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Michael Landesmann and Sandra Leitner

The Vienna Institute for International Economic Studies
Wiener Institut für Internationale Wirtschaftsvergleiche

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MICHAEL LANDESMANN
SANDRA LEITNER

Michael Landesmann is Senior Research Associate at The Vienna Institute for International Economic Studies (wiiw) and Professor of Economics at the Johannes Kepler University, Linz. Sandra Leitner is Economist at wiiw.

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Abstract

This paper estimates conditional demand models and, using a joint approach for the period 2008-2017, examines the impact of immigration and different measures of offshoring on the labour demand and demand elasticities of native workers in four different types of occupational groups: managers/professionals, clerical workers, craft (skilled) workers and manual workers. The analysis is conducted using data for four EU economies: Austria, Belgium, France and Spain. Our results point to important and occupation-specific direct and indirect effects of immigration and offshoring. Both offshoring – particularly services offshoring – and immigration have negative direct employment effects on all occupations, but native clerks and manual workers are affected the most, and native managers/professionals the least. Generally, offshoring exerts a stronger direct negative employment effect than does immigration. Our results also identify an important (labour demand) elasticity-channel of immigration and offshoring and show that some groups of native workers can also actually gain from globalisation through an improvement in their wage-bargaining position. Overall, our results indicate a deterioration in the bargaining power of native manual workers arising from both immigration and offshoring; an improvement in the bargaining position of native craft workers in the case of both immigration and offshoring; and an improvement in the bargaining position of native clerical workers and managers/professionals in the case of offshoring only. Finally, our analysis of the cross-effects of immigration highlights the important role of migrant managers/professionals for the labour demand and demand elasticities (bargaining power) of native clerical workers, craft and manual workers.

Keywords: Offshoring, immigration, labour demand elasticity, bargaining power, occupations

JEL classification: F16, F22, F66

CONTENTS

TABLES AND FIGURES

Annex

1. Introduction

1.1. MOTIVATION AND THEORETICAL CONSIDERATIONS

Over the past few decades, the process of globalisation has proceeded rapidly, particularly in terms of the expansion of international production networks (offshoring), but also in terms of international migration, which has reached unprecedented levels, as more and more people migrate for economic, political or environmental reasons.

While these forces of globalisation undoubtedly bring about gains for some, there is growing concern that they harm others in various ways. In this respect, workers – particularly unskilled workers – in advanced economies are considered to be on the losing side. As a result of the possible substitution of migrant workers for native workers, and the offshoring of mainly low-skill-intensive tasks (but increasingly also more skill-intensive tasks) to low-wage countries, native workers in advanced economies perceive not only that their employment opportunities are dwindling, but also that their wages are being squeezed and that inequality is increasing.

Theoretically, there might be two main direct effects on labour markets of these two channels of international economic integration. The first is the direct effect of 'competition for jobs': certain jobs get transferred abroad through offshoring, and hence the employment level of workers in the 'home country' declines. Or migrants might compete directly for jobs currently occupied by native workers, who then again experience an employment decline. These are direct *substitution effects*. The second is the *scale effect*, which results from the positive output or productivity effects brought about by the cost advantages of importing intermediate inputs or of hiring migrant workers. This leads to a better competitive position on product markets. The cost advantage might simply be a price effect (i.e. sourcing the same type of inputs more cheaply) or it may be a 'variety' effect, as the import of intermediate inputs widens the range of intermediates that can be used in production, thus providing a productivity boost. The same can be said of migrants, who might be either 'perfect substitutes' for native workers, but willing to work for a lower wage (in which case there would be simply a price effect), or they may offer somewhat differentiated 'skills', allowing for increased task specialisation (Ottaviano and Peri, 2008). This would bring a certain *complementarity* benefit to native workers even in the same occupational category.

Any analysis of scale effects, meanwhile, has to distinguish between the impact on output and on productivity levels. A straightforwardly negative productivity effect on factor demand – at a constant level of output (i.e. saving inputs per unit of output) – would, however, only be outcome if imported intermediate inputs were homogeneous with respect to domestically produced inputs; or if immigrant workers were perfect substitutes (in terms of skills and job performance) for native workers. However, where there is an 'increase in variety' through the use of intermediate inputs or immigrant labour (as is generally assumed in most 'new growth' and 'new trade' models that rely on a monopolistic competition framework),[1] the productivity-enhancing effects of offshoring or of the employment of migrant labour need not lead to a reduction in employment among the native labour force (assuming a constant level of output) – or at any rate any negative impact on the employment of native workers can be mitigated.

1 See, for example, Romer (1990) or Grossman and Helpman (1991).

As for the impact of offshoring and migration on the elasticity of labour demand, Rodrik (1997) conjectured, without a strong theoretical treatment of the issue, that ‘globalisation’ weakens the bargaining power of native workers, as the shift of jobs abroad – or even the threat of a shift – would reduce their bargaining power. This would imply an increase in the elasticity of labour demand, which amounts to a flattening of the labour demand schedule (i.e. a stronger quantity reaction to a wage change). The same can be argued with respect to the influx (or even the possibility of an influx) of an immigrant work force. In our analysis, we shall give this argument a new twist: outsourcing is a process that also implies the complex readjustment of a country in terms of ‘intra-industry’ or ‘task’ specialisation in the international division of labour (Grossman and Rossi-Hansberg, 2008; Costinot and Vogel, 2010; Ottaviano et al., 2013), and therefore also of occupational structures within an industry, as well as across industries within a country. Such readjustment opens up the possibility that international integration could lead not to an increase, but rather to a decrease in the elasticity of labour demand, at least in the longer run. The reason is that a new intra-industry or inter-industry specialisation of tasks might strengthen the position of those workers whose jobs remain in the country (or of native workers who have retained their jobs), as they gain from a ‘specialisation advantage’ with regard to the jobs or tasks they carry out within the international division of labour. This would amount to a reduction of substitution elasticities with respect to the immigrant labour force or with workers employed in offshored activities.

Another dimension should be added to the analysis: the role of price elasticity on the output markets and its link to the demand elasticity on factor markets. The scale effect mentioned above also depends very much on the impact of international integration on the ‘price elasticity’ on output markets. The standard assumption here is that more international competition increases the price elasticity on output markets (e.g. Levinsohn, 1993) and that such increased price elasticity gives employers less room for manoeuvre, which then affects employer–employee relationships and thus increases the elasticity of labour demand.[2] The relationship between price elasticity on product markets and factor demand elasticities was analysed by Hicks (1963) and later established in a number of contributions.[3] But here again, there might be a modifying factor, in that international product market integration could provide an incentive for producers to undertake more product differentiation. This might even allow to charge higher mark-ups in the different product market segments (that is, if product differentiation reduces the number of suppliers in the differentiated product market segment; the mark-up furthermore depends on cross-product substitution elasticities). This, in turn, could increase the scope for employees to bargain over ‘rents’ (i.e. a share of such mark-ups). Thus again, while the simple model of increased product market competition might suggest increased price elasticities when an economy ‘opens up’ (and thus increases intra-industry trade flows), leading to an increase in employment elasticities, increased product differentiation could well counteract or modify this impact.

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2 Hijzen and Swaim (2010) and Senses (2006) show, furthermore, that the impact of offshoring (and we can argue the same with respect to immigration) is theoretically ambiguous. Making use of the decomposition of the determinants of labour demand elasticity into a substitution (between factors of production) and a scale effect, the impact of an increase in the (constant output) substitution elasticity and a reduction in the cost share of a particular factor will have opposite effects on the total elasticity of labour demand: the latter dampens the scale effect. If the price elasticity of product demand is large relative to the elasticity of substitution in production, then offshoring can reduce the labour demand elasticity, rather than increase it. In our case, offshoring combined with international changes in task specialisation can affect the cost shares of different types of labour in many ways and this is particularly relevant in the context of our analysis differentiating between different types of occupation. The analysis also applies with respect to changes in work allocations between migrants and natives as a result of immigration flows that show particular occupational compositions.

3 See, for example, Slaughter (2001), Krishna et al. (2001), Panagariya (2000) or Fajnzylber and Maloney (2005).

1.2. RELATED LITERATURE

Given the focus of this paper, we can distinguish between two types of studies in the first instance: those that look at the impact of various forces of 'globalisation' on employment, taking the slope of the labour demand schedule (i.e. employment elasticity) as given; and those that also consider a change in the slope (i.e. globalisation's impact on employment elasticities). The latter point was first raised by Rodrik (1997) and then explored in several studies dealing with trade integration more generally and with offshoring specifically. With regard to the impact of migration on employment, we could find no studies that also considered the impact on employment elasticities, although many studies cover the impact on employment in great detail.

The first study to pick up Rodrik's interest in the impact of globalisation on employment elasticities was Slaughter (2001). This study uses industry data for US manufacturing, and estimates the separate effects of trade on *employment elasticities* for production and non-production workers. He finds significant time trends in employment elasticities for both types of labour: nonetheless, employment elasticities became markedly more elastic for production workers from the late 1970s to the early 1990s, whereas this was not the case for non-production workers. However, his study could not attribute these trends directly to trade variables. Krishna et al. (2001) studied the impact of trade liberalisation in Turkey over the years 1983 to 1986, when there were big tariff reductions. Their study included data on 10 three-digit industries, and confirmed the impact of trade liberalisation on mark-ups; this pointed to increased competitive pressures on product markets (see also Levinsohn, 1993). However, they found no evidence of any impact on labour demand elasticities. Bruno et al. (2004) analysed an industry panel for a number of industrialised countries, including major European economies, Japan and the US for the period 1970-1996. They found a significant effect of import penetration on labour demand elasticities only for the United Kingdom. For Italy and France, the evidence was mixed; and for the remaining countries they found no evidence that trade integration had significantly affected labour demand elasticities. Similarly, using a 31-sector industry breakdown for Italy, Bruno et al. (2005) found that Rodrik's conjecture could not be corroborated. Hasan et al. (2007), in a study on India, used industry-level data, disaggregated by states. This was one of the first studies also to include variation in the extent of labour market regulation (across states) when examining the impact of trade reforms on labour markets. The authors found that trade liberalisation increased labour demand elasticities. Furthermore, the absolute level of these elasticities was lower in states and industries with a higher level of protection. Thus they were higher in Indian states that had more flexible labour regulations, and trade reforms also had more of an impact.

Fajnzylber and Maloney (2005) studied the impact of trade liberalisation in Mexico (1984-1990), Chile (1979-1985) and Colombia (1977-1991), using plant-level data. For Mexico, where trade liberalisation was accompanied by a strong depreciation of the real exchange rate, they did find a significant effect on labour demand elasticities; but this was not the case for Chile or Colombia. Senses (2010) used detailed plant-level data for US manufacturing to analyse the relationship between *offshoring and labour demand elasticities* over the period 1972-2001. She found that conditional demand elasticities for production workers were positively related to increased exposure to offshoring both in the short and in the long term. Controlling for skill-biased technical change does not affect the magnitude or significance of this relationship. Senses concluded that the advantage of plant-level (compared to industry-level) analysis is that it allows 'identification of within-industry movements in relative employment and relative wages due to offshoring, as well as the plant characteristics that affect the ease with which foreign labor can be substituted for domestic labor' (Senses, 2010, p. 98).

We now come to Hijzen and Swaim (2010) and Foster-McGregor et al. (2016), which are the studies most closely related methodologically to our own (see section 2). Both these studies use industry-level data – the former relying on the OECD's Structural Analysis (STAN) database; the latter on the World Input-Output Database (WIOD). Hijzen and Swaim (2010) find a significant cross-sectional association between higher average offshoring intensity and higher labour demand elasticity, but no such positive association over time between the increases in offshoring and demand elasticity experienced during the second half of the 1990s. They also examine the impact of employment protection, and find that strict employment protection legislation weakens the cross-sectional association between offshoring and higher labour demand elasticity. Foster-McGregor et al. (2016) examine the impact of offshoring (using the same indicators that we use in this paper) on labour demand elasticities over the period 1995-2009 for a sample of 40 economies. They differentiate the labour force by educational attainment levels (low, medium and high) based on the International Standard Classification of Education (ISCED) – unlike our analysis, which is based on International Standard Classification of Occupations (ISCO) categories. The econometric specification is similar to ours, except that we examine jointly the impact of migration and offshoring on labour demand and labour demand elasticities. They find that offshoring has a negative impact on labour demand – in particular, on the demand for low- and medium-educated workers – and offer some evidence that offshoring also increases labour demand elasticities. Differentiating between sub-samples of developed and developing economies, they find that the negative effects of offshoring in developed countries are strongest among highly educated employees, and trace this back to the impact of offshoring by developed economies on other developed economies.

The literature on the impact of *immigration on labour markets* is vast and has been well reviewed in a number of excellent surveys. (For a recent assessment of this literature, see Dustmann et al., 2016; see also the earlier meta-study by Longhi et al., 2010.) It will therefore not be reviewed in this paper. However, as mentioned earlier, in this literature we could find no studies that estimated the impact of immigration on changing employment elasticities (unlike in the trade and offshoring literature). There are studies that analyse the determinants of differentiated employment elasticities in different local labour markets that take account of cross-regional labour mobility, which is found to affect such elasticities (see the study by Monte et al., 2018); but they use a different notion of employment elasticity (i.e. labour supply responses to labour demand shocks) from the one we employ in this paper. Our notion refers to estimating the impact on the labour demand schedule; it is therefore equivalent to that used in the offshoring studies mentioned above.

Since our focus is the joint estimation of the impact on labour markets of both 'forces of globalisation' – i.e. international migration and offshoring – we shall also refer to the very interesting papers by Ottaviano et al. (2013; 2016). In both papers, the authors look at complementarity and substitutability effects between offshoring and migration, and locate their analytical framework within the context of task allocation (among workers), task specialisation and the 'trade in tasks' (see Grossman and Rossi-Hansberg, 2008). In Ottaviano et al. (2013), the authors are interested – as we are in this paper – in the employment effects of immigration and offshoring on native workers. They explore the impact of falling offshoring and migration costs: this highlights, first of all, the impact of offshoring on domestic jobs, involving as it does both productivity/scale and substitution effects. It also brings out the trade-off between offshoring and migrant jobs, and what a fall in migration and offshoring costs does to the task specialisation between migrants, natives and offshore workers. The authors use US data on immigrants' and natives' employment and information on offshore workers supplied by US multinational affiliates for the period 2000-2007. Furthermore, they attempt to capture task specialisation by using information regarding the 'complexity' of the tasks to be performed in particular jobs. In Ottaviano et al. (2016), the analysis is further extended to explore the relationship between trade in services (imports and exports) and immigration on the basis of UK firm-level data and other data sources. The paper focuses on service-producing firms, and so concentrates on services in which local knowledge (about legal norms, institutional settings and language) might be particularly important. This sheds light on the tradestimulating role that immigrants from a particular country can have for trade with that country. Immigration can thus have a number of impacts: an ‘import substitution’ effect and various ‘export promotion’ effects (through productivity improvements and the saving of trade costs).

This paper contributes to the existing literature in several ways. First, aside from Landesmann and Leitner (2018), it is one of the first studies to directly estimate the impact of immigration on the demand elasticities of native workers. Second, it simultaneously looks at the effects of immigration and offshoring on the demand elasticities of native workers. The joint analysis of both forces of globalisation allows us to determine their *relative* importance and to identify the underlying globalisation force with the strongest effect. Third, it focuses on the labour demand elasticities of native workers in four different occupation groups: managers/professionals, clerical workers, craft (skilled) workers and manual workers. This occupation-based analysis allows us to identify those professional groups that either benefit or suffer most from immigration and offshoring. Just as we do for native workers, we also differentiate migrant workers by type of occupation; this allows us to determine any immigration-induced employment elasticity effects when migrants and natives actually compete for the same jobs. The use of occupational categories (rather than educational attainment levels, as in almost all research hitherto) avoids the potential bias inherent in educational attainment-based analyses and that stems from the non-negligible job-skill mismatch that is typical of migrant workers, and from the underutilisation of their skills in jobs that require few qualifications. Fourth, in addition to the own-effects of immigration, we also shed light on the more complex cross-effects: in particular, we not only determine how immigrants in a particular occupation affect the employment elasticities of native workers in the same occupation (the ‘own effect’), but also show how immigrants in each of the other three types of occupation affect the employment elasticities of native workers in a particular occupation (‘cross effects’). Finally, our analysis uses different measures of offshoring also used in the literature, and decomposes the total offshoring measure into a narrow (intra-industry) and a broad (inter-industry) component; we further decompose broad offshoring into a manufacturing and a services component, in order to account for the growing importance of services offshoring over the past two decades.

The findings of this paper indicate important direct and indirect effects of immigration and offshoring – effects that differ across occupations. While offshoring – particularly services offshoring – and immigration have negative direct employment effects on all occupations, some occupations (such as native clerical workers and manual workers) are affected more than others (such as native managers/professionals). In general, however, offshoring has a stronger negative employment effect than does immigration. Furthermore, we also find an important indirect elasticity-channel of immigration and offshoring. These elasticity effects are sometimes also positive, which suggests that some native workers actually gain from globalisation, through an improvement in their bargaining power. In particular, our results point to a deterioration in the bargaining power of native manual workers as a result of both immigration and offshoring; an improvement in the bargaining position of native craft workers arising from both immigration and offshoring; and an improvement in the bargaining position of native clerks and managers/professionals in the case of offshoring only. Finally, our analysis of the cross-effects of immigration highlights the important role of migrant managers/professionals, who are associated with an increase in the employment of native clerical workers and native manual workers, but a decline in their bargaining position.

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 employ the log-linear model of labour demand (Hamermesh, 1993); but closely following Hijzen and Swaim (2010), we focus on the conditional labour demand model, where the profit-maximising level of labour demand is determined by minimising production costs conditional on output. Thus, we determine the technology effect of offshoring and migration by keeping output constant. Hence, if offshoring or immigration has any productivity-enhancing effects, we will observe a negative effect on native employment (since the same amount of output can be produced with fewer inputs). Furthermore, as is common in the literature, we treat capital as quasi-fixed, in order to avoid measurement problems of the user cost of capital. The conditional labour demand equation can be written as follows:

$$lnL_{ict}^{N} = \alpha_0 + \alpha_w lnw_{ict} + \alpha_{ip} lnip_{ict} + \beta_k lnk_{ict} + \beta_y lny_{ict} + \sum_{i=l}^{L} \gamma_l lnz_{ilct} + \varepsilon_{ict} \quad (1)$$

where L_{ict}^{N} refers to the labour demand of native workers of industry i in country c at time t. Furthermore, w_{ict} is the average gross annual wage of native workers and ip_{ict} the price of materials. Given the log-linear specification of labour demand, the parameters α_w and α_{ip} refer to the own- and cross-price (constant output, constant capital) labour demand elasticities at time t. Furthermore, k_{ict} and y_{ict} refer to the real capital stock and to real gross output, respectively. z_{ilct} refers to a set of l different demand shifters for native workers. In this respect, we include several different offshoring indicators together with the share of immigrants (as discussed in detail in section 2.2 below). Furthermore, following Hijzen and Swaim (2010), we also include import penetration (IP) as a measure of general trade openness, defined as $Imports/(GDP + Imports - Exports)$. Finally, we include a measure of technological change to capture the fact that recent changes in relative labour demand are the result of an increase either in trade or in skill-biased technical change (SBTC). However, in the absence of suitable and reliable data to capture SBTC, we include a set of country-sector linear time trends, which control for unobserved changes across time in labour demand for each industry in each country. Finally, ε_{ict} refers to a random normally distributed disturbance term with zero mean and constant variance.

