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A Fresh Look at the EU Experience

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Abstract

This paper analyses the contribution of immigration, trade and FDI to wage inequality of native workers in a sample of old and new EU Member States between 2008 and 2013. Methodologically, we use the regression-based Shapley value decomposition approach of Shorrocks (2013) to filter out their relative importance. We find that globalisation has very mixed effects and generally contributes little to wage inequality. Regarding their relative contributions, immigration and FDI are key contributors to wage inequality in old EU Member States, while trade is the key source of wage inequality in new EU Member States. For immigration, the associated increase in wage inequality is strongest and most consistent among Southern EU Member States. We also show that immigration, trade and FDI have different effects across the wage distribution that are however strongest at its centre. For trade and FDI, we also find sporadic inequality-reducing effects that are strongest at the top of the wage distribution.

Keywords: wage inequality, trade, FDI, immigration, Shapley value decomposition

JEL classification: J31, O15, F16

CONTENTS

1. Introduction

In recent decades, the globalisation of economic activities has expanded rapidly through both international trade and the fast expansion of international production networks as well as international investment, particularly in the form of foreign direct investment (FDI). At the same time, international migration has reached unprecedented levels as people migrate in search of better labour market opportunities elsewhere and to escape poverty, political unrest, war or the consequences of climate change.

In advanced countries, these developments have sparked a heated and partly controversial debate as to the economic and social consequences of globalisation. In this context, labour market effects have received a fair amount of attention particularly since ongoing globalisation is seen to go in tandem with rising income inequality and high unemployment among low-skilled workers. In fact, there is broad agreement among economists that globalisation harms some groups in society while benefiting others. In particular, through the substitution of migrant for native workers or the exploitation of offshoring and outsourcing opportunities of low-skill-intensive tasks, globalisation is considered to reduce the demand for and subsequently the wages of native low-skilled workers. As a consequence of this wage squeeze among low-skilled workers, inequality is increasing.

Understanding the underlying causes of inequality is fundamental to devising policy measures. Hence, this paper studies the effects of three forces of globalisation, namely immigration, value chain trade and FDI, together with different worker and firm characteristics, on wage inequality of native workers in a sample of 14 old (OMS) and new (NMS) EU Member States between 2008 and 2013.

This paper makes several contributions to the literature. First, from a methodological perspective, based on results from Mincer-type multilevel wage regressions, it applies the Shapley value decomposition method of Shorrocks (2013) to decompose wage inequality for native workers. This allows us to shed light on the various sources of wage inequality and helps us to determine the *relative* contributions of the three different dimensions of globalisation, in addition to different individual worker and firm characteristics, to observable wage inequality of native workers in the EU. Traditionally, the effects of immigration, trade and FDI are analysed separately which makes it impossible to determine their relative roles for wage inequality. The simultaneous analysis of all three dimensions of globalisation in this paper provides a clearer picture in this respect. Second, it compares results for three different inequality measures, namely the Gini index and two Generalised Entropy Indexes (GE(0) and GE(2)), which all place different weights on different segments of the wage distribution. This allows us to draw a more differentiated picture and identify the particular wage segment and wage group which is more strongly affected – positively or negatively – by the three forces of globalisation of interest. Third, the split of the overall period under consideration (2008-2013) into a crisis period (2008-2010) and a post-crisis period (2011-2013) allows us to examine the relative contributions of immigration, trade and FDI to wage inequality from a dynamic perspective.

Our results show that globalisation has very mixed and country-specific effects on wage inequality among native workers and generally contributes little to it: taken together, immigration, trade and FDI explain between 1 per cent and 20 per cent of overall wage inequality among native workers. However, in view of data issues related to the high level of aggregation of the three measures of globalisation and the fact that individuals' labour market participation decisions could not be taken into consideration, these results need to be considered the lower bound of the overall effect of globalisation. The three dimensions of globalisation play different roles in different countries and while migration and FDI contribute the most to wage inequality in the OMS, trade is the key source of wage inequality in the NMS. Furthermore, immigration, trade and FDI have different effects across the wage distribution which are mostly felt by medium-wage earners. In important countries of immigration, such as Greece or Italy, immigration contributes the most to inequality at the centre and the top of the wage distribution. Moreover, trade and FDI enhance wage inequality in both OMS and NMS, but the consequences are felt in different wage segments. In the more skill-abundant OMS, trade and FDI increase wage inequality the most at the centre and top of the wage distribution, while in the more low skill-abundant NMS, the associated increase in wage inequality is strongest at the centre and in some cases also at the bottom. In some European countries, trade and FDI also contribute to lower wage inequality, which is however only true for the tails of the wage distribution and is most pronounced at its top.

