | 0.902** | 1.123 | 1.103 | 0.619 | 0.502 |
| | (2.041) | (1.527) | (0.171) | (0.986) | (0.153) | (2.748) | (1.607) | (2.393) | (1.433) | (0.550) | (2.332) | (1.191) | (1.421) | (0.714) | (0.445) |
| IP | 0.591** | -0.220 | -0.200 | 1.300** | -0.738 | 0.661** | -0.185 | -0.957 | 0.934 | -0.232 | -0.103 | -0.017 | -2.070*** | 0.351 | -0.324 |
| | (2.308) | (-0.585) | (-0.306) | (2.253) | (-0.776) | (2.512) | (-0.494) | (-1.438) | (1.603) | (-0.238) | (-0.366) | (-0.034) | (-3.358) | (0.693) | (-0.391) |
| $IIM^T$ | -0.063 | 0.023 | 0.063 | 0.500** | -0.257 | -0.075 | -0.074 | 0.343 | 0.450 | -0.148 | -0.073 | 0.066 | 0.219 | 0.134 | 0.075 |
| | (-0.742) | (0.182) | (0.179) | (2.530) | (-1.033) | (-0.604) | (-0.479) | (0.991) | (1.566) | (-0.503) | (-0.421) | (0.187) | (0.496) | (0.352) | (0.188) |
| RD | -0.289*** | -0.087 | -0.328 | -0.159 | -0.152 | -0.256** | -0.189 | -0.079 | -0.097 | -0.099 | -0.162 | 0.076 | -0.113 | -0.171 | 0.092 |
| | (-3.324) | (-0.666) | (-1.634) | (-0.609) | (-0.941) | (-2.396) | (-1.017) | (-0.312) | (-0.323) | (-0.392) | (-1.075) | (0.176) | (-0.240) | (-0.434) | (0.197) |
| MS | -0.231*** | -0.180*** | -0.379*** | -0.260*** | -0.328*** | -0.206*** | -0.183*** | -0.405*** | -0.202*** | -0.316*** | -0.143*** | -0.140*** | -0.414*** | -0.201*** | -0.240*** |
| | (-4.923) | (-5.753) | (-4.534) | (-4.829) | (-4.876) | (-4.516) | (-4.873) | (-5.315) | (-4.708) | (-4.382) | (-3.203) | (-3.371) | (-5.019) | (-4.456) | (-3.510) |
| $LF_L$ | 0.337*** | -0.112 | 0.284 | 0.322 | 0.191 | 0.473*** | -0.014 | -0.099 | 0.235 | 0.506 | 0.362* | -0.545 | -0.420 | -0.077 | 0.218 |
| | (2.976) | (-0.597) | (1.050) | (1.232) | (0.552) | (3.054) | (-0.067) | (-0.342) | (0.704) | (1.298) | (1.706) | (-0.910) | (-0.703) | (-0.154) | (0.351) |
| $LF_M$ | -0.505 | -0.920 | 1.535 | 1.038 | -0.335 | -0.102 | -0.639 | 2.061* | 1.298 | 0.546 | 0.208 | -0.891 | 0.993 | 1.155 | 0.382 |
| | (-1.401) | (-1.107) | (1.202) | (1.207) | (-0.319) | (-0.283) | (-0.913) | (1.897) | (1.479) | (0.514) | (0.411) | (-0.864) | (0.601) | (1.072) | (0.406) |
| $LF_H$ | -0.035 | 0.200 | 0.535* | 0.172 | 0.471 | 0.004 | 0.284 | 0.711* | 0.225 | 1.203* | -0.236 | 0.184 | -0.046 | -0.204 | 1.086* |
| | (-0.188) | (0.731) | (1.848) | (0.423) | (1.002) | (0.019) | (1.037) | (1.892) | (0.526) | (1.932) | (-0.922) | (0.428) | (-0.095) | (-0.316) | (1.664) |
| Constant | 0.030 | 0.045 | 0.074 | 0.145 | 0.003 | 0.068 | -0.054 | 0.094 | 0.098 | 0.042 | 0.019 | 0.196 | 0.040 | 0.973*** | 0.357* |
| | (0.568) | (0.327) | (0.498) | (0.504) | (0.012) | (0.759) | (-0.219) | (0.428) | (0.176) | (0.123) | (0.113) | (1.596) | (0.207) | (5.723) | (1.881) |
| Obs | 403 | 285 | 285 | 285 | 285 | 358 | 244 | 244 | 244 | 244 | 313 | 206 | 206 | 206 | 206 |
| $R^2$ | 0.604 | | | | | 0.580 | | | | | 0.516 | | | | |
| Underid. | 12.91*** | | | | | 12.51*** | | | | | 9.922*** | | | | |
| K-P | 16.080 | | | | | 15.111 | | | | | 10.572 | | | | |
| W-H | 9.256*** | | | | | 9.695*** | | | | | 6.597** | | | | |