Furthermore, the data are differenced to account for any time-invariant industry fixed effects that affect the level of labour demand. Typically, in this literature, longer differences are used not only to account for any lags in the adjustment of native labour demand to shocks, but also to reduce measurement errors. However, in view of the rather short time horizon of our data (10 years), we take shorter differences to increase degrees of freedom and the variation in our data. In particular, we use five different differencing periods – 1 year, 2 years, 3 years, 4 years and 5 years – which allows us to determine the robustness of our results to the chosen differencing period and to produce more appropriate results, should measure error not be an issue in our data. For the sake of brevity, however, we will not report results for the 2-year differences, as these are similar to those of 1-year differences.[4] The conditional labour demand equation then becomes:

[4] Results for the 2-year differences are available from the authors upon request.

$$\Delta lnL_{ict}^{N} = \alpha_0 + \alpha_w \Delta lnw_{ict} + \alpha_{ip} \Delta lnip_{ict} + \beta_k \Delta lnk_{ict} + \beta_y \Delta lny_{ict} + \sum_{i=l}^{L} \gamma_l \Delta lnz_{ilct} + \varepsilon_{ict} \tag{2}$$

where Δ refers to the difference of a variable.

However, since this approach only allows us to determine the (technology-related) effects of offshoring and immigration on the labour demand of native workers, but not its *impact on labour demand elasticities*, we follow Hijzen and Swaim (2010) and include interaction terms of our offshoring and migration measures with the wage variable for natives. The final estimation equation is therefore:

$$\Delta lnL_{ict}^{N} = \alpha_0 + \alpha_w \Delta lnw_{ict} + \alpha_{ip} \Delta lnip_{ict} + \beta_k \Delta lnk_{ict} + \beta_y \Delta lny_{ict} + \sum_{i=l}^{L} \gamma_l \Delta lnz_{ilct} + \delta_{wl}(\Delta lnw_{ict} * \sum_{i=l}^{L} \Delta lnz_{ilct}) + \varepsilon_{ict} \tag{3}$$

To make the interpretation of coefficients easier and more meaningful, all measures used in the interaction terms are centred.[5]

This general approach is further refined in two different ways. First, 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: (i) *managers/professionals*,[6] (ii) *clerks*, (iii) *craft workers* and (iv) *manual workers* (as defined and shown in 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)

There is a rich and steadily growing strand of literature that analyses the effects of offshoring and immigration on domestic employment. This literature looks either at the overall employment effects or (increasingly) at the employment effects differentiated by skill group (in terms of low-, medium- and high-educated workers) to shed light on the potential skill-bias of offshoring and the degree of substitutability (complementarity) of native workers for foreign workers with similar (dissimilar) skills. In contrast, however, comparable evidence by occupation is scarce, but is generally of great importance. As for offshoring, the differentiation by occupation is important, as it allows us to determine which jobs are particularly prone to offshoring – and consequently which professional groups are most affected. As for immigration, the analysis of employment effects based on skills may produce a distorted picture due to the often found substantial job-skill mismatch[7] among migrant workers – particularly in terms of their

5 The interaction term in general can be interpreted as how a percentage increase in the migrant share (of offshoring) affects employment of natives at a given wage rate. Centring refers to setting the variables always in relation to the average values (of wage rates, of migrant shares, of offshoring).

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

7 See, for example, Landesmann et al. (2015) for an overview.

pronounced over-education – which reflects the fact that natives and migrants with comparable skills do not compete for the same jobs. By contrast, our occupation-based analysis allows us to determine the effects when migrants and natives do compete for the same jobs. In this context, we expect even stronger substitution effects; these, however, need not necessarily translate into higher unemployment, but can result in the greater occupational upward mobility of native workers (for empirical evidence on Europe, see, for example, Cattaneo et al., 2015). In this case, the dependent variable in the estimation is the industry-level labour demand for native workers of a particular occupation type; the wage variable is the average annual gross wage of native workers in that particular occupation type; and the migration measure is the share of immigrants in that particular occupation type.

Second, for each occupation we also determine the more complex *cross-effects of immigration* to show whether (and how) immigrants in each of the four occupations affect the employment elasticity of native workers in a particular occupation. In this respect, we shed light on both the own-effects and the cross-effects of migration by determining the effects of migration in all four types of occupation jointly on the demand elasticity of natives in one particular occupation. In this case, we not only include for each occupation the share of immigrants (and its interaction with the domestic wage measure) in that particular occupation, but also the share of immigrants (and their interactions with the domestic wage measure) in all the other occupations.

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), which allows for the contemporaneous correlation of error terms across all four regression equations, and is thus more efficient than separate estimation by OLS. To account for any potential heteroskedasticity issues and to guarantee unbiased estimates, we report heteroskedasticity-robust *t*-values.

As is standard in the literature, we estimate industry labour demand elasticities on the identification assumption that industry labour supply is perfectly elastic. Consequently, any shifts in labour supply – as measured by changes in wages – trace out the labour demand curve, so that estimated parameters can be interpreted as labour demand elasticities (Slaughter, 2001). The appropriateness of this assumption depends, however, on the level of aggregation of the data and is plausible for firms, but less plausible for industries (as in our case) and entirely implausible for entire economies, which face perfectly inelastic labour supply curves. A violation of this assumption results in upward-biased labour demand elasticities, due to the positive correlation between wages and labour supply. Following Hijzen and Swaim (2010), we therefore use an instrumental variable (IV) approach to control for this potential endogeneity. In this context, we use the female labour force participation rate of natives and the fertility rate of female natives as instruments, and conduct Durbin–Wu–Hausman tests to check for the exogeneity of the wage variables. However, both instruments are only available at the country level, and therefore lack any industry dimension. To deal with this limitation, we interact them with industry dummies. The results from the Durbin–Wu–Hausman tests suggest, however, that endogeneity is not an issue in our data. Hence, the reported (heteroskedasticity-robust) coefficients from our OLS/SUR estimations are unbiased.

2.2. OFFSHORING, MIGRATION AND LABOUR ELASTICITIES

Offshoring is measured using imported intermediate inputs obtained from use matrices of international input-output tables.

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:

$$IIM_{i,c}^{T} = \frac{\sum_{j=1}^{J} O_{j,c}}{GO_{i,c}} \tag{4}$$

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 two different dimensions.

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

$$IIM_{i,c}^{N} = \frac{O_{j=i,c}}{GO_{i,c}} \text{ and } IIM_{i,c}^{B} = \frac{\sum_{j=1,j\neq i}^{J} O_{j,c}}{GO_{i,c}}. \tag{5}$$

Second, we also differentiate between manufacturing (M) and services (S) offshoring, in order to account for the growing importance of services offshoring over the past two decades (Jensen and Kletzer, 2005). Traditionally, global production networks have predominantly referred to the offshoring of manufactured intermediate inputs. By contrast, since the production and consumption of services used to be considered inseparable, any geographic relocation of services production away from consumers was precluded. However, recent advances in information and communication technology (ICT) have helped to (partly) overcome this constraint and to foster the relocation of services activities to foreign bases. Manufacturing and services offshoring are defined as follows:

$$IIM_{i,c}^{M} = \frac{\sum_{m=1}^{M} O_{m,c}}{GO_{i,c}} \text{ and } IIM_{i,c}^{S} = \frac{\sum_{s=1}^{S} O_{s,c}}{GO_{i,c}}, \tag{6}$$

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

In addition to offshoring, we also analyse the effect of immigration on the labour demand elasticity of native workers. In particular, migrant workers may complement or substitute for native workers, depending on the relative skill endowment of native and foreign workers. In particular, 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:

$$MS_{ict} = \frac{migrant\ workers_{ict}}{total\ workers_{ict}}, \tag{7}$$

where $migrant\ workers_{ict}$ refers to the total number of migrant workers (as determined by country of birth) employed in industry i of country c at time t, and $total\ workers_{ict}$ refers to the total number of employees in industry i of country c at time t.

As in the case of native workers, we also differentiate migrant workers by type of occupation (in terms of managers/professionals, clerks, craft workers and manual workers) to capture the occupation-specific substitution and complementarity effects of migration on the employment elasticity of native workers.

2.3. DATA SOURCES

We used three different data sources to construct our database. First, we used the EU Statistics on Income and Living Conditions (EU-SILC) for key labour market-related information such as native, migrant and total employment, as well as annual gross wages. 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). Generally, standardised and anonymised EU-SILC microdata are available from Eurostat for all countries that have agreed to their publication. These microdata are, however, only available at the very rough one-digit industry level, and some industries are even lumped together to form more aggregate and larger industry groups: this is 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 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 and migration. For this reason, we contacted national statistical offices to acquire 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, but are also major immigration countries (particularly for immigrants from other parts of Europe, especially the new EU member states).[8] All in all, we received detailed national EU-SILC data from four countries – Austria, Belgium, France and Spain – and for different time periods; from these, we constructed a balanced sample for the period 2008-2017. All occupation-related data were corrected for the ISCO break between 2010 and 2011 by means of double-coded ISCO information in 2011 and suitable correction for all preceding years to follow the ISCO-08 occupational classification.

Secondly, trade-related data were taken from the use tables of input-output statistics, as provided by Eurostat. In the columns, use table matrices show the input structure for the different industries, while column sums refer to the total output of an industry. In the rows, use table matrices show the distribution of commodities between intermediate demand and final demand. Use tables are available for both domestic and imported inputs at the detailed two-digit industry level for the period 1995-2017, and are used to construct the different offshoring measures (as discussed above) for 2008-2017.

Finally, information on input prices, the real capital stock and real gross output was taken from the EU-KLEMS Growth and Productivity Accounts 2019 release. It is generally available for all EU28 member states (plus Norway, Japan and the US) for the period 1995-2017, for 40 detailed industries (plus some aggregates), according to the NACE Rev. 2 industry classification.

Because of certain data limitations (e.g. scant information on migrant workers in some detailed two-digit industries, and no information on real capital stocks at the detailed two-digit industry level for industries G and H for Belgium, France and Spain), we ultimately used an industry classification scheme that

8 We did not include Luxembourg, whose migration numbers and patterns are too different from the other 'old' EU member states.

closely follows the EU-KLEMS (2019 release), but is less detailed in some service industries (see Table 2 below for the list of industries). In the analysis, we use all industries, but exclude all public sector industries, such as O, P, Q and R-S and T.

Table 2 / Industry classification – NACE Rev. 2

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

Note: M/low – Low-tech manufacturing; M/med – Medium-tech manufacturing; M/high – High-tech manufacturing; S/low – Low-tech services; S/med – Medium-tech services; S/high – High-tech services.

In the analysis, we use two different data samples: the total economy sample (comprising all industries but NACE O-T) and a manufacturing sample (comprising all manufacturing sectors from NACE 10 to 33) which is available at the more detailed two-digit industry level.

3. Descriptive analysis

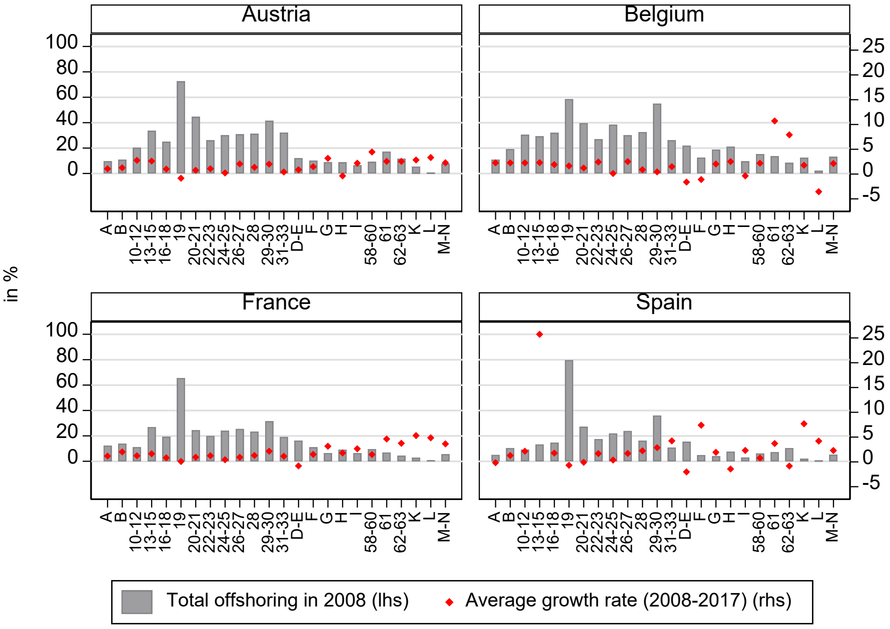
This part of the analysis gives a detailed descriptive account of the two key forces of globalisation under scrutiny. For each of the four countries under consideration, Figures 1 to 5 show the five different measures of offshoring by industry in 2008 – as the first year of our period of analysis – as well as the average growth rate between 2008 and 2017 to capture developments and changes over time. Figures 6 to 8 then look at migration and give a detailed account of various migration-related developments.

3.1. OFFSHORING

Figure 1 depicts the *total offshoring* measure in 2008 and its average growth rate between 2008 and 2017. It first of all shows that, by and large, in 2008 total offshoring was higher in Austria and Belgium than in France and Spain. Secondly, there is a great deal of heterogeneity in the extent of total offshoring across industries. Irrespective of the country considered, total offshoring is generally higher in the more detailed manufacturing industries (10-12 to 31-33) than in the service industries (G to M-N). Within the manufacturing sector, total offshoring is always highest in industry 19 (Coke and refined petroleum products), followed by industries 29-30 (Transport equipment) and 20-21 (Chemicals), but tends to be lowest in industry 10-12 (Food products, beverages and tobacco). For the service industries, no such regularity is observable, though total offshoring is high in industry H (Transportation and storage) in Belgium, France and Spain and in industry 62-63 (IT and other information services) in Austria and Spain. Thirdly, as concerns changes between 2008 and 2017, in all four countries considered total offshoring increased in almost all industries. Notable exceptions were industries 19 (Coke and refined petroleum products) and H (Transportation and storage) in Austria; industries D-E (Electricity, gas, water, steam and air conditioning supply & sewerage), F (Construction), I (Accommodation) and L (Real estate) in Belgium; industry D-E (Electricity, gas, water, steam and air conditioning supply & sewerage) in France; and industries A (Agriculture), 19 (Coke and refined petroleum products), 20-21 (Chemicals), D-E (Electricity, gas, water, steam and air conditioning supply & sewerage), H (Transportation and storage) and 62-63 (IT and other information services) in Spain. Total offshoring generally increased the most in the service industries. In Spain, however, the strongest increases in total offshoring occurred outside the services sector, namely in industry 19 (Coke and refined petroleum products) and industry F (Construction).

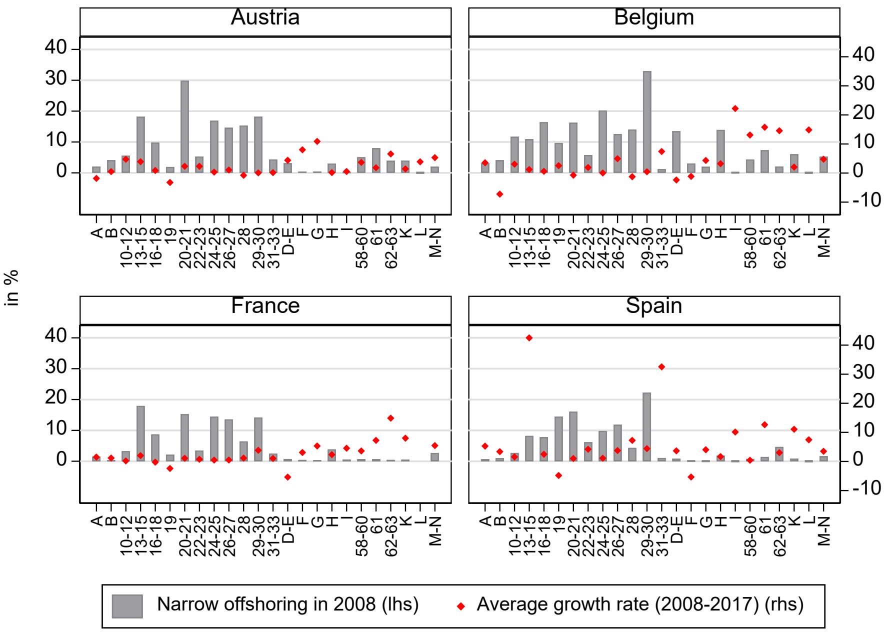
The following two figures depict the two constituent components of total offshoring, namely *narrow (within-industry) offshoring* in Figure 2 and *broad (between-industry) offshoring* in Figure 3. In terms of the relative importance of the two offshoring sub-components, a comparison of both figures clearly shows that broad offshoring activities dominate in almost all industries, while narrow offshoring is the most important offshoring activity in only a few industries – particularly manufacturing industries. Across all four countries, broad offshoring in 2008 was highest in industry 19 (Coke and refined petroleum products). In Austria, with more than 20%, broad offshoring was also fairly high in industries 29-30 (Transport equipment) and 31-33 (Other manufacturing). Besides industry 19, broad offshoring was highest in industries 20-21 (Chemicals) and 31-33 (Other manufacturing) in Belgium; in industries 28 (Machinery and equipment) and 29-30 (Transport equipment) in France; and in industries 24-25 (Basic metals and fabricated metal products) and 26-27 (Computer & electrical equipment) in Spain. By contrast, narrow offshoring was the most important offshoring activity in industry 20-21 (Chemicals) in Austria; in industry 29-30 (Transport equipment) in Belgium and Spain; and in industry 13-15 (Textiles & leather) in France.

Figure 1 / Total offshoring by industry in 2008 (lhs) and the average offshoring growth rate between 2008 and 2017 (rhs)



Source: Input-output tables (IOTs), own calculations.