The rest of the paper is structured as follows: section 2 reviews both theoretical arguments and international empirical evidence on the effects of immigration, trade and FDI on wage inequality. Section 3 discusses the underlying two-step empirical framework while section 4 describes the data sources and variable definitions. Section 5 presents and discusses results for the three different inequality measures. Section 6 summarises and concludes.

2. Review of related literature

From a theoretical perspective there are different theories and arguments – with partly conflicting implications and conclusions – as to the effects of immigration, trade and FDI on wages and wage inequality. This is also reflected in the rich strand of related empirical literature, which reaches equally mixed and inconclusive conclusions. Hence, in what follows, we provide a brief overview and discussion of different theories of and international empirical evidence on the effects of immigration, trade and FDI on wage inequality.

2.1. INCOME INEQUALITY AND IMMIGRATION

According to the theoretical literature, effects of immigration on wages crucially depend on the socioeconomic and demographic characteristics of both the immigrant and native populations – particularly in terms of skills – and the associated degree of substitutability or complementarity of their labour. In this respect, an inflow of immigrant labour will increase competition in the labour market and subsequently reduce wages of native workers if immigrants and natives possess similar skills so that the level of substitution of foreign for native workers is high. This negative wage effect (for native workers with similar skills as immigrants) is mitigated and translated into increased unemployment should wages prove inflexible downwards due to the unwillingness or inability of strong trade unions to accommodate increased immigration. Conversely, the negative wage effect is further exacerbated if non-member immigrants are willing to work for lower pay which undercuts the wages of native members with the same skills and initiates a 'race to the bottom' in terms of wages (Krings, 2009). By contrast, if immigrants and natives possess different skills so that immigrants are complements to native workers, an inflow of immigrant labour will improve productivity and subsequently increase wages of native workers with skills different from those of immigrants.

Previous empirical literature predominantly looked at the differential effect of immigration on various skill, occupation or education groups to shed light on the potential immigration-induced income and wage inequality effects. By and large, this strand of literature finds evidence in support of the differential effect of immigration, which tends to be to the detriment of less skilled and less educated native workers whose wages fall, thereby contributing to income inequality among native workers. For instance, Card (2009) emphasises that immigration increased inequality in the United States; the effect was, however, rather small. On the other hand, Borjas (2003) shows for the US that the strong influx of immigrants of the 1980s and 1990s had a strong and particularly harmful effect on high school dropouts with simulations pointing to a wage drop of 8.9 per cent. Likewise, Jaeger (2007) emphasises that while immigration to the US in the 1980s widened the wage gap between low- and high-skilled workers, high school dropouts experienced the most substantial loss in real wages of roughly a third of the total decline in their real wages. This is also corroborated by Ottaviano and Peri (2012) who find a modest negative long-run effect of immigration to the US between 1990 and 2006 on real wages of the least educated natives. Occupation-based empirical analyses provide further insights into which particular occupations were affected the most in different countries and show that manual labourers or skilled production workers and semi- or unskilled services workers experienced the strongest immigration-induced drop in their wages (Orrenius and Zavodny, 2007 for the US; Nickell and Saleheen, 2015 for the UK). However, income inequality not only increases due to the detrimental wage effects at the lower end of the income distribution but may also result from relatively stronger wage improvements at the upper end of the income distribution. In this context, Foged and Peri (2015) demonstrate that the inflow of unskilled non-EU immigrants to Denmark increased the wages of both unskilled and skilled native workers, with however stronger effects for skilled workers. In particular, stronger competition from unskilled immigrants induced less skilled native workers to move to more complex occupations that pay higher wages in other firms, while the complementarity of unskilled immigrant and native skilled workers improved the latter's wages even more but without the need for occupational upgrading.