Note: All variables are in logs. Standard errors clustered at the country-industry level. Robust t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1. w refers to average gross annual wages, p to the price of materials, GO to gross output, IP to import penetration, $IIM^T$ to total offshoring, RD to robot density, MS to the share of migrants and $LF_L$, $LF_M$ and $LF_H$ to the native labour force (aged 18-45) with low, medium and high level of educational attainment, respectively. Underid. refers to the underidentification test, K-P to the Kleinbergen-Paap rk Wald F statistic, Hansen to the Hansen J-test and W-H to the Wu-Hausman test.

## Table A.14 / Instrumental variable approach for endogenous migration (total economy)

| | 3-year differences (D3) | | | | | 4-year differences (D4) | | | | | 5-year differences (D5) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** | **(7)** | **(8)** | **(9)** | **(10)** | **(11)** | **(12)** | **(13)** | **(14)** | **(15)** |
| | **total** | **manag** | **clerk** | **craft** | **manual** | **total** | **manag** | **clerk** | **craft** | **manual** | **total** | **manag** | **clerk** | **craft** | **manual** |
| w | 0.275* | 0.136 | -0.315 | -0.294** | -0.290 | 0.312** | 0.206 | -0.325 | -0.267** | -0.226 | 0.133 | 0.436 | -0.362 | -0.094 | -0.107 |
| | (1.918) | (0.400) | (-0.234) | (-2.215) | (-1.567) | (2.539) | (0.616) | (-0.187) | (-1.989) | (-1.263) | (0.678) | (0.469) | (-0.520) | (-0.423) | (-0.682) |
| p | 0.075 | 0.371 | 1.277 | -0.086 | 0.312 | 0.174 | 0.339 | 1.729 | -0.005 | 0.032 | 0.348* | -0.094 | 1.484 | 0.252 | -0.260 |
| | (0.510) | (0.486) | (0.223) | (-0.269) | (0.450) | (1.502) | (0.518) | (0.119) | (-0.016) | (0.040) | (1.871) | (-0.098) | (0.519) | (0.593) | (-0.483) |
| GO | 0.667*** | 0.630 | -0.029 | 1.027** | 0.946** | 0.554*** | 0.739 | 0.076 | 1.121** | 1.264 | 0.305 | 2.365 | 0.171 | 0.426 | 0.860 |
| | (4.139) | (0.643) | (-0.008) | (2.361) | (2.134) | (5.048) | (1.171) | (0.010) | (2.390) | (1.405) | (1.436) | (0.631) | (0.086) | (0.648) | (1.270) |
| IP | 0.554** | -1.157 | 0.193 | 1.281*** | -0.824 | 0.361 | -1.515 | -0.217 | 1.352*** | -1.336 | 0.109 | -0.982 | -1.552 | -0.166 | -0.067 |
| | (2.234) | (-0.773) | (0.044) | (3.138) | (-1.120) | (1.486) | (-1.284) | (-0.026) | (2.990) | (-0.634) | (0.393) | (-0.270) | (-0.648) | (-0.293) | (-0.131) |
| $IIM^T$ | 0.035 | -0.165 | 0.413 | 0.202*** | 0.086 | 0.050 | -0.042 | 0.442 | 0.221*** | 0.063 | 0.009 | -0.261 | 0.299 | 0.279*** | 0.056 |
| | (0.423) | (-0.405) | (0.497) | (2.754) | (0.690) | (0.502) | (-0.212) | (0.217) | (3.622) | (0.356) | (0.051) | (-0.285) | (0.846) | (2.733) | (0.842) |
| IT | 0.123*** | 0.066 | -0.096 | 0.021 | 0.020 | 0.133*** | 0.003 | -0.174 | 0.029 | 0.055 | 0.115*** | -0.029 | -0.160 | 0.002 | 0.046 |
| | (3.339) | (0.467) | (-0.356) | (0.420) | (0.415) | (4.398) | (0.038) | (-0.198) | (0.558) | (0.803) | (2.697) | (-0.211) | (-0.737) | (0.023) | (0.844) |
| CT | -0.030 | -0.488 | 0.469 | -0.069 | -0.018 | -0.021 | -0.125 | 0.887 | -0.081 | -0.020 | -0.010 | -0.210 | 0.567 | 0.062 | -0.028 |