Figure 2 / Narrow offshoring by industry in 2008 (lhs) and the average narrow offshoring growth rate between 2008 and 2017 (rhs)

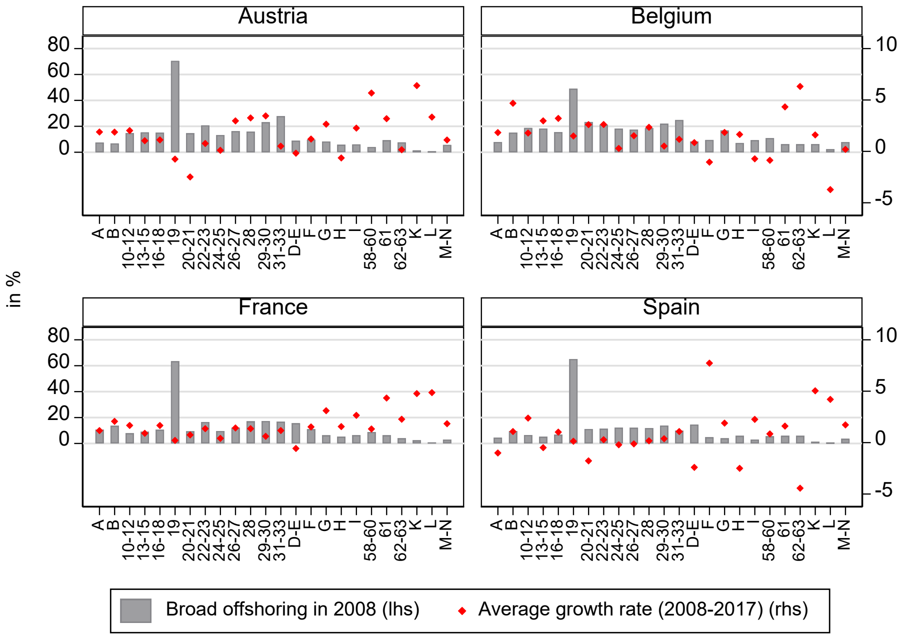


Source: IOTs, own calculations.

As concerns changes in both offshoring measures between 2008 and 2017, more industries saw a decline in both narrow and broad offshoring than in total offshoring (see Figure 2). In this respect, narrow offshoring declined the most in industry 19 (Coke and refined petroleum products) in Austria; in industry B (Mining and quarrying) in Belgium; in industry D-E (Electricity, gas, water, steam and air conditioning supply & sewerage) in France; and in industry F (Construction) in Spain (Figure 2). While narrow offshoring increased in all service industries, it increased the most in industry G (Wholesale and retail trade) in Austria; in industry I (Accommodation) in Belgium; and in industry 62-63 (IT and other information services) in France. In Spain, narrow offshoring increased the most in a couple of manufacturing industries: namely in industries 13-15 (Textiles & leather) and 31-33 (Other manufacturing).

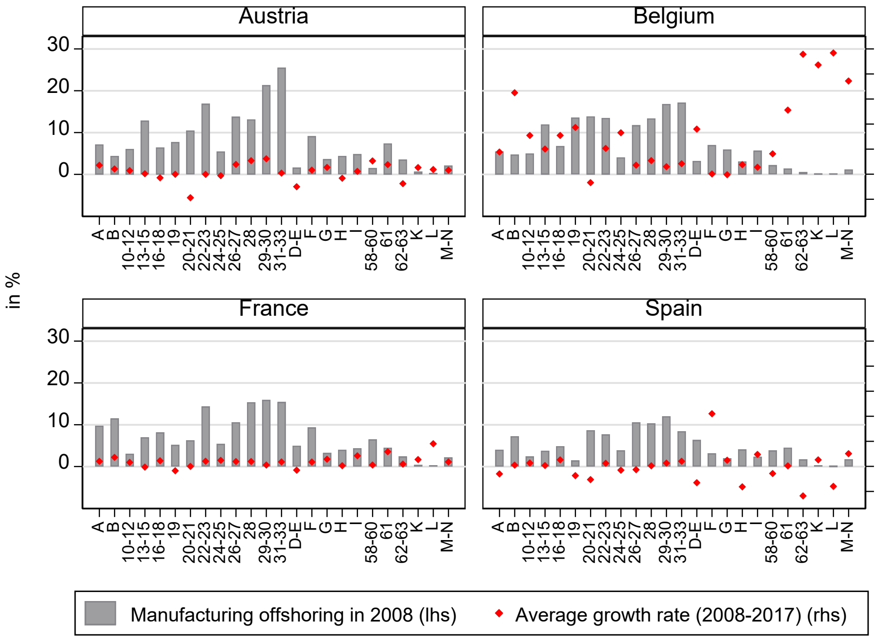
While broad offshoring (Figure 3) declined in more industries than narrow offshoring, these declines were generally smaller but also observable in some service industries, most notably in industries L (Real estate) in Belgium and 62-63 (IT and other information services) in Spain, where broad offshoring declined the most (by around 4 percentage points on average between 2008 and 2017). Observable increases in broad offshoring were smaller than in narrow offshoring and generally highest in some service industries. For instance, in Austria, broad offshoring increased the most in industries K (Financial and insurance activities) and 58-60 (Publishing, audio-visual and broadcasting activities); in Belgium, in industries 61 (Telecommunications) and B (Mining and quarrying); in France industries K (Financial and insurance activities) and L (Real estate) and in Spain in industries F (Construction) and K (Financial and insurance activities).

Figure 3 / Broad offshoring by industry in 2008 (lhs) and the average broad offshoring growth rate between 2008 and 2017 (rhs)



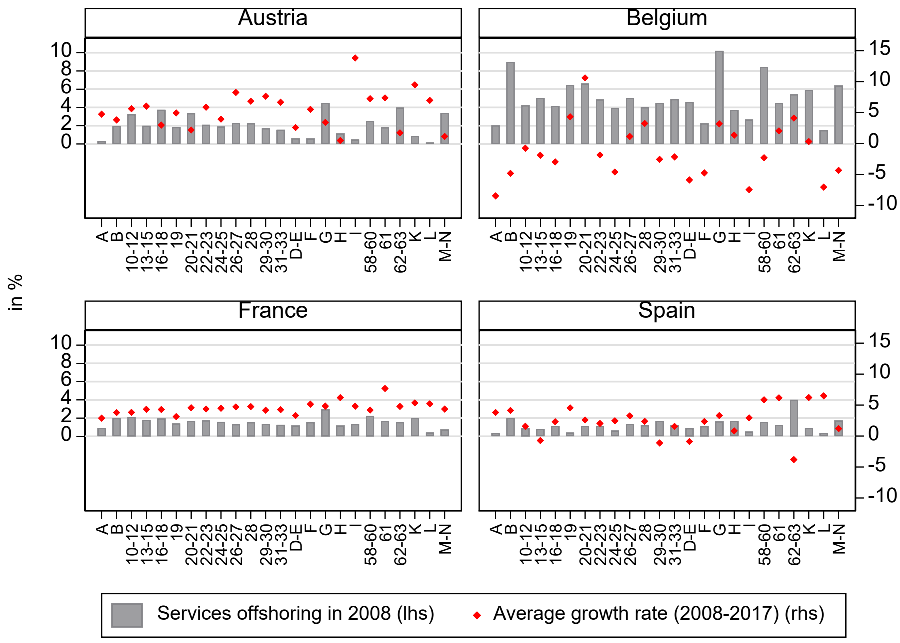
Source: IOTs, own calculations.

Figure 4 / Manufacturing offshoring by industry in 2008 (lhs) and the average manufacturing offshoring growth rate between 2008 and 2017 (rhs)



Source: IOTs, own calculations.

Figure 5 / Services offshoring by industry in 2008 (lhs) and the average services offshoring growth rate between 2008 and 2017 (rhs)



Source: IOTs, own calculations.

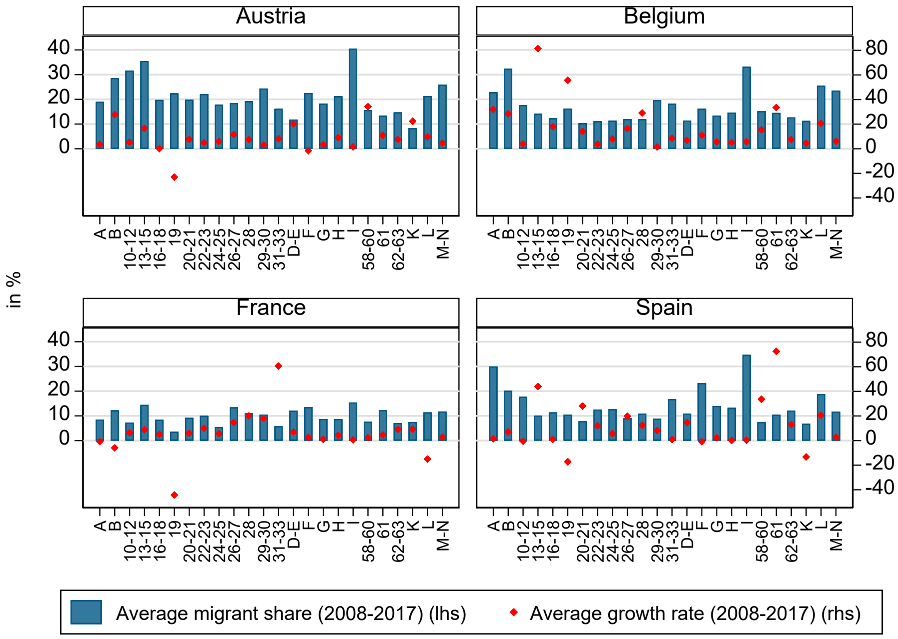
Figures 4 and 5 show (between-industry) manufacturing and services offshoring in 2008, as well as their average growth rates between 2008 and 2017. A comparison of the two figures indicates the following:

first, in 2008, across all industries considered, manufacturing offshoring was generally higher than services offshoring. Second, manufacturing offshoring was generally higher in the manufacturing industries, most notably in industries 29-30 (Transport equipment) and 31-33 (Other manufacturing). At over 20%, manufacturing offshoring was particularly high in the Austrian industries 29-30 (Transport equipment) and 31-33 (Other manufacturing). Third, services offshoring tends to be higher in the service industries than in the manufacturing industries. In particular, services offshoring is highest in industry G (Wholesale and retail trade) in Austria, Belgium and France; in industry 58-60 (Publishing, audio-visual and broadcasting activities) in Belgium and France; and in industry 62-63 (IT and other information services) in Austria and Spain. Fourth, as concerns average growth rates in manufacturing offshoring, Figure 4 shows that (except for Spain) manufacturing offshoring increased in the majority of industries. These increases were relatively moderate in Austria and France, but were more pronounced in Belgium, and particularly in some service industries, such as 61 (Telecommunications), 62-63 (IT and other information services), K (Financial and insurance activities), L (Real estate) and M-N (Professional, scientific and technical activities). By contrast, in Spain, manufacturing offshoring decreased in a large number of industries, and above all in some of the service industries, such as 62-63 (IT and other information services), H (Transportation and storage) and L (Real estate). Fifth, as concerns average services offshoring growth rates, Figure 5 shows that, while services offshoring started from a low level in 2008, it increased quite substantially between 2008 and 2017. In both Austria and France, services offshoring increased in all industries, without exception. In Austria, increases in services offshoring are most pronounced in the service industries, particularly in industries I (Accommodation) and K (Financial and insurance activities). In France, while services offshoring growth rates tend to be more similar across all industries, some service industries such as H (Transportation and storage) and 61 (Telecommunications) show somewhat higher growth rates than the rest of the industries. By contrast, in Spain, while services offshoring increased in the majority of industries (particularly some service industries), it decreased in a few industries – most notably in industry 62-63 (IT and other information services) by around 3% on average. In this context, Belgium is something of an outlier, as services offshoring decreased in the majority of industries. In some industries, these decreases were quite substantial, reaching almost 10%, such as in industries A (Agriculture), I (Accommodation) and L (Real estate). Also outstanding is industry 20-21 (Chemicals), whose services offshoring *increased* by almost 11% between 2008 and 2017.

3.2. MIGRATION

Next, we provide an overview of various migration-related measures, as shown in Figures 6 to 8 below. For each of the four countries, Figure 6 shows the average share of migrants, as well as their average growth rate between 2008 and 2017, for each of the industries under consideration. It shows that, first, the share of migrants in total employment is highest on average in Austria, followed by Belgium and Spain, and is very low in France, where the average migrant share ranges from only 4% to 15%. Secondly, cross-industry patterns of migrant share generally differ across countries, but are similar in some cases. For instance, the share of migrants is always highest in industry I (Accommodation) and is fairly high in industry B (Mining and quarrying), but is fairly low in industry K (Financial and insurance activities). Moreover, as concerns country-specific patterns, the migrant share in Austria is highest (at over 30%) in the two manufacturing industries 13-15 (Textiles, wearing apparel, leather and related products) and 10-12 (Food products, beverages and tobacco), as well as in industry I (mentioned above). Apart from industry K (at around 8%), none of the industries in Austria has a share of migrants below 10%. In Belgium, at more than 20% on average, the migrant share is highest in industries L (Real estate activities), M-N (Professional, scientific and technical activities) and A (Agriculture), besides industries I and B mentioned above. Similarly to Austria, the average migrant share exceeds 10% in all industries. In France, aside from industry I, the migrant share is highest in industries 13-15 (Textiles & leather products), 26-27 (Computer & electrical equipment) and F (Construction), and is lowest in industries 19 (Coke and refined petroleum products), 24-25 (Basic metals and fabricated metal products) and 31-33 (Other manufacturing & repair and installation of machinery and equipment). In Spain, aside from industry I, the migrant share is highest in industry A (Agriculture), at just over 30%. But in a number of industries (such as K, 58-60, 20-21, 29-30 and 26-27), the migrant share is below 10% on average. Thirdly, between 2008 and 2017, with only a few exceptions (such as industries 19, F, K and L), the migrant share increased in all industries in all four countries. And in Belgium, the migrant share increased in all industries, without exception. Finally, patterns of changes in the migrant share between 2008 and 2017 are very country specific: in Austria, the migrant share increased most in industries 58-60 (Publishing, audio-visual and broadcasting activities), B (Mining and quarrying) and K (Financial and insurance activities); in Belgium, it increased most in industries 13-15 (Textiles & leather products), 19 (Coke and refined petroleum products) and 61 (Telecommunications); in France – in industry 31-33 (Other manufacturing & repair and installation of machinery and equipment); and in Spain – in industries 61 (Telecommunications), 13-15 (Textiles & leather products), 58-60 (Publishing, audio-visual and broadcasting activities).

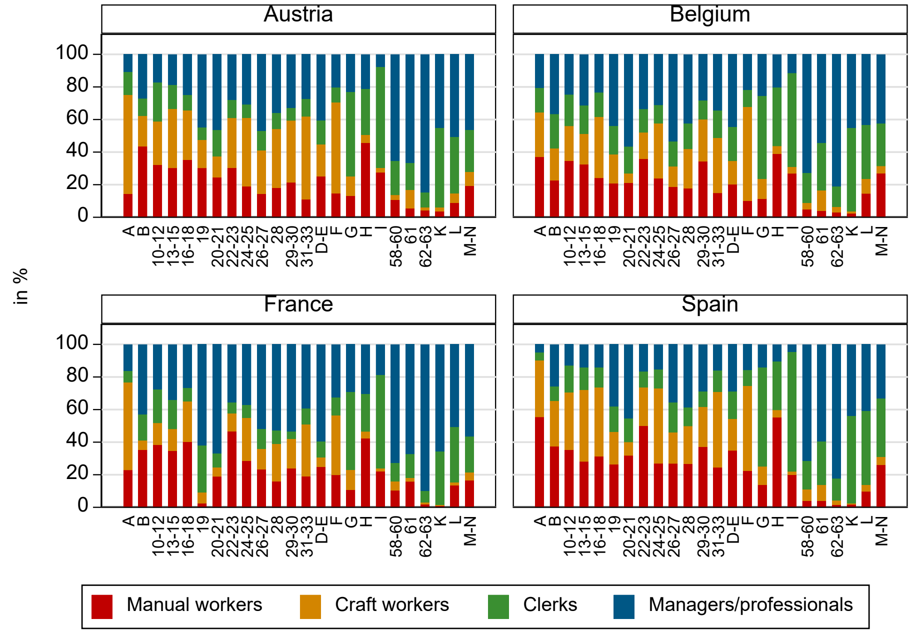
Figure 6 / Average share and growth rate of migrants in each industry (2008-2017)



Source: National EU-SILC, own calculations.

Figure 7 depicts the average *occupational composition* of the total workforce between 2008 and 2017 in all four countries. It generally points to rather similar compositional patterns across countries. For instance, manual workers form the largest group in industry H (Transportation and storage), as well as in a number of low-tech manufacturing industries, such as 10-12 (Food products, beverages and tobacco), 13-15 (Textiles & leather products), 16-18 (Wood and paper products & printing and reproduction of recorded media) and 22-23 (Rubber and plastics products & other non-metallic mineral products). By contrast, craft workers dominate in industries 24-25 (Basic metals and fabricated metal products, except machinery and equipment) and F (Construction); meanwhile clerks make up the biggest group in industries I (Accommodation), G (Wholesale and retail trade) and K (Financial and insurance activities). Managers/professionals form the largest group in medium- and high-tech manufacturing industries (such as industries 19, 20-21, 26-27, 28, 31-33), some high-tech service industries (such as industries 58-60, 61, 62-63, M-N), as well as industry D-E (Electricity, gas, water, steam and air conditioning supply & sewerage).

Figure 7 / Occupational composition of the total workforce (average 2008-2017)

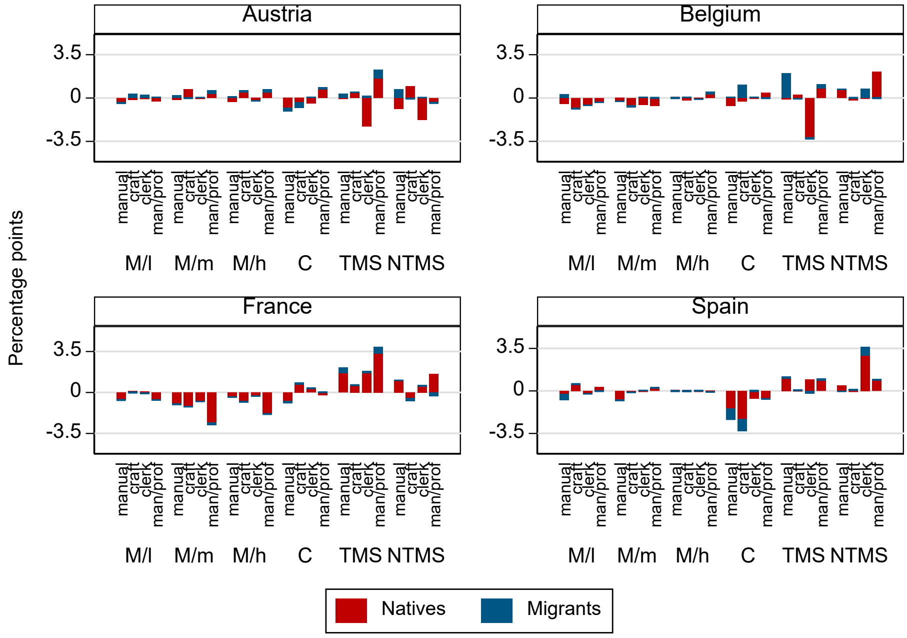


Source: National EU-SILC, own calculations.