In contrast, a number of European studies tend to find only a negligible or no effect of immigration on wages of and inequality among native workers. For instance, Bauer et al. (2011) fail to find any significant wage effect of a higher share of foreign workers in the West German labour market, neither for all native workers together, nor for skilled and unskilled native workers separately. Little evidence of any immigration-induced wage effect is also found by Dustmann et al. (2005) and Manacorda et al. (2012), both for the UK. The latter stress that, in line with Ottaviano and Peri (2012), previous immigrants – particularly university immigrants – experienced the most pronounced drop in wages as a result of immigration between the mid-1970s and the mid-2000s.

In addition, limited empirical evidence directly looked at distributional effects of immigration by means of standard income inequality measures such as the Gini coefficient. This line of literature generally finds an inequality-enhancing effect of immigration. For instance, Dustmann et al. (2013) stress that the wage effect depends on the relative density of immigrants and native workers at different parts of the income distribution. They find that due to the higher density of immigrants (relative to native workers) at the lower end of the income distribution, immigration reduced wages of native workers below the 20th percentile. In contrast, the relatively lower density of immigrants at the upper end of the income distribution contributed to wage growth above the 40th percentile. Likewise, Hibbs and Hong (2015) find an inequality-enhancing effect of immigration between 1990 and 2000 into US metropolitan cities and quantify that, for a given metropolitan area, a 1 per cent increase in the immigrant population is associated with an about 0.66 point increase in the Gini coefficient. Similarly, Xu et al. (2016) study inequality at the US state level and stress that, both in the short and long run, a higher share of foreign-born population is related to higher state-level income inequality. They emphasise that this inequality-enhancing effect is predominantly driven by low-skilled immigration. In contrast, no significant effect of immigration on different measures of inequality and entropy are found by Korpi (2008), who shows that neither the total stock of the foreign-born population nor the share of recent immigrants had any significant effect on income inequality among Swedish native workers.

2.2. INCOME INEQUALITY AND TRADE

Traditionally, the effects of trade on income inequality have been analysed in the context of the workhorse model of trade, namely the Heckscher-Ohlin (HO) model. The standard HO model with two factors of production – skilled and unskilled – and two countries – the skill-abundant North and the unskill-abundant South – which produce two goods – skilled and unskilled labour-intensive – predicts that countries specialise in and export goods that use the relatively abundant factor more intensely. Accordingly, trade liberalisation induces an expansion of production and exports of products intensive in the abundant factor which results in an increase in the price of the abundant factor. Hence, countries well endowed with unskilled labour – the South – experience an increase in the demand for and wages of unskilled workers, while countries well endowed with skilled labour – the North – see an increase in the demand for and wages of skilled workers. Consequently, wage inequality will decrease in the South but increase in the North.

In contrast to this, Feenstra and Hanson (1996) go beyond the two-goods, two-types-of-skills HO model but assume a continuum of goods that can be ordered by the respective level of skill intensity. In their model, trade liberalisation induces a shift of intermediate input production from the skill-abundant North to the unskill-abundant South, which subsequently increases imports of intermediate inputs (such as parts and components) by the North from the South. In this process, stages of production that are less skill-intensive from the North's perspective but more skill-intensive from the South's perspective are outsourced and moved southwards so that the relative demand for and wages of more skilled workers increases in both regions, generating a rise in income inequality in both the North and the South.

Furthermore, trade can help facilitate the diffusion of technology from the technologically leading North to the technologically lagging South, either through imports of more advanced technologies embodied in goods or through easier access to technological knowledge and more advanced foreign technologies through exports and export links. The effects on income inequality are then determined by the skill intensity of the transferred technology. In this respect, if the transferred technologies are skill-biased and require skills for an effective and efficient operation, the subsequent increase in the demand for and wages of skilled labour increases inequality in the technology-receiving South.