| | (-1.030) | (-0.601) | (0.558) | (-0.460) | (-0.076) | (-0.694) | (-0.366) | (0.236) | (-0.483) | (-0.054) | (-0.251) | (-0.195) | (1.049) | (0.248) | (-0.165) |
| DB | 0.157* | 0.856 | 0.241 | 0.357** | -0.292 | 0.075 | 0.728 | 0.041 | 0.318** | 0.051 | -0.049 | 0.875 | -0.016 | 0.503 | -0.345 |
| | (1.770) | (0.712) | (0.242) | (2.228) | (-1.321) | (0.840) | (1.002) | (0.038) | (1.974) | (0.068) | (-0.324) | (0.396) | (-0.018) | (1.634) | (-1.153) |
| MS | -0.443 | 0.845 | 0.648 | -0.335 | -0.969 | -0.191 | 0.488 | 1.684 | -0.312 | -1.571 | 0.332 | 1.789 | 1.303 | -0.795* | 0.255 |
| | (-1.581) | (0.589) | (0.155) | (-1.267) | (-1.113) | (-0.910) | (0.642) | (0.127) | (-1.456) | (-0.646) | (0.699) | (0.370) | (0.454) | (-1.818) | (0.429) |
| $LF_L$ | 0.041 | -0.427 | 0.432 | 0.303 | -0.212 | 0.170 | -0.628 | 0.323 | 0.184 | -0.129 | 0.257 | -1.059 | 0.252 | 0.220 | 0.549 |
| | (0.277) | (-0.660) | (0.443) | (1.277) | (-0.621) | (1.311) | (-0.855) | (0.139) | (0.785) | (-0.176) | (1.127) | (-0.542) | (0.180) | (0.524) | (1.188) |
| $LF_M$ | -1.115 | 0.514 | 1.402 | 0.393 | -1.444 | -0.048 | -0.873 | 0.766 | 0.363 | 0.123 | 1.234 | -0.552 | 0.395 | 0.281 | 1.522 |
| | (-1.282) | (0.267) | (0.924) | (0.347) | (-0.975) | (-0.069) | (-0.591) | (0.120) | (0.355) | (0.075) | (0.915) | (-0.197) | (0.166) | (0.206) | (0.920) |
| $LF_H$ | -0.068 | 0.311 | 1.124 | -0.292 | -0.330 | 0.295 | 0.249 | 1.980 | -0.532 | 0.730 | 0.506 | -0.772 | 0.295 | -0.797 | -0.115 |
| | (-0.250) | (0.461) | (0.311) | (-0.738) | (-0.633) | (1.367) | (0.474) | (0.181) | (-1.341) | (0.803) | (1.478) | (-0.224) | (0.202) | (-1.594) | (-0.224) |
| Constant | -0.089* | 0.047 | -0.165 | 0.040 | -0.067 | -0.044 | -0.193 | -0.406 | -0.004 | -0.015 | 0.035 | -0.194 | -0.044 | 0.128 | 0.288 |
| | (-1.896) | (0.283) | (-0.486) | (0.343) | (-0.566) | (-0.956) | (-1.064) | (-0.193) | (-0.023) | (-0.074) | (0.299) | (-0.468) | (-0.092) | (0.486) | (1.067) |
| Obs | 779 | 777 | 777 | 777 | 777 | 692 | 690 | 690 | 690 | 690 | 606 | 604 | 604 | 604 | 604 |
| $R^2$ | 0.209 | | | | | 0.249 | | | | | -0.231 | | | | |
| Underid. | 4.389** | | | | | 7.066*** | | | | | 2.818* | | | | |
| K-P | 4.401 | | | | | 7.023 | | | | | 2.504 | | | | |
| W-H | 0.278 | | | | | 0.048 | | | | | 1.918 | | | | |

Note: All variables are in logs. Standard errors clustered at the country-industry level. Robust t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1. w refers to average gross annual wages, p to the price of materials, GO to gross output, IP to import penetration, $IIM^T$ to total offshoring, IT to information technology, CT to communication technology, DB to software and database, MS to the share of migrants and $LF_L$, $LF_M$ and $LF_H$ to the native labour force (aged 18-45) with low, medium and high level of educational attainment, respectively. Underid. refers to the underidentification test, K-P to the Kleinbergen-Paap rk Wald F statistic, Hansen to the Hansen J-test and W-H to the Wu-Hausman test.