Finally, the relative changes in the occupational employment shares of both native and migrant workers in six different industry aggregates are shown in Figure 8 below. The six industry aggregates refer to low-, high- and medium-tech manufacturing (M/l, M/m and M/h), construction (C), tradable market services (TMS) and non-tradable market services (NTMS).[9] Industry aggregates are shown instead of single industries to facilitate the presentability and interpretation of results. A more detailed graphical representation and interpretation of occupational employment changes of both native and migrant workers is provided in Annex B. Generally, all shares are expressed relative to total employment in all six industry aggregates together, and therefore give an indication of substitution processes between native and migrant workers in the four occupations. Figure 8 shows some interesting patterns. First, it highlights the fact that losses in the employment share of native (and migrant) workers are most common in manufacturing, particularly in Belgium, France and Spain.

9 See Table 2 for the underlying industry classification.

Figure 8 / Average change in occupational employment shares of natives and migrants by broad industry categories (2008-2017)



Note: Man/prof refers to managers/professionals; M/l refers to low-tech manufacturing; M/m to medium-tech manufacturing; M/H to high-tech manufacturing; C to construction (NACE F); TMS to tradable market services; and NTMS to non-tradable market services. Shares are expressed relative to the total overall employment in all six industry aggregates.
Source: National EU-SILC, own calculations.

Second, it also points to important cross-occupational differences in the employment share changes of native workers. Generally, losses in employment share are most widespread among less skill-intensive occupations, such as manual workers and clerks. In particular, native manual workers have experienced the most widespread losses in employment share –most consistently in the low- and medium-tech manufacturing sectors and in construction. In the case of Austria, the employment share losses of native manual workers are observable in almost all industry aggregates, but are generally most pronounced in non-tradable market services (NTMS) and construction (C). Similarly, losses in employment share are also more commonly observable among native clerks, particularly in medium- and high-tech manufacturing. In this respect, Austria again stands out: native clerks lost employment share in each of the six industry aggregates, but particularly in tradable and non-tradable market services (TMS and NTMS). By contrast, employment share losses were less common among more skill-intensive occupations, such as managers/professionals and craft workers. While native craft workers also lost employment share in some industries (mostly medium- and high-tech manufacturing), they gained employment share in tradable market services (TMS) in all the countries considered. Losses in employment share are generally least common among native managers/professionals, and altogether absent among native managers/professionals in tradable market services (TMS). Third, it points to important substitution effects of migrant for native workers (so that employment share losses among native workers coincide with employment share gains among migrant workers). These effects, however, differ across countries and occupations. In particular, such substitution effects were most widespread in Austria and Belgium, particularly among clerks and manual workers in Austria and craft workers in Belgium. By contrast, the substitution of migrant for native workers was less common in Spain – where clerks were most affected – and was almost absent in France.

4. Results

This section is split into four parts. The first reports the results when the total offshoring measure is used in addition to immigration. The second part reports the results when the two narrow and broad offshoring measures are used instead of total offshoring; and the third part reports the results when manufacturing and services offshoring are further distinguished. Finally, the fourth part reports the results when the more complex cross-effects of immigration are taken into consideration and the joint effects of immigration in all four types of occupation on the demand elasticity of natives in one particular occupation are determined. Generally speaking, in all specifications, the interaction terms of the different offshoring and immigration measures with the wage variables for natives capture the indirect effects of globalisation through a change in the elasticity of labour demand for native workers, while the offshoring and immigration measures by themselves capture the direct effects of globalisation on the labour demand for native workers. Similarly, the wage variables for natives themselves capture the direct (own) wage labour demand elasticity. In all four parts, we discuss the results for two different samples: the sample for the total economy (NACE A to M-N) and the sample for the manufacturing sector only (NACE 10 to 33).

4.1. TOTAL OFFSHORING, IMMIGRATION AND LABOUR DEMAND ELASTICITIES

Tables A1 and A2 (in Annex A) report the results for the impact of total offshoring and immigration on the labour demand elasticities for total employment, and for the four types of occupation, respectively. Results are reported for four different year differences: 1 year, 3 years, 4 years and 5 years.[10]

In general, coefficients on the own-wage variables are negative, but rarely significant. The only exceptions are craft workers in the total economy sample and clerks in the manufacturing sector. This suggests that (at average levels of total offshoring and immigration) an increase in their wages is associated with a reduction in their employment. Moreover, there is some indication that in the manufacturing sector, the wage elasticities of managers/professionals are positive. The coefficient is, however, only significant in the longer run (i.e. when longer year differences are used).

With respect to the direct and indirect effects of *total offshoring* on native workers, our results are mixed and differ not only across types of occupation, but also across industry samples. In particular, we find some sparse evidence that total offshoring is associated with an increase in demand for native workers. This direct and positive employment effect of offshoring is apparent over the longer run (i.e. when longer year differences are used) and is generally more pronounced and widespread in the manufacturing sector, where both managers/professionals and manual workers experience an increase in labour demand. In fact, as indicated by the size of the respective coefficients, manual workers appear to benefit somewhat more from offshoring than do managers/professionals. By contrast, looking at the economy as a whole, total offshoring is only beneficial for managers/professionals, whose labour demand increases (though less than for managers/professionals in the manufacturing sector). Furthermore, in

[10] Results for 2-year differences will not be reported here since they are similar to the results for 1-year differences. They are available from the authors upon request.

line with much of the literature, our results show that total offshoring is associated with an increase in the labour demand elasticities of native workers, which suggests a loss of native workers' bargaining power as a result of offshoring. However, this negative elasticity effect of offshoring is stronger and more prevalent in the manufacturing sector, and mainly concerns manual workers – who appear to be affected the most initially, but then tend to become unaffected as time goes by. Interestingly, some occupations seem to benefit from offshoring through a reduction in their labour demand elasticities (as indicated by a positive coefficient on the interaction term). In particular, craft workers in the manufacturing sector initially see a strong increase in their labour demand elasticities, but over the longer term they experience a non-negligible reduction in their labour demand elasticities, which is indicative of an improvement in their bargaining position in the longer run. This is in line with findings by Foster-McGregor et al. (2016), who also show that more highly educated workers in developed countries experience a decrease in their labour demand elasticities as a result of total offshoring.

Furthermore, as concerns the direct and indirect effects of *immigration* on native workers, our results are generally more robust than for total offshoring. In particular, we find that immigration is associated with a loss in the demand for all types of native workers. This negative employment effect of immigration is persistent, but tends to decline somewhat over time. Furthermore, not all types of occupation are affected in the same way: while native managers/professionals experience a comparatively moderate loss in labour demand, native manual workers are most affected and experience the most pronounced drop in labour demand. Interestingly, in the manufacturing sector, the relative losses in labour demand across occupations follow a different pattern: whereas immigration-induced employment losses are still lowest among native managers/professionals, native clerks and craft workers experience the strongest employment losses. In addition, we also find some little evidence that immigration is associated with an increase in the labour demand elasticities of native workers. But this indirect elasticity-enhancing effect of immigration is only apparent for manual workers in the longer run (and the total economy sample). Taken together with the direct negative employment effect of immigration, this suggests that immigration affects native manual workers twice: first, through employment loss, and second, through an additional loss in bargaining power. By contrast, immigration tends to have an elasticity-reducing effect on craft workers. This is again a longer-term result and is only observable for the total economy sample. Together with the direct negative employment effects of immigration, this implies that while immigration is associated with an employment loss among native craft workers, those native craft workers who remain – and who enjoy the advantage of better language skills, qualifications and knowledge of local standards and conditions – gain bargaining power, which in turn reduces their demand elasticities.

As concerns the remaining control variables, we find mixed and occupation-specific results. For instance, intermediate inputs appear to be complementary to managers/professionals, but have a negative substitution impact on craft workers. These effects are generally stronger in the manufacturing sector than in the total economy. Moreover, while the real capital stock is generally statistically unrelated to labour demand, import penetration is negatively related to labour demand – and particularly to the demand for managers/professionals, clerks and manual workers in the manufacturing sector. This suggests that a greater openness to trade in general damages their employment prospects. By contrast, real gross output increases labour demand for all occupations. In the manufacturing sector, this output-driven increase in labour demand is mainly observable for clerks and manual workers. The coefficients on the trend, which is included to capture SBTC, are significantly negative only for managers/professionals and clerks, which suggests that SBTC is associated with lower labour demand and fewer employment opportunities for these two occupational groups. However, this only holds for the total economy, and is absent for the manufacturing sector; this therefore suggests that SBTC mainly negatively affects labour demand for managers/professionals and clerks in the service industries.

4.2. NARROW AND BROAD OFFSHORING, IMMIGRATION AND LABOUR DEMAND ELASTICITIES

Tables A3 and A4 in Annex A report the results when total offshoring is split into a narrow and a broad component, as defined above. The results are again reported for total employment, as well as for the four types of occupation, and for four different year differences: 1, 3, 4 and 5 years. Since the effects of the other control variables are similar to what is observed above (Tables A1 and A2), in what follows we concentrate on the key variables of interest: namely, narrow and broad offshoring, and their interaction terms with the wages of native workers.

Concerning the direct effects of *narrow and broad offshoring*, there is little evidence of any significant employment effects related to either type of offshoring. There are, however, a few specific exceptions. For instance, in the total economy sample and over the longer term, broad offshoring is associated with a loss in employment of native clerks, while native manual workers tend to profit from broad offshoring through an increase in their employment. Moreover, in the shorter run, craft workers in manufacturing experience an increase in employment related to narrow offshoring. Furthermore, as concerns the indirect effects of narrow and broad offshoring on labour demand elasticities, our results are more mixed and differ across occupations and industry samples. For instance, in the total economy sample, narrow offshoring is associated with a reduction in the labour demand elasticity of managers/professionals, who appear to gain bargaining power – at least in the longer term. Conversely, native manual workers in manufacturing experience an increase in their labour demand elasticities, which points to a loss in their bargaining position through narrow offshoring. By contrast, broad offshoring has a more differentiated effect across occupations. For instance, native manual workers experience an increase in their labour demand elasticities, which is indicative of a loss in their bargaining position. This finding is more consistent for the total economy, and is only a short-term phenomenon among manual workers in the manufacturing sector. Conversely, broad offshoring is associated with a decrease in the labour demand elasticities of native managers/professionals and clerks: both groups profit from broad offshoring through an improvement in their bargaining positions. This finding shows that broad offshoring is also beneficial for less-educated workers, such as clerks. On the whole, the relative size of the coefficients suggests that the elasticity effects of broad offshoring – both positive and negative – are more pronounced in the manufacturing sector than in the economy as a whole. Overall, in contrast to Foster-McGregor et al. (2016), we generally find a stronger and more consistent role for broad offshoring. In particular, our results suggest that broad offshoring not only has a greater effect than narrow offshoring, but also affects native workers in different occupations more strongly and consistently through an indirect elasticity-channel, rather than a direct employment channel.

4.3. MANUFACTURING AND SERVICES OFFSHORING, IMMIGRATION AND LABOUR DEMAND ELASTICITIES

Tables A5 and A6 in Annex A report the results when (broad) offshoring is further differentiated in terms of manufacturing and services offshoring. The results are again reported for total employment and the four types of occupation, and for four different year differences (i.e. 1, 3, 4 and 5 years). In what follows, we again focus on the key variables of interest: namely, on manufacturing and services offshoring, as well as their interaction terms with the wages of native workers, since the effects of the other control variables are similar to what was observed above (Tables A1 and A2).

As concerns the direct effects of *manufacturing and services offshoring*, our results point to important differences: while services offshoring is associated with negative employment effects that are pretty consistent across occupations and time, manufacturing offshoring generates negative employment effects for only a few selected occupations. In particular, for the economy as a whole, services offshoring is associated with significantly lower employment among native managers/professionals and clerks. In the shorter term, native craft workers also experience a loss in employment, but this effect disappears in the longer term. Interestingly, the employment of native manual workers remains unaffected by services offshoring. In general, the relative size of the coefficients also suggests that the negative employment effect of services offshoring is strongest for clerks and weakest for managers/professionals. The negative employment effects of services offshoring are even more apparent and pronounced in the manufacturing sector, where, without exception, all occupations suffer employment losses that are generally also substantially stronger than for the economy as a whole. Moreover, the negative employment effects differ in size across occupations and are generally strongest for clerks in the short term, and for craft workers and manual workers in the longer term. Concerning the indirect effects of manufacturing and services offshoring on labour demand elasticities, we again observe important differences. In particular, in contrast to manufacturing offshoring, the elasticity effects of services offshoring are generally more widespread and are felt among more occupations. Furthermore, while labour demand elasticities generally decrease in almost all native occupations, some occupations still experience an increase in their labour demand elasticities. For instance, in the economy as a whole, services offshoring is associated with lower labour demand elasticities, and therefore a better bargaining position for native managers/professionals, craft workers and clerks. For native managers/professionals and clerks, this is a longer-term result, while craft workers tend to profit the most in the short term. By contrast, in the medium term manual workers experience an increase in their labour demand elasticities, and therefore a deterioration in their bargaining power. In the manufacturing sector, the elasticity effects of services offshoring are also more widespread across occupations. However, the decline in labour demand elasticity is most consistent for native craft workers, whose gain in bargaining power is most enduring; meanwhile, native managers/professionals and clerks gain the most in the medium term. By contrast, the labour demand elasticities of native manual workers remain unaffected by services offshoring. Generally, however, the elasticity effects of services offshoring are more pronounced in the manufacturing sector than in the economy as a whole. Hence, our results generally suggest that services offshoring exerts the strongest effects, both directly (through a loss in employment in all occupations) and indirectly (through an improvement in the bargaining power of those native workers who can maintain their employment).

4.4. CROSS-EFFECTS OF IMMIGRATION

Finally, Tables A7 and A8 in Annex A report the results of the more complex cross-effects of immigration. The cross-effects of immigration are calculated for all different specifications and are generally qualitatively similar. Hence, for the sake of brevity, Tables A7 and A8 only report results when the total offshoring measure is used.[11] In the following, we again concentrate on the key variables of interest: the different occupation-specific migration shares and their respective interaction effects with

[11] Results for the remaining specifications are not reported here but are available from the authors upon request.

the wages of native workers. The results are again reported for four different year differences (i.e. 1, 3, 4 and 5 years).

In line with the above results (Tables A1 and A2), we generally observe similar direct and indirect effects of immigrants in a particular occupation on the labour demand and labour demand elasticities of native workers in the *same* occupation. At the same time, we also find some interesting effects *across* occupations, which point to important side effects in occupations not directly affected by immigration and reflect existing interdependencies across native occupations.

In this respect, as concerns the *direct cross-effects of immigration*, our results highlight the fact that an increase in migrant managers/professionals is associated not only with a persistent increase in demand for native clerks, but also with an increase in demand for native manual workers. But for the latter group, this employment-enhancing effect of migrant managers/professionals only emerges in the medium to long term. Migrant manual workers produce a similar employment-enhancing effect among native craft workers, at least in the medium term. A similar pattern emerges for the manufacturing sector, where positive employment effects generally tend to be stronger.

Concerning the *indirect cross-effects of immigration*, we find evidence that an increase in migrant clerks initially has a negative effect for native managers/professionals, by increasing their labour demand elasticities. But this negative effect not only decreases over time, but eventually turns positive, before completely disappearing in the longer term. In contrast, more complex patterns emerge in the manufacturing sector. Native managers/professionals again experience an increase in their labour demand elasticities as a result of an increase in migrant craft workers. However, this is only observable in the very short term and quickly becomes positive, turning native managers/professionals into ‘winners’ from immigration, thanks to an improvement in their bargaining position. Overall, however, our results show that migrant managers/professionals have the strongest and most widespread elasticity effect on native workers. In particular, in the medium to longer term, native clerks, craft and manual workers all see their labour demand elasticities increase and their bargaining power decline as a consequence of an increase in migrant managers/professionals. Hence, while the employment of native clerks, craft and manual workers expands in response to more migrant managers/professionals, their bargaining position is weakened.

5. Summary and conclusions

This paper analyses, for the period 2008-2017, the impact of immigration and different measures of offshoring on the labour demand and labour demand elasticities of native workers in different occupation groups. It addresses Rodrik's (1997) conjecture as to the elasticity effects of globalisation, and directly tests whether globalisation – either through a shift of jobs abroad or increased competition for jobs between migrants and natives – is associated with a loss in the bargaining power of (native) workers, or whether any concomitant readjustments in terms of task and occupational specialisation might help even to improve their bargaining power.

It contributes to the existing literature in different and important ways. First, it is one of the first studies to directly estimate the role of immigration in the demand elasticities of native workers. So far, similar analyses have only been undertaken for offshoring. Second, it analyses the effects of immigration and offshoring together in a joint approach, which allows their relative impact on the labour demand elasticities of native workers to be discerned. Third, it deviates from the existing literature and looks at occupational, rather than educational, categories. In particular, it looks at four occupation groups: managers/professionals, clerks, craft workers and manual workers. In view of the frequently recorded substantial job-skill mismatch of migrants (which mainly manifests itself in immigrants holding jobs for which they are overqualified), this differentiation is important, as it allows us to determine more directly the complementarity or substitutability in production of migrant and native workers when they actually compete for the same job. Finally, it looks at more complex cross-effects of immigration and analyses how immigrants in each of the four types of occupation affect the employment elasticities of native workers in a particular occupation.

The findings of this paper point to important direct and indirect effects of immigration and offshoring – effects that differ, however, across occupations. First, as concerns the *direct* employment effects, our results show that, of all the offshoring measures considered, services offshoring – which, starting from a low level, has expanded strongly over recent years – exerts the most consistent and negative effect on employment. The negative employment effects of services offshoring are observable for all occupations, but affect native clerks the most and native managers/professionals the least. Furthermore, compared to the economy as a whole, the negative employment effects of services offshoring are more pronounced in the manufacturing sector.

Second, as with offshoring, immigration is also associated with a loss of employment for all types of native workers. However, the effect again differs across occupations and is strongest among native manual workers and weakest (again) among native managers/professionals (though the ranking is somewhat different in the manufacturing sector, where native clerks and craft workers experience the biggest losses in employment).