However, up to now, empirical evidence as to the impact of globalisation on income inequality is controversial and inconclusive, which is partly the result of differences in econometric specifications, estimators, definitions of variables, samples or time horizons. By and large, most empirical studies show that trade has an inequality-enhancing effect in developing countries and an inequality-reducing effect in developed countries, which is in contradiction to the predictions of the HO-model (Asteriou et al., 2014; Barro, 2000; Cornia and Kiiski, 2001; Faustino and Vali, 2011; Goldberg and Pavcnik, 2007; Jaumotte et al., 2013; Lim and McNelis, 2014; Lundberg and Squire, 2003; Mah, 2013; Mahesh, 2016 or Ravallion, 2001). The exact extent of the effect differs across studies but seems quantitatively limited. For instance, Milanovic and Squire (2005) highlight that a 1 point decrease in the average tariff rate is associated with a 5.7 per cent annual increase in inequality. However, this effect is lower among very poor economies and is only associated with a 1 per cent increase in inequality; it reverses and becomes positive for richer economies. Similarly, Mah (2013) reports for China that a 1 per cent increase in trade openness (as the share of the sum of exports and imports in GDP) increases the decile ratio by 0.17 and the RIPO ratio (defined as the average income of the top 10 per cent divided by that of the bottom 40 per cent) by 0.9. Furthermore, the relationship between trade and inequality seems to be non-linear in nature such that trade may induce an increase in inequality in the short run; in the long run, however, as trade expands further, inequality may decrease (Franco and Gerussi, 2013; Jalil, 2012). In addition, some studies lend support to the skill-biased nature of technology diffusion which emphasises the importance of the level of technological development of the trading partner for any income distributional effects. In this respect, Grimalda et al. (2010) show for a set of new EU Member States, Commonwealth of Independent States and South Eastern European economies that trade with the technologically more advanced EU – but not other developing countries – had an inequality-enhancing effect, particularly in new EU Member States. In a similar vein, Meshi and Vivarelli (2009) demonstrate for a large set of 65 developing countries that trade with industrialised countries further increased inequality while trade with other developing countries helped reduce inequality.

By contrast, some studies lend support to the predictions of the HO model, pointing to the inequality-reducing effect of trade in developing countries but the inequality-enhancing effect of trade in developed countries such as Acar and Dogruel (2010) for 6 MENA countries or Calderón and Chong (2001). However, exact distributional effects of trade differ across studies and tend to be small. For instance, Calderón and Chong (2001) find for a rich sample of 102 developing and developed countries that a 5 per cent increase in the volume of trade results in 1.3 points decline of the Gini index. However, the volume of trade has opposing effects on inequality in developing and developed countries. For developing countries, the inequality-reducing effect is even more pronounced where a 5 per cent increase in the volume of trade results in 3.5 points decline of the Gini index. In contrast, inequality tends to increase in developed countries in response to an increase in the volume of trade.

A few authors also point to the absence of any significant relationship between inequality and trade (such as Beaton et al., 2017; Edwards, 1997; Li et al., 1998).

2.3. INCOME INEQUALITY AND FDI

From a theoretical point of view, inward FDI can have different effects on income inequality, both in the home as well as the host country. As concerns the distributional effects of FDI in a developing country context, the HO model of international trade predicts that FDI inflows benefit the more abundant low-skilled labour in developing countries. The subsequent increase in the demand for as well as wages of low-skilled labour helps reduce wage dispersion and income inequality in the developing host country. Conversely, in the developed source country, a reverse process takes place, resulting in an increase in income inequality.

However, other theories arrive at different conclusions. For instance, according to the North-South endowment-driven model of vertical FDI of Feenstra and Hanson (1997), FDI by Northern multinational enterprises (MNEs) serves to outsource part of the input production to the South. Since the outsourced activities are relatively unskilled-labour-intensive from the North's perspective but relatively skilled-labour-intensive from the South's perspective, both regions see an increase in the demand for and wages of skilled labour. Hence, income inequality increases in both regions.

Such North-South models are, however, generally less useful in explaining distributional consequences of FDI in richer, more advanced host countries. In this respect, MNE models prove more insightful which stress that relative to their domestic counterparts, MNEs are more productive due to, among other things, superior technology and knowledge (Markusen, 1995). Since these technologies require more skilled labour, MNEs have different labour demand requirements than domestic firms. Hence, inward FDI – through the entry of MNEs – increases inequality due to higher demand for and, consequently, higher wages of skilled labour. By contrast, inequality may also decline once the skill intensities of headquarter services as opposed to plant operations and the dual role of more advanced economies as both home and host countries of MNEs are taken into consideration. Since skill-intensive headquarter services are predominantly undertaken in the more advanced home countries of MNEs, demand for skilled labour is high, which tends to increase inequality. However, with the establishment of less skill-intensive plant operations in advanced economies through inward FDI, the demand for skilled labour may decline, which helps to reduce inequality in more advanced economies.