**Table A.15 / Instrumental variable approach for endogenous migration (manufacturing)**

| | 3-year differences (D3) | | | | | 4-year differences (D4) | | | | | 5-year differences (D5) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
| | **total** | **manag** | **clerk** | **craft** | **manual** | **total** | **manag** | **clerk** | **craft** | **manual** | **total** | **manag** | **clerk** | **craft** | **manual** |
| w | 0.435*** | 0.246 | -0.081 | 0.113 | -0.668 | 0.344 | 0.830 | -0.227 | 0.002 | -0.460 | 0.263 | -24.113 | -0.146* | 0.194 | -0.250 |
| | (2.768) | (0.491) | (-0.695) | (0.557) | (-1.469) | (1.591) | (0.459) | (-1.181) | (0.009) | (-0.777) | (1.315) | (-0.018) | (-1.691) | (0.511) | (-0.984) |
| p | 0.600* | 0.367 | 1.190 | 0.833 | -0.223 | -0.010 | 0.769 | 0.691 | 0.883 | 0.744 | 0.051 | -1.091 | 0.790 | 0.581 | 0.961 |
| | (1.838) | (0.314) | (0.986) | (1.551) | (-0.111) | (-0.022) | (0.351) | (0.569) | (1.254) | (0.244) | (0.143) | (-0.012) | (0.676) | (0.748) | (1.460) |
| GO | -0.016 | -0.032 | -0.229 | -0.491 | 0.125 | 0.549 | 0.686 | 0.477 | -0.403 | -0.358 | 0.489 | -31.927 | 0.409 | -0.401 | -0.271 |
| | (-0.053) | (-0.025) | (-0.212) | (-0.811) | (0.152) | (1.391) | (0.334) | (0.596) | (-0.491) | (-0.236) | (1.566) | (-0.018) | (0.523) | (-0.449) | (-0.384) |
| IP | 0.619** | -1.687 | -0.067 | 1.625*** | 0.578 | 0.870** | -4.392 | -0.694 | 0.980 | -0.599 | 0.237 | 110.393 | -1.903*** | 0.110 | -0.237 |
| | (2.099) | (-0.602) | (-0.108) | (2.605) | (0.270) | (2.066) | (-0.533) | (-1.131) | (1.613) | (-0.107) | (0.835) | (0.018) | (-2.950) | (0.170) | (-0.273) |
| $IIM^T$ | -0.203* | 0.886 | -0.061 | 0.342* | -0.336 | -0.291** | 2.416 | 0.072 | 0.437* | -0.253 | -0.442*** | -38.919 | -0.129 | 0.305 | 0.078 |
| | (-1.875) | (0.626) | (-0.152) | (1.818) | (-0.804) | (-2.508) | (0.525) | (0.194) | (1.677) | (-0.185) | (-2.793) | (-0.018) | (-0.438) | (0.894) | (0.241) |
| RD | -0.510*** | -0.254 | -0.423*** | -0.457*** | -0.331* | -0.500*** | -0.068 | -0.372*** | -0.419*** | -0.442** | -0.433*** | -7.903 | -0.411*** | -0.335*** | -0.432*** |
| | (-10.968) | (-1.311) | (-3.448) | (-5.403) | (-1.827) | (-9.682) | (-0.148) | (-4.428) | (-3.929) | (-2.220) | (-8.010) | (-0.019) | (-3.597) | (-3.662) | (-3.768) |
| MS | -0.486 | 1.195 | -0.189 | -0.642*** | 0.510 | 0.145 | 2.087 | -0.087 | -0.628** | -0.566 | 0.273 | -65.959 | -0.128 | -0.655 | -0.709** |