Third, as concerns the relative impact of immigration and offshoring, our results suggest that offshoring generally exerts a stronger negative employment effect than does immigration.

Fourth, in addition to the largely negative direct employment effects of immigration and offshoring, our results also point to an important *indirect* elasticity-channel of both forces of globalisation. However, the elasticity effect is not always negative: it can also be positive, which points to an improvement in the bargaining position of those native workers who manage to remain employed. Overall, our results indicate a deterioration in the bargaining power of native manual workers as a consequence of both immigration and offshoring, but an improvement in the bargaining position of native craft workers stemming from both immigration and offshoring (and of native clerks and managers/professionals, but only from offshoring). The effects again seem to be larger in the manufacturing sector than in the overall economy.

Finally, our analysis also points to some interesting cross-effects of immigration and to the important role of migrant managers/professionals in this respect. In particular, while an increase in migrant managers/professionals is associated with an increase in the employment of native clerks and native manual workers, both of these native occupations (as well as native craft workers) also experience an increase in their labour demand elasticities and a weakening of their bargaining positions.

6. Annex A

Table A1 / Employment elasticity effects (total economy): Total offshoring (D1 & D3)

	1-year differences (D1)					3-year differences (D3)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	total	man/prof	clerk	craft	manual	total	man/prof	clerk	craft	manual
w_i	0.160	-0.136	-0.081	-0.163*	-0.101	0.244*	0.057	-0.088	-0.182	-0.107
	(1.100)	(-0.904)	(-1.025)	(-1.699)	(-1.380)	(1.895)	(0.464)	(-1.124)	(-1.611)	(-1.540)
w_{II}	0.137	-0.039	0.208	-0.262	-0.082	0.478**	0.302	0.386	0.571	0.651
	(0.463)	(-0.102)	(0.522)	(-0.568)	(-0.135)	(2.274)	(1.125)	(1.024)	(1.405)	(1.572)
K	-0.373	-0.602	0.229	-0.212	-0.391	-0.311	-0.373	0.128	-0.107	-0.597
	(-1.387)	(-0.977)	(0.284)	(-0.221)	(-0.529)	(-1.413)	(-1.126)	(0.246)	(-0.250)	(-1.332)
GO	0.591***	0.538**	0.438	0.372	0.505*	0.955***	0.766***	1.168***	0.812***	1.062***
	(3.051)	(1.964)	(1.422)	(1.236)	(1.667)	(6.269)	(3.379)	(3.344)	(2.958)	(3.251)
IP	-0.431	-0.836	-0.816	-0.661	-0.407	-0.060	-0.394	-0.437	0.116	0.490
	(-0.858)	(-1.515)	(-1.202)	(-1.170)	(-0.532)	(-0.157)	(-0.847)	(-0.510)	(0.235)	(0.729)
IIM^T	0.455	0.872*	0.606	0.700	0.553	0.090	0.431	0.236	0.142	-0.426
	(1.169)	(1.937)	(1.125)	(1.450)	(0.843)	(0.288)	(1.080)	(0.322)	(0.356)	(-0.788)
MS_i	-0.162***	-0.160***	-0.401***	-0.255***	-0.384***	-0.180***	-0.120***	-0.351***	-0.263***	-0.366***
	(-5.708)	(-7.407)	(-10.222)	(-8.540)	(-9.518)	(-5.614)	(-5.671)	(-9.105)	(-8.338)	(-9.624)
w_i*IIM^T	-4.376***	-1.389	0.277	0.497	-1.752**	-0.858	1.262	0.827	0.669	-0.711*
	(-4.065)	(-0.870)	(0.232)	(0.315)	(-2.119)	(-1.367)	(1.600)	(1.449)	(1.426)	(-1.843)
w_i*MS_i	0.077	0.010	-0.032	-0.046	0.030	-0.133	0.097	-0.147	0.119	-0.108
	(0.326)	(0.050)	(-0.268)	(-0.280)	(0.196)	(-0.707)	(0.758)	(-1.218)	(1.190)	(-1.084)
Trend	-0.006*	-0.018***	-0.014*	0.002	-0.009	-0.013	-0.036***	-0.035*	-0.000	-0.014
	(-1.815)	(-2.919)	(-1.747)	(0.235)	(-1.156)	(-1.196)	(-3.090)	(-1.931)	(-0.031)	(-0.877)
Const.	0.073**	-0.034	-0.111	0.030	0.455	0.116	0.513**	-0.080	0.101	-0.315
	(2.227)	(-0.229)	(-0.789)	(0.435)	(1.070)	(1.148)	(1.982)	(-0.309)	(0.360)	(-1.484)
Obs.	800	800	800	800	800	610	610	610	610	610
R^2	0.122	0.128	0.242	0.184	0.211	0.211	0.170	0.233	0.247	0.262

Note: All variables are in logs. Robust z-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table A2 / Employment elasticity effects (manufacturing): Total offshoring (D1 & D3)

	1-year differences (D1)					3-year differences (D3)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	total	man/prof	clerk	craft	manual	total	man/prof	clerk	craft	manual
w_i	0.283	0.196	-0.220**	-0.205	-0.014	0.217	0.009	-0.277**	0.101	-0.034
	(1.414)	(0.945)	(-2.240)	(-1.139)	(-0.090)	(1.316)	(0.067)	(-2.266)	(0.619)	(-0.203)
w_{II}	0.114	-0.045	-0.174	-0.229	0.021	0.724**	0.591	0.400	0.962*	0.854*
	(0.255)	(-0.089)	(-0.277)	(-0.396)	(0.035)	(2.186)	(1.400)	(0.708)	(1.678)	(1.646)
K	-0.477	-1.043	-0.150	0.212	0.382	0.018	-0.244	-0.277	0.106	-0.787
	(-1.012)	(-1.116)	(-0.122)	(0.150)	(0.320)	(0.050)	(-0.472)	(-0.347)	(0.154)	(-1.253)
GO	0.232	-0.147	0.309	0.257	0.355	0.553**	0.180	1.283***	0.485	0.795**
	(1.064)	(-0.398)	(0.679)	(0.826)	(0.962)	(2.571)	(0.537)	(2.753)	(1.163)	(2.265)
IP	-0.076	0.647	-0.667	-0.097	-0.464	-0.493	-0.301	-2.296	0.190	-0.395
	(-0.113)	(0.713)	(-0.606)	(-0.117)	(-0.577)	(-0.698)	(-0.409)	(-1.420)	(0.183)	(-0.408)
IIM^T	0.410	-0.230	0.541	0.259	0.519	0.535	0.534	1.722	0.422	-0.045
	(0.866)	(-0.339)	(0.723)	(0.472)	(1.041)	(1.317)	(1.185)	(1.618)	(0.652)	(-0.069)
MS_i	-0.157***	-0.144***	-0.429***	-0.231***	-0.273***	-0.160***	-0.119***	-0.332***	-0.255***	-0.234***
	(-3.330)	(-5.590)	(-7.372)	(-5.697)	(-7.412)	(-3.984)	(-4.516)	(-5.511)	(-6.293)	(-6.360)
w_i*IIM^T	-5.900***	2.409	-1.200	-0.082	-6.286**	-1.605	0.641	-0.880	-0.535	-1.292**
	(-3.465)	(0.736)	(-0.643)	(-0.016)	(-2.320)	(-1.604)	(0.637)	(-1.270)	(-0.435)	(-2.442)
w_i*MS_i	0.135	0.170	0.102	-0.408	0.134	-0.341	-0.057	-0.057	-0.035	-0.000
	(0.285)	(1.205)	(0.505)	(-1.418)	(0.659)	(-1.344)	(-0.416)	(-0.318)	(-0.218)	(-0.003)
Trend	0.003	-0.004	-0.004	0.006	0.000	-0.008	-0.011	-0.048	0.005	-0.007
	(0.557)	(-0.449)	(-0.334)	(0.610)	(0.034)	(-0.409)	(-0.576)	(-1.564)	(0.255)	(-0.279)
Const.	0.038	0.030	-0.106	-0.009	-0.040	0.149	0.077	0.290	-0.168	-0.265
	(0.690)	(0.382)	(-0.794)	(-0.074)	(-0.378)	(0.737)	(0.259)	(0.854)	(-0.761)	(-0.981)
Obs.	358	358	358	358	358	272	272	272	272	272
R^2	0.129	0.133	0.270	0.188	0.208	0.261	0.199	0.291	0.258	0.204

Note: All variables are in logs. Robust z-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table A1 / contd. (D4 & D5)

	4-year differences (D4)					5-year differences (D5)				
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
	total	man/prof	clerk	craft	manual	total	man/prof	clerk	craft	manual
w_i	0.393***	-0.042	-0.086	-0.195	-0.028	0.484***	-0.023	0.043	-0.232*	-0.071
	(2.745)	(-0.323)	(-0.992)	(-1.515)	(-0.374)	(3.260)	(-0.180)	(0.382)	(-1.783)	(-0.815)
w_{II}	0.737**	0.823**	0.510	0.037	0.939**	0.574**	0.762***	0.163	0.095	0.454
	(2.471)	(2.386)	(1.069)	(0.086)	(2.131)	(2.476)	(2.907)	(0.399)	(0.200)	(1.054)
K	-0.151	-0.227	0.293	-0.126	-0.487	-0.179	-0.142	0.351	-0.220	-0.285
	(-0.745)	(-0.777)	(0.701)	(-0.360)	(-1.251)	(-0.992)	(-0.549)	(0.933)	(-0.594)	(-0.849)
GO	0.839***	0.734***	0.930***	0.726***	1.121***	0.891***	0.867***	0.511*	0.728**	0.767***
	(4.730)	(3.234)	(2.886)	(2.681)	(3.434)	(5.000)	(4.250)	(1.711)	(2.408)	(2.772)
IP	-0.294	-1.011**	-0.420	0.168	-0.105	-0.452	-0.816*	-0.138	0.052	-0.444
	(-0.694)	(-2.062)	(-0.518)	(0.289)	(-0.135)	(-1.084)	(-1.704)	(-0.170)	(0.077)	(-0.580)
IIM^T	0.222	0.903**	0.052	0.153	-0.113	0.211	0.710*	-0.134	0.052	-0.067
	(0.642)	(2.214)	(0.074)	(0.328)	(-0.174)	(0.556)	(1.698)	(-0.184)	(0.093)	(-0.105)
MS_i	-0.177***	-0.118***	-0.340***	-0.286***	-0.417***	-0.178***	-0.100***	-0.294***	-0.296***	-0.343***
	(-4.509)	(-4.055)	(-7.623)	(-8.879)	(-8.789)	(-3.933)	(-3.822)	(-6.042)	(-8.098)	(-6.785)
w_i*IIM^t	-1.417*	1.156	1.336***	0.308	-1.016***	-0.821	0.337	0.809	0.731	-0.050
	(-1.911)	(1.591)	(2.677)	(0.616)	(-2.675)	(-0.914)	(0.656)	(1.430)	(1.171)	(-0.109)
w_i*MS_i	-0.365***	0.069	-0.065	0.179*	-0.128	-0.272	0.002	-0.058	0.155	-0.259*
	(-2.840)	(0.359)	(-0.553)	(1.897)	(-1.408)	(-1.108)	(0.014)	(-0.481)	(1.634)	(-1.918)
Trend	-0.021	-0.049***	-0.047**	-0.023	-0.025	-0.010	-0.046**	-0.034	0.006	-0.022
	(-1.377)	(-2.932)	(-1.990)	(-1.067)	(-1.211)	(-0.685)	(-2.470)	(-1.162)	(0.216)	(-0.829)
Const.	0.123	0.054	0.012	0.204	-0.411*	0.069	0.753**	-0.409	0.057	0.094
	(0.780)	(0.268)	(0.036)	(1.008)	(-1.668)	(0.421)	(2.149)	(-1.003)	(0.233)	(0.379)
Obs.	516	516	516	516	516	422	422	422	422	422
R^2	0.284	0.229	0.241	0.278	0.319	0.336	0.273	0.236	0.326	0.338

Table A2 / contd. (D4 & D5)

	4-year differences (D4)					5-year differences (D5)				
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
	total	man/prof	clerk	craft	manual	total	man/prof	clerk	craft	manual
w_i	0.491**	0.083	-0.215	0.121	0.208	0.656***	0.267*	0.064	0.129	0.292
	(2.392)	(0.615)	(-1.581)	(0.576)	(1.064)	(3.654)	(1.671)	(0.424)	(0.716)	(1.478)
w_{II}	0.649***	1.045**	0.103	-0.273	0.836*	0.724*	1.463***	-0.547	-1.500**	0.588
	(3.158)	(2.564)	(0.159)	(-0.441)	(1.660)	(1.827)	(3.068)	(-0.753)	(-2.022)	(1.206)
K	0.085	-0.441	0.026	0.391	-0.664	-0.077	-0.158	-0.122	0.500	-0.403
	(0.249)	(-1.054)	(0.039)	(0.758)	(-1.300)	(-0.219)	(-0.375)	(-0.189)	(0.877)	(-0.912)
GO	0.416*	0.158	0.950**	0.544	0.662*	0.386	0.476*	0.447	0.309	-0.157
	(1.685)	(0.450)	(2.106)	(1.438)	(1.716)	(1.602)	(1.677)	(0.944)	(0.842)	(-0.457)
IP	-1.292	-2.110**	-2.336*	-0.539	-3.117***	-1.138	-2.080**	-2.850**	0.208	-2.823***
	(-1.604)	(-2.463)	(-1.828)	(-0.553)	(-2.757)	(-1.589)	(-2.329)	(-1.984)	(0.201)	(-3.150)
IIM^T	0.928*	1.685***	1.487	0.808	1.842**	0.736	1.699***	1.507	0.312	1.897***
	(1.994)	(3.123)	(1.635)	(1.448)	(2.562)	(1.618)	(3.048)	(1.514)	(0.514)	(3.308)
MS_i	-0.170***	-0.095***	-0.308***	-0.287***	-0.221***	-0.170***	-0.085***	-0.286***	-0.321***	-0.170***
	(-3.967)	(-2.954)	(-4.928)	(-7.674)	(-5.354)	(-3.156)	(-2.748)	(-4.192)	(-6.964)	(-4.688)
w_i*IIM^T	-0.806	1.316	-0.372	1.184*	-0.987	0.756	1.082	-0.664	2.252**	-0.129
	(-1.082)	(1.181)	(-0.514)	(1.678)	(-1.524)	(0.531)	(1.575)	(-1.060)	(2.505)	(-0.292)
w_i*MS_i	-0.449***	-0.190	0.171	0.120	-0.009	-0.638**	-0.137	0.029	0.067	-0.053
	(-5.690)	(-1.475)	(1.056)	(0.764)	(-0.072)	(-2.033)	(-0.956)	(0.211)	(0.499)	(-0.438)
Trend	-0.018	-0.010	-0.083**	-0.058*	-0.044	0.014	0.016	-0.069	-0.020	-0.018
	(-0.677)	(-0.333)	(-2.327)	(-1.900)	(-1.443)	(0.717)	(0.525)	(-1.474)	(-0.541)	(-0.564)
Const.	0.262	-0.136	-0.151	0.235	0.024	0.052	-0.787**	-0.691	-0.248	-0.685**
	(0.906)	(-0.421)	(-0.378)	(0.883)	(0.073)	(0.179)	(-2.433)	(-1.353)	(-0.625)	(-2.028)
Obs.	230	230	230	230	230	188	188	188	188	188
R^2	0.392	0.311	0.325	0.315	0.246	0.482	0.411	0.365	0.384	0.314

Table A3 / Employment elasticity effects (total economy): Narrow & broad offshoring (D1 & D3)

	1-year differences (D1)					3-year differences (D3)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	total	man/prof	clerk	craft	manual	total	man/prof	clerk	craft	manual
w_i	0.139	-0.151	-0.088	-0.178*	-0.076	0.215	0.066	-0.091	-0.188	-0.092
	(0.921)	(-0.995)	(-1.127)	(-1.846)	(-1.003)	(1.582)	(0.565)	(-0.913)	(-1.622)	(-1.320)
w_{ii}	-0.034	-0.222	-0.114	-0.277	-0.508	0.393*	0.183	0.199	0.451	0.677
	(-0.111)	(-0.531)	(-0.251)	(-0.590)	(-0.644)	(1.748)	(0.649)	(0.503)	(1.098)	(1.421)
K	-0.388	-0.644	0.201	-0.189	-0.411	-0.312	-0.388	0.076	-0.033	-0.668
	(-1.469)	(-1.048)	(0.250)	(-0.196)	(-0.555)	(-1.413)	(-1.161)	(0.148)	(-0.076)	(-1.496)
GO	0.579***	0.512*	0.401	0.359	0.544*	0.932***	0.737***	1.152***	0.750***	1.254***
	(3.100)	(1.888)	(1.293)	(1.218)	(1.833)	(6.191)	(3.244)	(3.300)	(2.814)	(3.783)
IP	-0.112	-0.188	-0.237	-0.394	-0.204	0.019	0.021	-0.238	0.363	-0.774**
	(-0.346)	(-0.441)	(-0.504)	(-0.997)	(-0.387)	(0.091)	(0.072)	(-0.633)	(1.038)	(-1.979)
IIM^N	-0.080	-0.154	0.077	0.163	-0.024	0.031	-0.006	0.084	0.124	0.129
	(-0.983)	(-1.508)	(0.501)	(1.178)	(-0.160)	(0.498)	(-0.069)	(0.713)	(0.971)	(0.947)
IIN^B	0.168	0.377	-0.134	0.338	0.315	-0.052	0.013	0.018	-0.131	0.803***
	(0.774)	(1.283)	(-0.412)	(1.087)	(0.905)	(-0.351)	(0.061)	(0.063)	(-0.458)	(2.706)
MS_i	-0.166***	-0.164***	-0.403***	-0.254***	-0.378***	-0.175***	-0.121***	-0.346***	-0.261***	-0.366***
	(-5.828)	(-7.555)	(-10.134)	(-8.480)	(-9.262)	(-5.421)	(-5.727)	(-8.910)	(-8.182)	(-9.615)
w_i*IIM^N	-0.579	0.141	0.641	-0.294	0.688	-0.329	0.414	0.169	-0.069	-0.234
	(-1.098)	(0.184)	(0.890)	(-0.670)	(1.283)	(-0.911)	(1.399)	(1.078)	(-0.236)	(-1.265)
wi*IIM^B	-3.066***	-1.195	-0.490	0.728	-2.338***	-0.483	1.142*	1.084**	0.298	-0.549*
	(-2.663)	(-0.923)	(-0.657)	(0.498)	(-2.830)	(-0.726)	(1.885)	(1.967)	(0.577)	(-1.675)
w_i*MS_i	0.079	-0.008	-0.016	-0.049	-0.005	-0.133	0.104	-0.156	0.104	-0.132
	(0.326)	(-0.038)	(-0.136)	(-0.294)	(-0.029)	(-0.715)	(0.804)	(-1.258)	(1.048)	(-1.344)
Trend	-0.005	-0.015**	-0.012	0.002	-0.007	-0.013	-0.035***	-0.035**	-0.004	-0.015
	(-1.498)	(-2.481)	(-1.502)	(0.287)	(-0.953)	(-1.282)	(-3.038)	(-1.977)	(-0.292)	(-0.958)
Const.	0.065**	0.201	0.083	0.046	0.686	0.133	0.234*	0.117	0.254	0.092
	(2.218)	(0.954)	(0.461)	(0.568)	(1.282)	(1.352)	(1.741)	(0.695)	(1.199)	(0.453)
Obs.	792	792	792	792	792	604	604	604	604	604
R^2	0.124	0.136	0.248	0.185	0.219	0.205	0.167	0.234	0.248	0.266