Finally, in line with the endogenous theory of economic growth, inward FDI can also serve as an important source of spillovers which increases the demand for as well as wages of skilled labour as domestic firms learn from MNEs and adopt more advanced technologies, at least as long as skilled labour is relatively short in supply. Over time, however, as the supply of skilled labour improves, wages of skilled labour tend to fall again (Aghion and Howitt, 1998). Hence, in the course of FDI-induced spillovers, inequality in the host country increases in the short run but decreases in the long run.

The continuously growing empirical evidence as to the FDI-inequality nexus, which predominantly looks at the experience of developing as well as transition and emerging economies, is also far from conclusive. For instance, in violation of the predictions of the HO model, a large body of empirical literature emphasises the inequality-enhancing effect of FDI. In this context, Tsai (1995) for a sample of 33 developing countries, Basu and Guariglia (2007) for a panel of 119 developing countries, Herzer et al. (2012) for a sample of Latin American countries, Halmos (2011) for a sample of 15 Eastern European countries or Grimalda et al. (2010) and Mihaylova (2015) for 10 new EU Member States all report that FDI is associated with higher income inequality in the host countries. Similarly, Gopinath and Chen (2003) find for a sample of 11 developing countries that inward FDI stocks increased the wage gap between skilled and unskilled workers while Bhandari (2007) highlights that inward FDI aggravated wage inequality in a set of 19 transition economies in Eastern Europe and Central Asia. This inequality-enhancing effect of FDI is also corroborated by studies on individual developing countries, such as Mexico (Feenstra and Hanson, 1997), China (Zhang and Zhang, 2003) and Indonesia (Lipsey and Sjöholm, 2001). However, as evidenced by Mah (2002) for South Korea, Asteriou et al. (2014) for the EU core or Taylor and Driffield (2005) for the UK manufacturing sector, the inequality-deepening effect of FDI is not a phenomenon only observable in developing or transition economies. Indeed, evidence is mounting that the effect of FDI strongly depends on the host country’s level of economic development. For instance, Mihaylova (2015) demonstrates for 10 new EU Member States that inward FDI generally increased inequality but that this effect lessened with an increase in GDP per capita. Similarly, Herzer and Nunnenkamp (2011) show that while FDI increased income inequality in a set of low-income old EU Member States, FDI decreased income inequality in a set of high-income old EU Member States. Moreover, limited empirical evidence finds support of the predictions of the model of Feenstra and Hanson (1997) in terms of the inequality-enhancing effect in both sending and receiving countries of FDI. For instance, Hsieh and Woo (2005) show that the skill premium increased in Hong Kong after firms relocated unskilled-labour-intensive production from Hong Kong to mainland China. Furthermore, limited empirical evidence suggests that the inequality-enhancing effect of FDI is sector-biased such that FDI exerts a stronger negative effect on income inequality if flowing into the manufacturing or services sectors but remains statistically insignificant if flowing into the primary sector (Suanes, 2016). Similarly, the inequality-deepening effect of FDI may differ by the direction of FDI. In this respect, Choi (2006) emphasises for a diverse set of over 100 countries that outward FDI exerted a stronger inequality-enhancing effect than inward FDI. Additionally, the relationship between FDI and inequality appears to be non-linear in nature such that inequality increases with inward FDI but this effect tends to diminish with further increases in FDI (Figini and Görg, 1999 and 2011). Relatedly, the FDI-inequality nexus is strongly time-dependent and while FDI tends to increase inequality in the short run, it decreases inequality in the long run (Herzer and Nunnenkamp, 2011; Ucal et al., 2014).

In contrast to the above, a number of empirical studies also find an inequality-reducing effect of FDI. For instance, Im and McLaren (2015) demonstrate for a sample of 127 developing countries that FDI helps to decrease inequality. Similarly, taking account of inter-state heterogeneity, several state-based studies stress that increased FDI inflows is associated with a decrease in inequality, with however different effects across states (see, e.g., Jensen and Rosas (2007) for Mexican states, Trinh (2016) for Vietnamese provinces) or time (Chintrakarn et al. (2010) for US states).