| | (-1.128) | (0.567) | (-0.438) | (-2.596) | (0.302) | (0.314) | (0.481) | (-0.184) | (-2.067) | (-0.212) | (0.716) | (-0.018) | (-0.276) | (-1.586) | (-2.018) |
| $LF_L$ | 0.318** | -0.409 | 0.401 | 0.256 | 0.926 | 0.637*** | -1.598 | 0.349 | 0.169 | 0.546 | 0.697*** | 22.549 | 0.089 | -0.116 | 0.243 |
| | (2.150) | (-0.497) | (1.262) | (0.737) | (0.736) | (2.902) | (-0.503) | (0.765) | (0.430) | (0.305) | (2.691) | (0.018) | (0.187) | (-0.233) | (0.414) |
| $LF_M$ | -0.408 | 0.872 | 1.720 | 0.926 | 1.559 | 0.659 | -0.501 | 2.791* | 1.098 | 0.531 | 1.727 | -109.162 | 1.582 | 1.021 | -0.820 |
| | (-0.718) | (0.238) | (1.304) | (0.873) | (0.448) | (0.764) | (-0.141) | (1.949) | (1.061) | (0.265) | (1.364) | (-0.018) | (0.906) | (0.740) | (-0.493) |
| $LF_H$ | -0.318 | 0.604 | 0.489 | -0.628 | 1.093 | 0.112 | 0.617 | 0.509 | -0.503 | 0.939 | -0.110 | -10.170 | -0.497 | -0.854 | 0.792* |
| | (-0.982) | (0.452) | (1.382) | (-1.088) | (0.698) | (0.371) | (0.333) | (1.050) | (-0.832) | (1.397) | (-0.384) | (-0.018) | (-0.827) | (-1.059) | (1.834) |
| Constant | 0.174*** | 0.375 | 0.158 | 0.182 | 0.338 | 0.263*** | -0.197 | 0.472 | 0.146 | 0.211 | 0.326*** | -7.341 | 0.466 | 0.939*** | 0.106 |
| | (4.379) | (0.731) | (0.825) | (0.793) | (0.596) | (4.279) | (-0.292) | (1.265) | (0.311) | (0.848) | (3.781) | (-0.018) | (0.727) | (5.275) | (0.341) |
| Obs | 403 | 285 | 285 | 285 | 285 | 358 | 244 | 244 | 244 | 244 | 313 | 206 | 206 | 206 | 206 |
| $R^2$ | 0.593 | | | | | 0.513 | | | | | 0.401 | | | | |
| Underid. | 1.671 | | | | | 1.187 | | | | | 2.244 | | | | |
| K-P | 1.552 | | | | | 1.102 | | | | | 2.175 | | | | |
| W-H | 0.551 | | | | | 0.862 | | | | | 2.471 | | | | |

Note: All variables are in logs. Standard errors clustered at the country-industry level. Robust t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1. w refers to average gross annual wages, p to the price of materials, GO to gross output, IP to import penetration, $IIM^T$ to total offshoring, RD to robot density, MS to the share of migrants and $LF_L$, $LF_M$ and $LF_H$ to the native labour force (aged 18-45) with low, medium and high level of educational attainment, respectively. Underid. refers to the underidentification test, K-P to the Kleinbergen-Paap rk Wald F statistic, Hansen to the Hansen J-test and W-H to the Wu-Hausman test.

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