Note: All variables are in logs. Robust z-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table A4 / Employment elasticity effects (manufacturing): Narrow & broad offshoring (D1 & D3)

	1-year differences (D1)					3-year differences (D3)				
	(1)	(2)	(3)	(4)	(5)	(11)	(12)	(13)	(14)	(15)
	total	man/prof	clerk	craft	manual	total	man/prof	clerk	craft	manual
w_i	0.292	0.199	-0.210**	-0.213	-0.012	0.182	0.002	-0.254**	0.058	-0.101
	(1.474)	(1.013)	(-2.151)	(-1.168)	(-0.067)	(1.200)	(0.012)	(-2.122)	(0.353)	(-0.578)
w_{ii}	0.139	-0.203	-0.087	-0.343	-0.028	0.588	0.442	0.226	0.765	0.777
	(0.295)	(-0.445)	(-0.138)	(-0.595)	(-0.045)	(1.527)	(0.995)	(0.423)	(1.363)	(1.528)
K	-0.536	-1.115	-0.127	0.207	0.342	-0.049	-0.360	-0.314	0.053	-1.002
	(-1.229)	(-1.234)	(-0.104)	(0.150)	(0.289)	(-0.128)	(-0.662)	(-0.394)	(0.072)	(-1.530)
GO	0.244	-0.155	0.230	0.239	0.302	0.491**	0.052	1.150**	0.532	0.721**
	(1.144)	(-0.440)	(0.515)	(0.796)	(0.814)	(2.526)	(0.155)	(2.465)	(1.304)	(2.064)
IP	0.042	-0.258	0.185	-0.275	0.147	0.222	0.759	-0.770	0.075	-0.321
	(0.054)	(-0.276)	(0.193)	(-0.446)	(0.225)	(0.544)	(1.441)	(-0.708)	(0.126)	(-0.515)
IIM^N	0.027	0.307	-0.055	0.199	-0.085	0.003	-0.190	0.302	0.273	-0.057
	(0.087)	(0.791)	(-0.155)	(0.778)	(-0.340)	(0.019)	(-0.895)	(0.894)	(1.332)	(-0.209)
IIM^B	0.117	0.412	-0.614	0.479	0.143	0.087	0.104	0.466	0.695	0.516
	(0.269)	(0.702)	(-0.837)	(0.917)	(0.311)	(0.279)	(0.292)	(0.740)	(1.271)	(1.029)
MS_i	-0.156***	-0.141***	-0.433***	-0.230***	-0.273***	-0.163***	-0.119***	-0.334***	-0.262***	-0.233***
	(-3.316)	(-5.500)	(-7.274)	(-5.703)	(-7.447)	(-4.209)	(-4.575)	(-5.470)	(-6.284)	(-6.359)
w_i*IIM^N	-0.260	2.256	0.664	-0.211	-1.597	-1.389*	-0.003	-0.019	-0.113	-0.787*
	(-0.136)	(1.504)	(0.538)	(-0.069)	(-0.590)	(-1.963)	(-0.005)	(-0.044)	(-0.173)	(-1.764)
w_i*IIM^B	-4.113	3.059	-1.103	1.841	-3.148	0.881	1.309	1.343	-2.729	-1.518
	(-1.220)	(1.059)	(-0.516)	(0.541)	(-1.445)	(0.605)	(1.110)	(0.946)	(-1.345)	(-1.172)
w_i*MS_i	0.127	0.200	0.133	-0.406	0.120	-0.343	-0.069	-0.030	0.013	-0.023
	(0.275)	(1.440)	(0.630)	(-1.433)	(0.586)	(-1.274)	(-0.516)	(-0.165)	(0.081)	(-0.159)
Trend	0.003	-0.008	-0.002	0.005	0.001	-0.002	-0.000	-0.039	0.006	-0.000
	(0.547)	(-0.771)	(-0.129)	(0.458)	(0.126)	(-0.138)	(-0.024)	(-1.386)	(0.296)	(-0.010)
Const.	0.041	0.060	-0.125	0.000	-0.058	0.096	-0.011	0.169	-0.136	-0.304
	(0.794)	(0.722)	(-0.944)	(0.000)	(-0.541)	(0.511)	(-0.038)	(0.566)	(-0.622)	(-1.100)
Obs.	358	358	358	358	358	272	272	272	272	272
R^2	0.122	0.150	0.272	0.190	0.201	0.263	0.202	0.287	0.264	0.208

Note: All variables are in logs. Robust z-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table A3 / contd. (D4 & D5)

	4-year differences (D4)					5-year differences (D5)				
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
	total	man/prof	clerk	craft	manual	total	man/prof	clerk	craft	manual
w_i	0.338**	-0.037	-0.077	-0.194	-0.034	0.456***	-0.028	0.140	-0.181	-0.100
	(2.265)	(-0.295)	(-0.668)	(-1.509)	(-0.436)	(3.167)	(-0.221)	(1.071)	(-1.293)	(-1.098)
w_{II}	0.453**	0.447	0.065	-0.114	0.767	0.503*	0.648**	-0.110	0.051	0.570
	(2.160)	(1.527)	(0.158)	(-0.262)	(1.567)	(1.853)	(2.082)	(-0.244)	(0.106)	(1.187)
K	-0.109	-0.253	0.269	-0.038	-0.458	-0.139	-0.137	0.353	-0.143	-0.248
	(-0.547)	(-0.845)	(0.655)	(-0.103)	(-1.167)	(-0.761)	(-0.517)	(0.942)	(-0.371)	(-0.727)
GO	0.707***	0.614***	0.812**	0.626**	1.138***	0.754***	0.727***	0.478	0.663**	0.688**
	(3.951)	(2.685)	(2.475)	(2.357)	(3.252)	(4.266)	(3.367)	(1.536)	(2.233)	(2.399)
IP	0.025	0.032	0.088	0.598	-0.606	-0.176	0.134	0.156	0.589	-0.337
	(0.111)	(0.111)	(0.246)	(1.480)	(-1.372)	(-0.733)	(0.497)	(0.440)	(1.250)	(-0.769)
IIM^N	0.103	-0.016	0.051	0.068	0.138	0.140*	0.057	-0.024	-0.038	0.081
	(1.388)	(-0.164)	(0.414)	(0.456)	(0.842)	(1.678)	(0.566)	(-0.197)	(-0.228)	(0.489)
IIN^B	-0.198	-0.141	-0.541*	-0.253	0.348	-0.125	-0.258	-0.527*	-0.440	-0.186
	(-1.221)	(-0.660)	(-1.913)	(-0.799)	(0.954)	(-0.673)	(-1.162)	(-1.675)	(-1.130)	(-0.485)
MS_i	-0.175***	-0.124***	-0.333***	-0.288***	-0.413***	-0.171***	-0.097***	-0.291***	-0.301***	-0.342***
	(-4.490)	(-4.292)	(-7.445)	(-8.905)	(-8.588)	(-3.831)	(-3.776)	(-5.941)	(-8.182)	(-6.525)
w_i*IIM^N	-0.787**	0.638*	0.246	-0.178	-0.338	-0.637	0.238	0.378	0.290	0.187
	(-2.159)	(1.713)	(1.358)	(-0.685)	(-1.454)	(-1.414)	(0.838)	(1.628)	(0.906)	(0.748)
w_i*IIM^B	-1.110	1.459*	1.447***	-0.416	-0.561*	-0.415	0.782	0.863	-0.271	-0.024
	(-1.472)	(1.790)	(2.578)	(-0.880)	(-1.758)	(-0.584)	(1.230)	(1.432)	(-0.515)	(-0.049)
w_i*MS_i	-0.418***	0.081	-0.092	0.152	-0.147	-0.306	0.029	-0.087	0.112	-0.267*
	(-3.159)	(0.437)	(-0.755)	(1.634)	(-1.599)	(-1.248)	(0.235)	(-0.738)	(1.115)	(-1.917)
Trend	-0.026*	-0.046***	-0.052**	-0.029	-0.029	-0.012	-0.044**	-0.039	0.006	-0.019
	(-1.691)	(-2.796)	(-2.293)	(-1.294)	(-1.273)	(-0.737)	(-2.353)	(-1.377)	(0.214)	(-0.693)
Const.	0.202	0.817***	0.039	0.046	0.263	0.102	0.063	0.020	-0.372	0.381
	(1.323)	(2.746)	(0.150)	(0.184)	(0.845)	(0.562)	(0.313)	(0.075)	(-1.036)	(0.994)
Obs.	511	511	511	511	511	418	418	418	418	418
R^2	0.283	0.227	0.244	0.282	0.314	0.340	0.278	0.245	0.327	0.342

Table A4 / contd. (D4 & D5)

	4-year differences (D4)					5-year differences (D5)				
	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)
	total	man/prof	clerk	craft	manual	total	man/prof	clerk	craft	manual
w_i	0.523**	0.132	-0.124	0.080	0.137	0.681***	0.367**	0.081	0.210	0.201
	(2.630)	(0.949)	(-0.871)	(0.347)	(0.644)	(3.714)	(2.345)	(0.560)	(1.038)	(1.110)
w_{II}	0.511*	0.638	-0.077	-0.552	0.548	0.538	1.246***	-0.716	-1.486**	0.223
	(2.014)	(1.613)	(-0.136)	(-0.892)	(1.060)	(1.238)	(2.650)	(-1.019)	(-2.131)	(0.435)
K	0.202	-0.687	0.199	0.451	-0.536	0.076	-0.201	0.226	0.799	-0.174
	(0.545)	(-1.563)	(0.311)	(0.804)	(-0.940)	(0.202)	(-0.445)	(0.344)	(1.257)	(-0.349)
GO	0.362	0.075	0.833*	0.554	0.540	0.366	0.552*	0.406	0.351	-0.397
	(1.532)	(0.210)	(1.863)	(1.485)	(1.379)	(1.435)	(1.767)	(0.853)	(0.974)	(-1.089)
IP	-0.321	0.202	-1.095	-0.108	-1.051	-0.187	-0.073	-1.223	0.435	0.040
	(-0.674)	(0.349)	(-1.277)	(-0.163)	(-1.311)	(-0.394)	(-0.133)	(-1.394)	(0.621)	(0.059)
IIM^N	0.180	-0.129	0.410	0.301	0.221	0.111	0.043	0.288	0.140	-0.003
	(1.141)	(-0.604)	(1.524)	(1.444)	(0.717)	(0.593)	(0.193)	(1.070)	(0.640)	(-0.011)
IIM^B	-0.192	-0.189	-0.312	0.586	0.108	-0.514*	-0.635	-0.777	-0.428	-0.648
	(-0.515)	(-0.461)	(-0.526)	(0.921)	(0.174)	(-1.789)	(-1.486)	(-1.150)	(-0.740)	(-1.362)
MS_i	-0.174***	-0.095***	-0.313***	-0.286***	-0.226***	-0.182***	-0.089***	-0.305***	-0.319***	-0.166***
	(-4.060)	(-2.922)	(-5.024)	(-7.527)	(-5.606)	(-3.269)	(-2.944)	(-4.449)	(-6.988)	(-4.372)
w_i*IIM^N	-0.476	0.105	0.018	0.258	-1.053*	0.400	-0.133	-0.282	0.933	-0.045
	(-0.723)	(0.251)	(0.042)	(0.410)	(-1.771)	(0.406)	(-0.254)	(-0.700)	(1.454)	(-0.090)
w_i*IIM^B	1.004	4.297***	2.965*	-2.175	1.045	2.545**	4.272***	-0.364	0.501	0.019
	(0.787)	(3.680)	(1.709)	(-1.207)	(0.548)	(2.033)	(4.661)	(-0.236)	(0.292)	(0.013)
w_i*MS_i	-0.412***	-0.152	0.229	0.173	-0.008	-0.656*	-0.116	0.000	0.052	-0.102
	(-3.647)	(-1.278)	(1.341)	(1.050)	(-0.061)	(-1.975)	(-0.759)	(0.002)	(0.365)	(-0.778)
Trend	-0.014	0.006	-0.088**	-0.050*	-0.028	0.015	0.022	-0.061	-0.019	0.010
	(-0.615)	(0.207)	(-2.527)	(-1.655)	(-0.938)	(0.721)	(0.792)	(-1.396)	(-0.518)	(0.323)
Const.	0.212	-0.327	-0.144	0.201	-0.403	0.037	-0.873***	-0.691	-0.210	-0.969***
	(0.782)	(-0.983)	(-0.386)	(0.745)	(-1.071)	(0.123)	(-2.726)	(-1.407)	(-0.522)	(-2.691)
Obs.	230	230	230	230	230	188	188	188	188	188
R^2	0.387	0.322	0.332	0.317	0.232	0.491	0.430	0.368	0.384	0.287

Table A5 / Employment elasticity effects (total economy): Manufacturing & services offshoring

	1-year differences (D1)					3-year differences (D3)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	total	man/prof	clerk	craft	manual	total	man/prof	clerk	craft	manual
w_i	0.163	-0.146	-0.077	-0.170*	-0.105	0.264*	0.035	-0.094	-0.188	-0.129**
	(1.158)	(-0.960)	(-1.005)	(-1.805)	(-1.396)	(1.812)	(0.260)	(-1.005)	(-1.623)	(-2.000)
w_{II}	0.065	-0.081	0.178	-0.351	-0.137	0.395*	0.286	0.180	0.469	0.660
	(0.223)	(-0.216)	(0.448)	(-0.756)	(-0.225)	(1.821)	(1.002)	(0.477)	(1.128)	(1.616)
K	-0.355	-0.612	0.217	-0.173	-0.385	-0.311	-0.311	0.092	-0.043	-0.601
	(-1.403)	(-0.981)	(0.269)	(-0.182)	(-0.519)	(-1.346)	(-0.919)	(0.175)	(-0.100)	(-1.338)
GO	0.429**	0.400	0.336	0.369	0.427	0.875***	0.688***	0.969***	0.769***	1.124***
	(2.548)	(1.558)	(1.118)	(1.324)	(1.472)	(5.724)	(2.933)	(2.762)	(2.877)	(3.421)
IP	0.225	0.080	0.407	0.288	0.242	0.225	0.211	0.365	0.449*	0.009
	(0.906)	(0.336)	(1.223)	(0.879)	(0.743)	(1.621)	(1.065)	(1.292)	(1.755)	(0.034)
IIM^M	-0.010	0.074	-0.298*	-0.132	0.046	0.021	0.070	0.123	-0.041	0.017
	(-0.093)	(0.720)	(-1.785)	(-0.636)	(0.288)	(0.315)	(0.749)	(0.847)	(-0.289)	(0.118)
IIM^S	-0.259**	-0.130	-0.464***	-0.331**	-0.141	-0.219***	-0.226**	-0.573***	-0.214*	0.077
	(-2.218)	(-1.108)	(-2.883)	(-2.211)	(-0.827)	(-2.782)	(-2.103)	(-3.921)	(-1.764)	(0.577)
Msi	-0.162***	-0.163***	-0.398***	-0.256***	-0.385***	-0.181***	-0.128***	-0.345***	-0.258***	-0.360***
	(-5.676)	(-7.351)	(-10.127)	(-8.609)	(-9.473)	(-5.801)	(-6.117)	(-8.909)	(-8.238)	(-9.391)
w_i*IIM^M	0.397	0.356	-0.149	-0.893	-0.739	-0.165	0.461	0.253	0.067	0.040
	(0.532)	(0.429)	(-0.239)	(-1.156)	(-1.155)	(-0.403)	(0.970)	(0.947)	(0.153)	(0.149)
w_i*IIM^S	-0.476	0.445	0.228	1.307**	-0.462	-0.381	0.402	0.791**	0.601*	-0.545***
	(-0.982)	(0.750)	(0.393)	(1.996)	(-0.793)	(-0.646)	(0.799)	(2.446)	(1.950)	(-2.669)
w_i*MS_i	0.092	0.006	-0.043	-0.059	0.049	-0.148	0.082	-0.179	0.121	-0.129
	(0.412)	(0.025)	(-0.345)	(-0.360)	(0.301)	(-0.731)	(0.630)	(-1.448)	(1.278)	(-1.293)
Trend	-0.007**	-0.017***	-0.011	0.003	-0.009	-0.013	-0.035***	-0.036**	-0.003	-0.017
	(-2.000)	(-2.837)	(-1.388)	(0.415)	(-1.097)	(-1.216)	(-3.124)	(-2.078)	(-0.193)	(-1.051)
Const.	0.085***	0.283	-0.110	0.060	0.047	0.142	0.423	-0.267	0.291	-0.295
	(2.781)	(1.379)	(-0.726)	(0.173)	(0.744)	(1.412)	(1.568)	(-1.035)	(1.398)	(-1.445)
Obs.	798	798	798	798	798	608	608	608	608	608
R^2	0.115	0.127	0.249	0.196	0.209	0.223	0.172	0.255	0.252	0.265

Note: All variables are in logs. Robust z-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table A6 / Employment elasticity effects (manufacturing): Manufacturing & services offshoring