A small number of studies also fails to find any significant relationship between FDI and income inequality (see, e.g., Sylwester, 2005; Franco and Gerussi, 2013) or any evidence of a non-linear relationship between FDI and income inequality for that matter (Milanovic, 2002).

3. Empirical framework

Methodologically, we follow a twofold approach to shed light on the relative importance of immigration, trade and FDI, together with different worker and firm characteristics, on wage inequality among native workers.

First, we specify a Mincer wage regression (Mincer, 1974), where we consider various individual worker characteristics and the three globalisation measures of interest to explain individual wages. However, as information on immigration, trade and FDI is only available at the industry level[1], we consider the individual and the industry level in the Mincer wage regression, by employing a multilevel regression model. Such a model allows us to appropriately incorporate explanatory variables at both levels and enables us to consider the hierarchy/structure in the data, which improves estimates' efficiency (Gelman and Hill, 2006). It is similar to a multi-stage regression model, where the model is first run at the individual level for each industry and the results are subsequently used to run the regression at the industry level. However, in a multilevel regression model, the regressions of both stages are estimated simultaneously. More formally, we estimate a two-level wage regression of the following form:[2]

$$y_{ijt} = \boldsymbol{X}'_{ijt}\boldsymbol{\beta} + \boldsymbol{Z}'_{jt}\boldsymbol{\gamma} + \delta_t + \upsilon_{jt} + \epsilon_{ijt}, \qquad \upsilon_{jt} \sim N(0, \sigma_2^2) \text{ and } \epsilon_{ijt} \sim N(0, \sigma_\epsilon^2) \qquad (1)$$

where y_{ijt} is the ihs-transformed[3] gross hourly wage of native individual i employed in industry j at time t. $\boldsymbol{X}_{ijt}$ denotes a $k \times 1$ vector of explanatory variables specified at the individual level. In this respect, we use information on demographic and socio-economic worker characteristics, such as gender, age, education and occupation, as well as information on the type of their work contract and the degree of urbanisation of their residential area to explain individual wages (see Table 1 for an overview of variable definitions). In particular, the role of gender is measured by means of a dummy variable for females which captures differences in gross hourly wages across genders. Starting with Becker (1957), a rich and continuously growing body of literature has demonstrated that even after controlling for other characteristics, women earn less than men (for Europe, see, e.g., Christofides et al., 2013; Nicodemo, 2009; Olivetti and Petrongolo, 2008). Concerning age, as advocated by the human capital theory (e.g. Becker, 1993) and shown by several cross-sectional analyses (see Willis,1986 for a survey), a concave age-earnings profile is expected since investments in human capital exceed depreciation in the early years of a worker's career, giving rise to increasing productivity and earnings. However, as workers age, on the one hand, investments in human capital become less profitable and attractive and, on the other hand, investments in human capital made in the early years depreciate, so that productivity and earnings

1 This approach enables us to use differences in the globalisation dimensions across industries. However, potential differences between firms with different exposure to globalisation activities within industries remain unconsidered. Most probably this results in an underestimation of the true impact.

2 Globalisation may also affect labour market participation decisions. Since we also apply industry-level explanatory variable, we cannot consider unemployed individuals in our analysis. This prevents us from using a Heckman correction procedure which most probably results in a downward bias of our estimates.

3 Inverse hyperbolic sine transformation: $ihs(y) = \ln(y + \sqrt{y^2 + 1})$ (see, for example, Burbidge et al., 1988). This has the advantage that the estimated constant becomes positive, which is useful for the Shapley value decomposition (see below).