	1-year differences (D1)					3-year differences (D3)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	total	man/prof	clerk	craft	manual	total	man/prof	clerk	craft	manual
w_i	0.226	0.071	-0.231**	-0.322*	-0.006	0.047	-0.090	-0.282**	-0.159	-0.127
	(0.941)	(0.351)	(-2.352)	(-1.886)	(-0.035)	(0.254)	(-0.662)	(-2.112)	(-0.812)	(-0.644)
w_{II}	0.145	0.096	-0.271	-0.536	-0.195	0.570	0.575	0.151	0.598	0.475
	(0.333)	(0.167)	(-0.453)	(-0.958)	(-0.297)	(1.365)	(1.252)	(0.309)	(1.063)	(0.955)
K	-0.601	-1.125	-0.291	0.115	0.199	0.006	-0.072	-0.249	0.490	-0.532
	(-1.567)	(-1.176)	(-0.243)	(0.080)	(0.168)	(0.015)	(-0.127)	(-0.314)	(0.678)	(-0.807)
GO	0.271	-0.022	0.301	0.199	0.350	0.370*	-0.024	0.926**	0.457	0.549
	(1.152)	(-0.066)	(0.686)	(0.675)	(0.989)	(1.852)	(-0.073)	(2.169)	(1.112)	(1.600)
IP	0.374	0.646*	0.447	0.280	0.138	0.174	0.355	-0.120	0.649*	-0.220
	(0.975)	(1.946)	(0.915)	(0.758)	(0.387)	(0.847)	(1.386)	(-0.282)	(1.680)	(-0.578)
IIM^M	-0.319	-0.345	-0.269	0.315	0.136	0.267	0.351	0.357	0.339	0.527
	(-0.863)	(-1.186)	(-0.695)	(0.930)	(0.365)	(1.254)	(1.348)	(0.974)	(0.906)	(1.509)
IIM^S	-0.512***	-0.427***	-1.026***	-0.581***	-0.383*	-0.503***	-0.405**	-0.857***	-0.789***	-0.479*
	(-2.907)	(-2.587)	(-3.790)	(-2.708)	(-1.673)	(-2.735)	(-2.399)	(-3.527)	(-3.004)	(-1.862)
MS_i	-0.154***	-0.141***	-0.429***	-0.235***	-0.272***	-0.168***	-0.129***	-0.345***	-0.237***	-0.230***
	(-3.761)	(-5.522)	(-7.633)	(-5.869)	(-7.578)	(-4.499)	(-5.189)	(-5.722)	(-6.044)	(-6.296)
w_i*IIM^M	1.090	1.914**	-0.684	0.319	-2.426	-0.276	0.397	0.077	-2.370	-1.195
	(1.243)	(2.177)	(-0.635)	(0.108)	(-1.418)	(-0.368)	(0.500)	(0.091)	(-1.583)	(-1.138)
w_i*IIM^S	-0.047	0.288	0.928	2.773	0.504	1.946*	1.029*	0.773	2.222*	0.477
	(-0.039)	(0.494)	(1.172)	(1.545)	(0.536)	(1.920)	(1.650)	(1.277)	(1.764)	(0.545)
w_i*MS_i	0.145	0.210	0.075	-0.402	0.096	-0.210	-0.055	-0.048	-0.127	0.018
	(0.358)	(1.427)	(0.443)	(-1.401)	(0.469)	(-0.776)	(-0.410)	(-0.263)	(-0.755)	(0.122)
Trend	0.000	-0.007	-0.005	0.004	-0.002	-0.005	-0.006	-0.033	0.008	-0.009
	(0.020)	(-0.832)	(-0.421)	(0.416)	(-0.190)	(-0.350)	(-0.326)	(-1.313)	(0.406)	(-0.367)
Const.	0.072	0.038	-0.076	0.005	-0.036	0.194	-0.044	0.120	-0.061	-0.234
	(1.329)	(0.515)	(-0.598)	(0.044)	(-0.343)	(1.130)	(-0.142)	(0.439)	(-0.293)	(-0.871)
Obs.	358	358	358	358	358	272	272	272	272	272
R^2	0.150	0.157	0.300	0.209	0.205	0.312	0.224	0.323	0.302	0.231

Note: All variables are in logs. Robust z-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table A5 / contd. (D4 & D5)

	4-year differences (D4)					5-year differences (D5)				
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
	total	man/prof	clerk	craft	manual	total	man/prof	clerk	craft	manual
w_i	0.382**	-0.076	-0.086	-0.204	-0.073	0.483***	-0.041	0.067	-0.243**	-0.054
	(2.627)	(-0.556)	(-0.837)	(-1.593)	(-1.024)	(3.219)	(-0.322)	(0.565)	(-1.982)	(-0.723)
w_{II}	0.625**	0.760**	0.284	-0.027	0.806*	0.515**	0.745***	0.069	0.055	0.417
	(2.093)	(2.156)	(0.605)	(-0.061)	(1.859)	(2.304)	(2.657)	(0.176)	(0.115)	(1.022)
K	-0.144	-0.082	0.286	-0.119	-0.380	-0.191	-0.103	0.327	-0.251	-0.186
	(-0.713)	(-0.273)	(0.692)	(-0.332)	(-0.970)	(-0.952)	(-0.389)	(0.881)	(-0.663)	(-0.530)
GO	0.751***	0.537**	0.797**	0.689**	1.030***	0.854***	0.761***	0.517*	0.675**	0.657**
	(4.224)	(2.428)	(2.512)	(2.525)	(3.023)	(4.689)	(3.659)	(1.759)	(2.264)	(2.336)
IP	0.181	0.203	0.383	0.416	0.022	-0.081	0.233	0.251	0.161	-0.233
	(1.292)	(1.115)	(1.506)	(1.534)	(0.081)	(-0.471)	(1.398)	(1.098)	(0.534)	(-0.774)
IIM^M	-0.020	0.002	-0.080	0.018	-0.096	0.008	-0.035	-0.054	-0.030	-0.329*
	(-0.258)	(0.020)	(-0.507)	(0.107)	(-0.604)	(0.111)	(-0.347)	(-0.354)	(-0.189)	(-1.821)
IIM^S	-0.265***	-0.283***	-0.703***	-0.037	-0.087	-0.117	-0.248***	-0.506***	0.067	-0.092
	(-3.517)	(-3.004)	(-4.569)	(-0.251)	(-0.587)	(-1.530)	(-2.620)	(-3.682)	(0.400)	(-0.655)
MS_i	-0.182***	-0.117***	-0.333***	-0.286***	-0.410***	-0.173***	-0.098***	-0.294***	-0.291***	-0.352***
	(-4.614)	(-4.432)	(-7.697)	(-8.696)	(-8.615)	(-3.781)	(-3.823)	(-6.234)	(-7.743)	(-6.792)
w_i*IIM^M	-0.503	0.147	0.588*	0.320	-0.057	-0.086	0.341	0.267	0.899***	0.058
	(-1.525)	(0.281)	(1.907)	(0.901)	(-0.241)	(-0.204)	(0.710)	(0.955)	(3.111)	(0.249)
w_i*IIM^S	0.075	1.410***	1.038***	0.106	-0.526**	0.133	0.685**	0.793***	-0.030	-0.289
	(0.154)	(2.772)	(3.297)	(0.342)	(-2.478)	(0.408)	(2.337)	(2.737)	(-0.087)	(-1.156)
w_i*MS_i	-0.331**	-0.054	-0.143	0.177*	-0.134	-0.269	-0.061	-0.124	0.155*	-0.267**
	(-2.464)	(-0.352)	(-1.219)	(1.938)	(-1.484)	(-1.090)	(-0.554)	(-1.118)	(1.678)	(-2.076)
Trend	-0.019	-0.044***	-0.044**	-0.025	-0.027	-0.008	-0.039**	-0.029	0.003	-0.016
	(-1.251)	(-2.711)	(-1.982)	(-1.154)	(-1.237)	(-0.531)	(-2.132)	(-1.016)	(0.111)	(-0.576)
Const.	0.143	0.659**	0.011	-0.575*	-0.423*	0.067	-0.108	-0.264	0.032	0.045
	(0.913)	(2.082)	(0.035)	(-1.800)	(-1.684)	(0.395)	(-0.522)	(-0.663)	(0.102)	(0.133)
Obs.	514	514	514	514	514	420	420	420	420	420
R^2	0.295	0.259	0.277	0.278	0.315	0.337	0.292	0.260	0.332	0.347

Table A6 / contd. (D4 & D5)

	4-year differences (D4)					5-year differences (D5)				
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
	total	man/prof	clerk	craft	manual	total	man/prof	clerk	craft	manual
w_i	0.445**	-0.088	-0.236*	-0.093	0.280	0.370	0.026	0.123	-0.051	0.372*
	(2.423)	(-0.607)	(-1.740)	(-0.388)	(1.246)	(1.673)	(0.170)	(0.738)	(-0.233)	(1.806)
w_{II}	0.549	1.005**	-0.238	-0.584	0.273	0.611	1.452**	-0.640	-1.396**	0.147
	(1.465)	(2.087)	(-0.445)	(-0.948)	(0.527)	(1.240)	(2.521)	(-0.890)	(-2.069)	(0.292)
K	0.373	0.390	0.191	0.803	-0.099	0.359	0.425	0.112	1.059*	-0.001
	(1.092)	(0.783)	(0.296)	(1.460)	(-0.157)	(0.856)	(0.908)	(0.162)	(1.714)	(-0.002)
GO	0.243	-0.109	0.723*	0.375	0.223	0.332	0.365	0.331	0.377	-0.401
	(1.089)	(-0.310)	(1.740)	(0.984)	(0.577)	(1.417)	(1.272)	(0.742)	(1.082)	(-1.164)
IP	0.071	-0.040	-0.050	0.531	-0.153	0.038	0.160	-0.907**	0.634	0.072
	(0.327)	(-0.134)	(-0.126)	(1.149)	(-0.383)	(0.139)	(0.483)	(-2.061)	(1.236)	(0.224)
IIM^M	-0.018	-0.123	-0.277	0.127	0.262	-0.348*	-0.298	-0.526	-0.640*	0.035
	(-0.088)	(-0.433)	(-0.700)	(0.319)	(0.643)	(-1.902)	(-1.052)	(-1.259)	(-1.720)	(0.128)
IIM^S	-0.544***	-0.671***	-0.733***	-0.569**	-0.732***	-0.327**	-0.467***	-0.216	-0.686***	-0.534***
	(-3.852)	(-3.763)	(-2.912)	(-2.411)	(-2.691)	(-2.293)	(-2.743)	(-0.804)	(-2.603)	(-2.767)
MS_i	-0.192***	-0.110***	-0.320***	-0.264***	-0.233***	-0.190***	-0.091***	-0.295***	-0.295***	-0.170***
	(-4.940)	(-3.412)	(-5.355)	(-7.384)	(-5.837)	(-3.620)	(-3.123)	(-4.441)	(-6.606)	(-4.869)
w_i*IIM^M	-0.914	1.709**	0.411	-1.983*	1.576	0.933**	1.780***	0.072	0.283	1.058
	(-0.792)	(2.068)	(0.345)	(-1.801)	(1.130)	(2.228)	(3.848)	(0.118)	(0.212)	(0.959)
w_i*IIM^S	1.459*	1.812**	1.696**	1.448*	-0.299	1.488*	0.510	-0.433	1.542*	-0.885
	(1.930)	(2.469)	(2.432)	(1.811)	(-0.325)	(2.007)	(0.832)	(-0.764)	(1.819)	(-1.259)
w_i*MS_i	-0.474***	-0.286**	0.144	0.065	0.049	-0.666**	-0.141	0.002	-0.052	-0.034
	(-6.969)	(-2.280)	(0.963)	(0.408)	(0.343)	(-2.481)	(-1.009)	(0.015)	(-0.367)	(-0.274)
Trend	-0.006	-0.001	-0.068**	-0.044	-0.015	0.017	0.026	-0.049	-0.003	0.013
	(-0.276)	(-0.046)	(-2.276)	(-1.629)	(-0.543)	(0.910)	(0.939)	(-1.141)	(-0.095)	(0.439)
Const.	0.167	-0.274	-0.239	0.089	-0.320	-0.040	-0.893***	-0.549	-0.233	-0.934***
	(0.720)	(-0.903)	(-0.712)	(0.368)	(-1.152)	(-0.151)	(-3.051)	(-1.057)	(-0.654)	(-2.839)
Obs.	230	230	230	230	230	188	188	188	188	188
R^2	0.436	0.336	0.360	0.339	0.257	0.492	0.424	0.366	0.406	0.307

Table A7 / Cross-effects of migration (total economy): Total offshoring (D1 & D3)

	1-year differences (D1)				3-year differences (D3)			
	(1) man/prof	(2) clerk	(3) craft	(4) manual	(5) man/prof	(6) clerk	(7) craft	(8) manual
w_I	-0.293**	-0.199**	-0.162*	-0.064	0.086	-0.137**	-0.188*	-0.150*
	(-2.119)	(-2.428)	(-1.689)	(-0.715)	(0.688)	(-2.157)	(-1.721)	(-1.697)
w_{II}	-1.019**	-0.245	-0.237	-0.774	-0.231	0.355	0.522	0.313
	(-2.407)	(-0.432)	(-0.514)	(-0.961)	(-0.680)	(0.675)	(1.224)	(0.699)
K	-0.129	0.156	-0.065	-0.386	0.087	-0.566	0.097	-0.411
	(-0.195)	(0.162)	(-0.067)	(-0.471)	(0.201)	(-0.902)	(0.225)	(-0.813)
GO	0.729***	0.397	0.393	0.782***	0.626**	1.317***	0.785***	0.817***
	(2.650)	(1.237)	(1.268)	(2.590)	(2.434)	(3.487)	(2.786)	(2.800)
IP	-1.865***	-1.381*	-0.773	-1.635*	-0.782	-1.277	0.255	0.517
	(-3.285)	(-1.949)	(-1.329)	(-1.914)	(-1.500)	(-1.523)	(0.498)	(0.752)
IIM^T	1.717***	1.130**	0.813*	1.501**	0.736*	0.972	0.011	-0.278
	(3.775)	(2.091)	(1.654)	(1.980)	(1.747)	(1.394)	(0.028)	(-0.491)
$MS_{manager}$	-0.162***	0.094***	0.028	0.029	-0.113***	0.076**	-0.007	0.048*
	(-6.783)	(3.304)	(1.139)	(1.240)	(-5.063)	(2.235)	(-0.239)	(1.732)
MS_{clerk}	-0.002	-0.398***	-0.029	-0.003	-0.012	-0.336***	-0.022	0.005
	(-0.093)	(-8.950)	(-1.224)	(-0.103)	(-0.569)	(-7.771)	(-0.862)	(0.189)
MS_{craft}	0.006	0.038	-0.256***	0.026	0.014	0.030	-0.267***	0.050*
	(0.258)	(1.436)	(-8.353)	(1.027)	(0.490)	(0.897)	(-7.940)	(1.719)
MS_{manual}	0.032	0.053	-0.013	-0.334***	0.036	0.000	0.025	-0.333***
	(1.279)	(1.283)	(-0.378)	(-9.191)	(1.238)	(0.001)	(0.735)	(-8.286)
w_I*IIM^T	-1.420	-0.627	0.502	-0.990	1.197	0.035	0.657	-1.477***
	(-0.930)	(-0.549)	(0.320)	(-1.191)	(1.327)	(0.069)	(1.401)	(-3.344)
w_I*$MS_{manager}$	-0.004	-0.067	-0.085	0.163	0.173	-0.155	-0.203	0.017
	(-0.017)	(-0.492)	(-0.858)	(1.450)	(1.315)	(-0.958)	(-1.636)	(0.155)
w_I*MS_{clerk}	-0.253**	0.005	-0.068	-0.277**	-0.182*	-0.064	-0.079	0.005
	(-1.985)	(0.043)	(-0.890)	(-2.446)	(-1.828)	(-0.522)	(-1.054)	(0.050)
w_I*MS_{craft}	-0.108	-0.009	-0.046	-0.069	-0.017	0.026	0.129	-0.063
	(-0.986)	(-0.073)	(-0.277)	(-0.584)	(-0.186)	(0.251)	(1.310)	(-0.689)
w_I*MS_{manual}	0.072	0.010	0.000	0.162	0.048	-0.057	-0.003	-0.084
	(0.979)	(0.104)	(0.002)	(1.093)	(0.559)	(-0.481)	(-0.032)	(-0.638)
Trend	-0.020***	-0.010	0.001	-0.008	-0.034***	-0.035*	-0.003	-0.007
	(-3.060)	(-1.279)	(0.168)	(-1.092)	(-2.712)	(-1.765)	(-0.172)	(-0.442)
Const.	0.316**	0.169	0.147	0.180	0.073	-0.238	-0.074	0.363
	(2.442)	(0.770)	(0.710)	(0.816)	(0.418)	(-0.939)	(-0.384)	(0.725)
Obs.	682	682	682	682	522	522	522	522
R^2	0.194	0.266	0.188	0.220	0.183	0.245	0.256	0.272

Note: All variables are in logs. Robust z-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table A7 / contd. (D4 & D5)

	4-year differences (D4)				5-year differences (D5)			
	(9) man/prof	(10) clerk	(11) craft	(12) manual	(13) man/prof	(14) clerk	(15) craft	(16) manual
w_i	-0.051	-0.155**	-0.179	-0.081	-0.027	-0.052	-0.228*	-0.118
	(-0.414)	(-2.238)	(-1.431)	(-0.814)	(-0.209)	(-0.518)	(-1.756)	(-1.228)
w_{II}	0.145	0.362	-0.025	0.365	0.320	0.557	0.031	0.981**
	(0.411)	(0.701)	(-0.055)	(0.794)	(0.980)	(0.923)	(0.064)	(2.212)
K	0.069	-0.212	0.026	-0.301	0.128	-0.122	-0.116	-0.445
	(0.191)	(-0.445)	(0.071)	(-0.745)	(0.433)	(-0.289)	(-0.303)	(-1.267)
GO	0.471*	1.049***	0.746***	0.626**	0.719***	0.377	0.681**	0.425
	(1.779)	(3.010)	(2.641)	(2.035)	(3.185)	(1.054)	(2.206)	(1.620)
IP	-1.765***	-1.603**	0.256	-0.426	-1.287***	-1.099	0.184	-1.084*
	(-3.479)	(-2.171)	(0.426)	(-0.629)	(-2.599)	(-1.349)	(0.258)	(-1.665)
IIM^T	1.513***	1.233**	0.113	0.429	1.090***	0.835	-0.034	0.711
	(3.803)	(2.057)	(0.229)	(0.794)	(2.653)	(1.203)	(-0.057)	(1.437)
$MS_{manager}$	-0.109***	0.087**	0.024	0.038	-0.093***	0.099**	0.026	0.073*
	(-3.683)	(2.347)	(0.654)	(1.240)	(-3.366)	(2.355)	(0.653)	(1.957)
MS_{clerk}	0.031	-0.312***	-0.049	0.012	0.010	-0.310***	-0.073**	-0.050
	(1.109)	(-6.621)	(-1.493)	(0.329)	(0.337)	(-5.770)	(-2.060)	(-1.456)
MS_{craft}	-0.032	0.020	-0.281***	0.015	-0.016	0.074*	-0.305***	0.049*
	(-1.277)	(0.553)	(-8.392)	(0.499)	(-0.589)	(1.698)	(-7.874)	(1.691)
MS_{manual}	0.048	-0.017	0.005	-0.353***	0.020	0.037	0.072**	-0.275***
	(1.528)	(-0.399)	(0.137)	(-7.964)	(0.661)	(0.749)	(2.183)	(-6.266)
w_i*IIMT	1.012	0.234	0.263	-1.430***	0.339	-0.080	0.563	-0.307
	(1.605)	(0.590)	(0.540)	(-2.995)	(0.710)	(-0.236)	(0.856)	(-0.651)
w_i*$MS_{manager}$	0.267	0.125	-0.091	0.084	0.031	-0.043	-0.147	-0.007
	(1.527)	(0.536)	(-0.689)	(0.605)	(0.252)	(-0.229)	(-1.048)	(-0.044)
w_i*MS_{clerk}	0.146*	-0.020	-0.112	0.021	0.082	-0.031	-0.074	-0.024
	(1.686)	(-0.171)	(-1.349)	(0.262)	(0.964)	(-0.251)	(-0.872)	(-0.304)
w_i*MS_{craft}	0.017	-0.169	0.177*	-0.080	0.153*	0.019	0.148	0.052
	(0.221)	(-1.501)	(1.820)	(-0.847)	(1.909)	(0.162)	(1.481)	(0.617)
w_i*MS_{manual}	0.093	0.046	-0.033	-0.077	0.039	0.022	-0.082	-0.227*
	(1.314)	(0.438)	(-0.352)	(-0.688)	(0.603)	(0.237)	(-0.927)	(-1.940)
Trend	-0.058***	-0.057**	-0.024	-0.028	-0.043**	-0.020	0.007	-0.009
	(-3.185)	(-2.230)	(-1.093)	(-1.226)	(-2.156)	(-0.590)	(0.261)	(-0.349)
Const.	0.594***	-0.077	0.154	0.672	0.215	-0.079	0.137	-0.277
	(2.650)	(-0.317)	(0.762)	(1.204)	(0.988)	(-0.248)	(0.324)	(-0.864)
Obs.	442	442	442	442	362	362	362	362
R^2	0.255	0.262	0.286	0.316	0.310	0.282	0.341	0.370

Table A8 / Cross-effects of migration (manufacturing): Total offshoring (D1 & D3)

	1-year differences (D1)				3-year differences (D3)			
	(1) man/prof	(2) clerk	(3) craft	(4) manual	(5) man/prof	(6) clerk	(7) craft	(8) manual
w_i	-0.098	-0.253**	-0.205	0.009	0.161	-0.217*	0.077	0.004
	(-0.787)	(-2.355)	(-1.176)	(0.061)	(1.098)	(-1.712)	(0.466)	(0.025)
w_{ll}	-0.475	-0.037	-0.286	0.082	-0.183	1.635**	1.032*	1.007*
	(-0.966)	(-0.048)	(-0.485)	(0.133)	(-0.413)	(2.348)	(1.743)	(1.820)
K	-0.511	0.130	0.294	0.452	-0.071	-1.064	0.171	-0.747
	(-0.679)	(0.099)	(0.207)	(0.369)	(-0.133)	(-1.250)	(0.255)	(-1.209)
GO	-0.076	0.005	0.203	0.306	0.140	1.220**	0.419	0.716**
	(-0.218)	(0.011)	(0.651)	(0.809)	(0.408)	(2.544)	(1.002)	(2.000)
IP	-0.510	-0.625	0.082	-0.378	0.212	-2.411	0.384	-0.453
	(-0.697)	(-0.606)	(0.102)	(-0.445)	(0.263)	(-1.493)	(0.356)	(-0.443)
IIM^T	0.585	0.611	0.170	0.475	0.204	1.581	0.211	0.022
	(1.202)	(0.865)	(0.326)	(0.883)	(0.445)	(1.460)	(0.326)	(0.032)
$MS_{manager}$	-0.141***	0.128***	0.015	0.034	-0.111***	0.091**	-0.019	0.063*
	(-5.388)	(3.375)	(0.478)	(1.225)	(-4.280)	(2.197)	(-0.530)	(1.804)
MS_{clerk}	0.011	-0.483***	-0.034	0.012	0.021	-0.381***	-0.012	0.003
	(0.446)	(-7.663)	(-0.979)	(0.374)	(0.716)	(-5.827)	(-0.297)	(0.098)
MS_{craft}	0.016	0.048	-0.225***	0.022	-0.038	0.016	-0.263***	0.023
	(0.622)	(1.246)	(-5.317)	(0.675)	(-1.196)	(0.381)	(-6.287)	(0.647)
MS_{manual}	0.012	0.129***	0.005	-0.289***	0.007	0.045	0.030	-0.254***
	(0.433)	(2.741)	(0.125)	(-8.133)	(0.225)	(0.916)	(0.751)	(-5.925)
w_i*IIM^T	1.184	0.481	-0.293	-6.725**	-2.329**	-0.568	-0.032	-1.158**
	(0.493)	(0.223)	(-0.056)	(-2.469)	(-2.084)	(-0.799)	(-0.029)	(-2.058)
$w_i*MS_{manager}$	0.229*	-0.201	-0.145	0.006	0.056	-0.355**	-0.226	-0.040
	(1.696)	(-1.036)	(-0.833)	(0.035)	(0.431)	(-2.028)	(-1.459)	(-0.293)
w_i*MS_{clerk}	0.149	0.057	0.031	0.044	-0.026	-0.125	-0.046	-0.009
	(1.574)	(0.257)	(0.309)	(0.437)	(-0.230)	(-0.635)	(-0.321)	(-0.051)
w_i*MS_{craft}	-0.316**	-0.185	-0.409	-0.513**	0.215*	-0.026	-0.031	-0.055
	(-2.230)	(-0.767)	(-1.410)	(-2.214)	(1.933)	(-0.165)	(-0.190)	(-0.477)
w_i*MS_{manual}	-0.010	-0.094	0.117	0.121	-0.010	-0.191	-0.158	-0.018
	(-0.059)	(-0.354)	(0.551)	(0.623)	(-0.063)	(-0.997)	(-0.753)	(-0.122)
Trend	-0.007	-0.005	0.007	0.003	-0.006	-0.033	0.006	-0.001
	(-0.726)	(-0.427)	(0.660)	(0.307)	(-0.337)	(-1.082)	(0.289)	(-0.047)
Const.	-0.012	-0.134	-0.036	-0.007	-0.156	0.109	-0.210	-0.212
	(-0.134)	(-1.045)	(-0.276)	(-0.061)	(-0.927)	(0.389)	(-1.136)	(-1.018)
Obs.	340	340	340	340	260	260	260	260
R^2	0.164	0.347	0.189	0.232	0.200	0.340	0.271	0.217

Note: All variables are in logs. Robust z-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

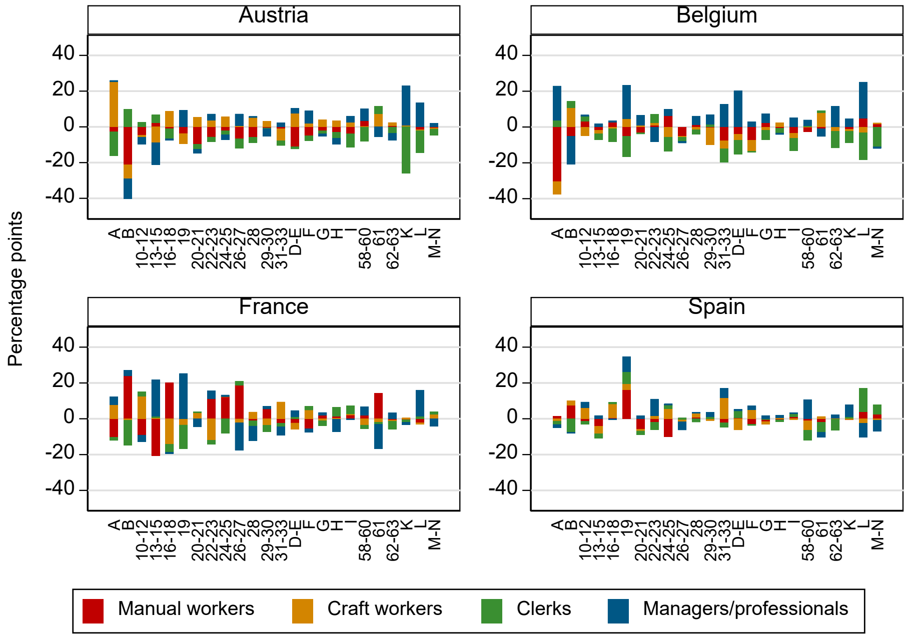
Table A8 / contd. (D4 & D5)

	4-year differences (D4)				5-year differences (D5)			
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	man/prof	clerk	craft	manual	man/prof	clerk	craft	manual
w_i	0.085	-0.168	0.106	0.222	0.266	0.075	0.131	0.309
	(0.596)	(-1.233)	(0.493)	(1.107)	(1.568)	(0.413)	(0.713)	(1.497)
w_{II}	0.020	1.088	-0.267	0.950*	0.062	-0.073	-1.468**	0.946*
	(0.043)	(1.629)	(-0.420)	(1.769)	(0.138)	(-0.085)	(-2.014)	(1.945)
K	-0.006	-0.498	0.430	-0.630	0.188	-0.337	0.529	-0.471
	(-0.013)	(-0.744)	(0.796)	(-1.240)	(0.442)	(-0.491)	(0.905)	(-1.075)
GO	0.263	0.780*	0.512	0.601	0.311	0.097	0.158	-0.284
	(0.753)	(1.782)	(1.354)	(1.545)	(1.082)	(0.198)	(0.439)	(-0.808)
IP	-2.261**	-3.396***	-0.461	-3.476***	-1.083	-2.328*	0.597	-2.915***
	(-2.386)	(-2.798)	(-0.433)	(-3.037)	(-1.254)	(-1.659)	(0.568)	(-3.351)
IIM^T	1.582***	2.855***	0.767	2.135***	0.835	1.094	0.094	2.029***
	(2.825)	(3.294)	(1.248)	(2.965)	(1.470)	(1.110)	(0.156)	(3.690)
$MS_{manager}$	-0.085***	0.135***	-0.011	0.073**	-0.077**	0.119**	0.009	0.066*
	(-2.659)	(3.065)	(-0.274)	(2.064)	(-2.412)	(2.300)	(0.216)	(1.898)
MS_{clerk}	0.045	-0.323***	-0.009	0.035	-0.017	-0.347***	-0.060	-0.021
	(1.251)	(-5.481)	(-0.185)	(0.814)	(-0.464)	(-4.932)	(-1.274)	(-0.582)
MS_{craft}	-0.058*	-0.025	-0.289***	-0.015	-0.041	0.022	-0.337***	0.032
	(-1.820)	(-0.555)	(-7.517)	(-0.375)	(-1.284)	(0.387)	(-6.752)	(0.976)
MS_{manual}	0.014	0.029	0.024	-0.237***	0.017	0.077	0.105***	-0.182***
	(0.413)	(0.591)	(0.558)	(-5.539)	(0.540)	(1.330)	(2.826)	(-4.880)
w_i*IIMT	0.159	-1.708**	1.299*	-0.776	-0.584	0.013	2.739***	-0.169
	(0.269)	(-2.375)	(1.765)	(-1.123)	(-0.756)	(0.016)	(2.792)	(-0.396)
w_i*$MS_{manager}$	-0.031	-0.484***	-0.158	-0.037	-0.071	-0.451**	-0.340**	-0.258*
	(-0.218)	(-2.887)	(-0.981)	(-0.228)	(-0.481)	(-2.319)	(-2.473)	(-1.845)
w_i*MS_{clerk}	0.253**	0.055	-0.026	0.142	0.184	0.004	0.011	0.064
	(2.338)	(0.293)	(-0.193)	(1.080)	(1.615)	(0.022)	(0.084)	(0.666)
w_i*MS_{craft}	0.258**	-0.224	0.124	0.091	0.230**	-0.010	0.071	-0.011
	(2.249)	(-1.356)	(0.723)	(0.635)	(2.316)	(-0.051)	(0.518)	(-0.086)
w_i*MS_{manual}	-0.022	0.051	-0.020	-0.028	-0.021	0.027	-0.081	-0.036
	(-0.136)	(0.282)	(-0.086)	(-0.226)	(-0.157)	(0.130)	(-0.568)	(-0.299)
Trend	-0.037	-0.075**	-0.056*	-0.043	0.009	-0.035	-0.009	0.007
	(-1.259)	(-2.111)	(-1.821)	(-1.395)	(0.325)	(-0.726)	(-0.236)	(0.229)
Const.	0.394	0.568**	0.233	0.187	-0.803***	-0.762*	-0.697**	-0.306
	(1.374)	(1.960)	(0.866)	(0.643)	(-3.321)	(-1.782)	(-2.079)	(-1.207)
Obs.	220	220	220	220	180	180	180	180
R^2	0.279	0.396	0.320	0.265	0.404	0.414	0.419	0.347

7. Annex B

Figures B1 and B2 below show average changes between 2008 and 2017 in occupational employment shares of natives and migrants, respectively.

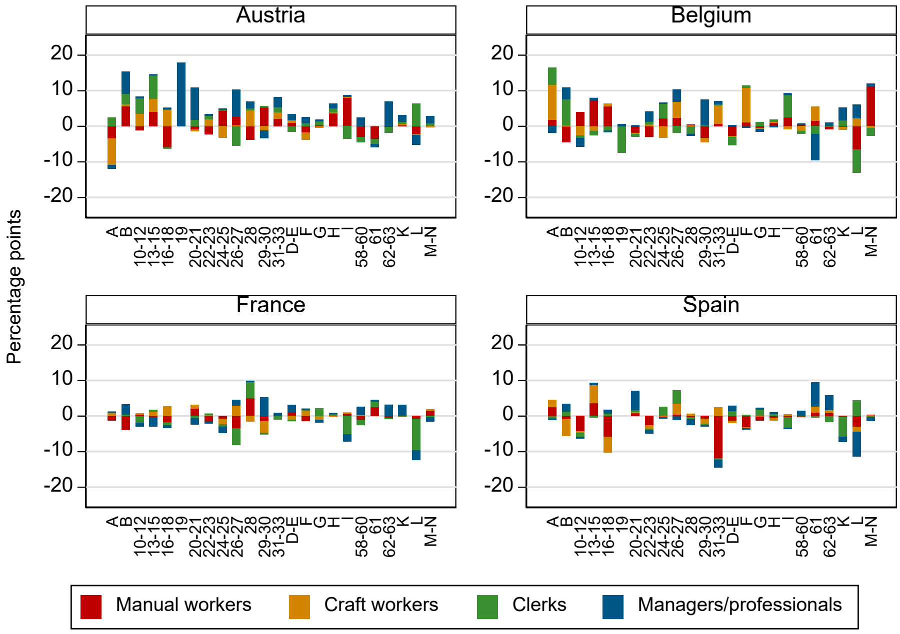
Figure B1 / Average change in occupational employment shares of natives (2008-2017)



Note: Absolute change (in percentage points) in native employment shares (relative to total employment) between 2008-2011 and 2015-2017.
Source: National EU-SILC, own calculations.

As concerns average *changes in the occupational employment shares of natives*, very country-specific patterns emerge (see Figure B1). For instance, in Austria, native manual workers and clerks lost employment share in almost all industries, while native managers/professionals lost out in only about half of the industries considered. The loss in the employment share of manual workers was most pronounced in industries B (Mining and quarrying), D-E (Electricity, gas, water, steam and air conditioning supply & sewerage) and 20-21 (Chemicals and chemical products), while clerks lost the most in industry A (Agriculture), as well as in some service industries, such as K (Financial and insurance activities), L (Real estate), I (Accommodation) and 58-60 (Publishing, audio-visual and broadcasting activities). The share of managers/professionals fell the most in industries B (Mining and quarrying) and 13-15 (Textiles & leather products). By contrast, with very few exceptions, the employment share of Austrian craft workers increased in the majority of industries, particularly A (Agriculture), 16-18 (Wood and paper products) and 61 (Telecommunications). In Belgium, manual workers, craft workers and clerks lost employment share in the majority of industries, while managers/professionals gained employment share in almost all industries (mainly B, 22-23, 26-27 and 61). In France, the loss in employment share was most widespread among clerks, craft workers and managers/professionals, while manual workers lost out in only a few industries, most notably 13-15 (Textiles & leather products), A (Agriculture) and 10-12 (Food products, beverages and tobacco). In Spain, losses in employment share were most common among manual workers, craft workers and clerks, while the employment share of managers/professionals only fell in a few industries, most notably L (Real estate) and M-N (Professional, scientific and technical activities).

Figure B2 / Average change in occupational employment shares of migrants (2008-2017)



Note: Absolute change (in percentage points) in native employment shares (relative to total employment) between 2008-2011 and 2015-2017.
Source: National EU-SILC, own calculations.

Average *changes in the occupational employment share of migrants* are shown in Figure B2 below. Interestingly, a comparison of the occupational employment changes of natives and of migrants points to important differences: migrant workers experienced losses in employment share not only in *fewer* industries than did natives, but also (partly) in *different* industries. Furthermore, by and large, losses (as well as gains) in employment share were lower for migrants than for natives. A case in point is Austria, where migrant manual workers lost employment share in half of all industries considered (most notably in industry 16-18 – Wood and paper products), while migrant craft workers, clerks and managers/professionals experienced an increase in their employment share in almost all industries. Indeed, among migrant managers/professionals, employment share decreased in only four industries: A (Agriculture), 29-30 (Transport equipment), 61 (Telecommunications) and L (Real estate), and then only by around 3 percentage points at most. In Belgium, compared to the same group of native workers, migrant manual workers, craft workers and clerks lost employment share in only about half of all industries considered. At about 6 percentage points on average, the loss in employment share was most pronounced among migrant manual workers and clerks in industry L (Real estate). At about 3 percentage points on average, the loss in employment share was most pronounced among migrant craft workers in industries 10-12 (Food products) and 24-25 (Basic metals and fabricated metal products). By contrast, compared to native managers/professionals, migrant managers/professionals experienced loss in a couple more industries. In France, both migrant manual workers and clerks experienced loss of employment share in about half of all industries considered. Among migrant clerks, loss of employment share was most pronounced in industries L (Real estate), I (Accommodation) and 26-27 (Computer & electrical equipment). For France, the starkest difference across native and migrant workers is observable among craft workers: while the employment share of native craft workers fell in about half of all industries, migrant craft workers saw their employment share increase in all but five industries. Finally, in Spain, the patterns of occupational employment share change also differ across native and migrant workers. This applies above all to craft workers and managers/professionals. While the employment share of migrant craft workers fell in only a few select industries, the loss of employment share was more pervasive among native craft workers. Conversely, loss of employment share was far more widespread among migrant managers/professionals than among native managers/professionals, and was more concentrated in the manufacturing sector.

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ZVR-Zahl: 329995655

Postanschrift: A 1060 Wien, Rahlgasse 3, Tel: [+431] 533 66 10, Telefax: [+431] 533 66 10 50
Internet Homepage: www.wiiw.ac.at

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