decline. We model diminishing returns by adding a squared term for age. Furthermore, human capital accumulation – and therefore education – is considered one of the key determinants of a worker's wage. Numerous studies have pointed to partly non-negligible returns to education (for Europe, see, e.g., Harmon et al., 2001; Glocker and Steiner, 2011; Middendorf, 2008 or Prieto-Rodriguez et al., 2008). Furthermore, occupation, which is closely related to and largely determined by education, matters for earnings. From the perspective of the human capital theory, post-school investments in training and education, which differ across occupations, are important determinants of productivity and earnings. Moreover, differences in skill requirements, ability, opportunities, supply and demand forces or labour market institutions help explain widely observable earnings differences across occupations in many countries (Tachibanaki, 1998). With respect to contract type, evidence is mounting that workers on temporary contracts earn less than those on permanent contracts (e.g. Brown and Session, 2003; Da Silva and Turrini, 2015). This is typically explained by the lack of outside options of employees due to strong employment protection (Lindbeck and Snower, 2001) or asymmetric information and the need of employers to learn about workers' qualifications and the quality of the worker-firm match. Furthermore, we also account for agglomeration effects and expect that the concentration of economic activities in urban areas is associated with higher wages relative to more rural areas. We proxy this by the degree of urbanisation of workers' residential area and therefore assume that workers' residential area is in close proximity to their workplace. We also consider firm-specific information, which is however limited to firm size. In particular, following comprehensive empirical evidence on prevailing firm-size wage premia, we expect firm size to be positively associated with workers' wages (for Europe see, e.g., Lallemand et al., 2007).

By contrast, $\boldsymbol{Z}_{jt}$ represents an $l \times 1$ vector of industry-level explanatory variables, comprising our three key globalisation measures of interest, namely immigration, trade and FDI, together with per-capita business enterprise R&D stocks and per-capita value-added levels. While per-capita business enterprise R&D stocks act as a proxy for skill-biased technological change (SBTC), per-capita value-added levels control for differences in the overall productivity across industries as well as industry-specific business cycles. SBTC is typically seen to favour skilled over unskilled workers (and therefore drives wage inequality) so that more skill-intensive industries are expected to pay higher wages, on average, than more unskill-intensive industries. Value added per capita reflects the overall productivity of an industry and is expected to be positively correlated with individual gross hourly wages. As concerns the three key globalisation measures of interest, the above extensive review of literature demonstrates that expected effects on wages are a priori unclear but need to be tested empirically. Furthermore, δ_t denotes time-fixed effects. υ_{jt} is the random effect corresponding to the intercepts of industries in a country and ϵ_{ijt} is the remaining error term, both assumed to be normally distributed.

Second, we use the estimated coefficients from the multilevel wage regression to conduct the Shapley value decomposition method of Shorrocks (2013) and assess the relative importance of the different variables for wage inequality. More specifically, we compute predicted values for all different variable combinations[4] and then calculate associated inequality measures. The comparison of the inequality measures for different variable combinations then helps us to assess the contribution of each variable to

[4] Since y_{ijt} is the ihs-transformed gross hourly wage, we compute the predicted values $\widehat{y_{\imath\jmath t}}$ and take $\exp\left(\widehat{\imath hs(y_{\imath\jmath t})}\right)$. We therefore basically apply the transformed fitted values$(\hat{y}_{ijt} + \sqrt{\hat{y}_{ijt}^2 + 1})$ instead of $\hat{y}_{ijt}$. Since we do not have large negative predicted values, the use of the transformed fitted values is less problematic (see Leitner, 2016 for a similar approach). Thus, inequality measures are based on absolute gross hourly wages.

wage inequality. The procedure can best be illustrated by means of an example with three explanatory variables. Suppose we have two individual explanatory variables (x_1,x_2) and one industry-level explanatory variable (z_3). We want to evaluate the contribution of variable x_1. The predicted values are then used to calculate wage inequality denoted by $\hat{I}^{(0)}_{\{123\}}$. Here, we consider all three explanatory variables as indicated by the subscript. In order to assess the overall contribution of x_1, we need to capture its marginal contribution[5] to wage inequality. Hence, first, we compare $\hat{I}^{(0)}_{\{123\}}$ with $\hat{I}^{(1)}_{\{23\}}$, where, for the computation of the predicted values and the wage inequality, only x_2 and z_3 are considered. This yields the first marginal contribution of x_1: $C_1^1 = \hat{I}^{(0)}_{\{123\}} - \hat{I}^{(1)}_{\{23\}}$. In a second step we also eliminate other variables from the computation. In doing so, we calculate $\hat{I}^{(1)}_{\{12\}}$ and $\hat{I}^{(1)}_{\{13\}}$, where we consider only x_2 and z_3 in addition to x_1, respectively. Based on these values, we obtain further marginal contributions:

$$C_2^1 = \hat{I}^{(1)}_{\{12\}} - \hat{I}^{(2)}_{\{2\}} \qquad\qquad C_3^1 = \hat{I}^{(1)}_{\{13\}} - \hat{I}^{(2)}_{\{3\}} \tag{2}$$

where $\hat{I}^{(2)}_{\{2\}}$ and $\hat{I}^{(2)}_{\{3\}}$ denote the wage inequality, where we only use the estimates for x_2 and z_3, respectively. Finally, the last contribution arises from $C_4^1 = \hat{I}^{(2)}_{\{1\}} - \hat{I}^{(3)}_{\{0\}}$ incorporating only the variable under consideration. Since $\hat{I}^{(3)}_{\{0\}} = 0$ we find that $C_4^1 = \hat{I}^{(2)}_{\{1\}}$. The overall contribution of x_1 to wage inequality is then the average over all marginal contributions: $C_1 = \frac{1}{4}(C_1^1 + C_2^1 + C_3^1 + C_4^1)$. We then also apply this procedure to the other variables x_2 and z_3. Analogously, the model can be easily extended to include additional explanatory variables. However, since the number of variable combinations to capture the marginal contributions increases exponentially with an additional explanatory variable, there is a natural limit to the overall number of variables.

5 The ihs-transformation of the gross hourly wage increases the likelihood of observing positive transformed fitted values. This is useful especially when only a small set of explanatory variables is considered for the calculation of marginal contributions to the inequality measure.

4. Data

The data for this analysis are drawn from different sources. Data on individual worker characteristics stem from the European Union Statistics on Income and Living Conditions (EU-SILC) which is an annual survey on income, poverty, social exclusion and living conditions in the EU. The EU-SILC was first launched in 2003 for a small set of EU Member States and has subsequently been expanded to cover all EU Member States plus a set of non-EU countries such as Macedonia, Iceland, Turkey, Norway and Switzerland. Although the EU-SILC is generally available in cross-sectional and longitudinal form, we use cross-sectional data since longitudinal data lack the necessary information on workers' industry affiliation. However, this information is only available at the 1-digit level (see Table B.1 in Annex B for an overview). Information in the EU-SILC allows us to identify individuals by country of birth, which we use to differentiate native (i.e. domestically-born) workers from migrant (foreign-born) workers. Given our interest in the effects of globalisation on native workers, we restrict our analysis to native individuals of working age (15-64 years old). We use EU-SILC information on months and hours spent in the main job and other jobs to compute gross hourly wages by dividing the yearly employee cash or near cash income by total hours worked.[6] Furthermore, we use information on native workers' gender, age, education, occupation, contract type and degree of urbanisation of their residential area as well as firm-specific information on firm size (see Table 1 for the definition of variables). In our analysis, we generally focus on the period 2008 to 2013 but differentiate between the crisis period (2008-2010) and the post-crisis period (2011-2013). This split further allows us to take into account the change in the ISCO classification between 2010 and 2011. Moreover, due to partly severe data limitations for some countries in the sample, we only consider the following: Austria (AT), Belgium (BE), Germany (DE), Denmark (DK), Greece (EL), Italy (IT), Spain (ES), France (FR) and the United Kingdom (UK) – as old EU Member States (OMS) and skill-abundant North – and Hungary (HU), Latvia (LV), Lithuania (LT), Poland (PL) and Romania (RO) – as new EU Member States (NMS) and unskill-abundant South.

Furthermore, we employ aggregate data at the industry level which are collected at the 1-digit level in accordance with the EU-SILC industry classification. In particular, trade indicators are drawn from the 2016 release of the World Input-Output Database (WIOD) which combines detailed information on national production activities and international trade. It provides information on international linkages of production processes and structures of final goods trade across 56 industries (ISIC Rev. 4) and 43 countries, comprising all 28 EU Member States and 15 other major countries in the world, plus an estimate for the rest of the world (RoW) over the period 2000 to 2014. From the WIOD we calculate various measures of value-chain (VC) trade to account for the growing fragmentation of production processes into geographically dispersed stages of production. In particular, we calculate the domestic and the foreign value added in exports (DVAiX and FVAiX, respectively) for each industry. DVAiX refers to the value added generated by the domestic economy in the production of goods and services for exports. FVAiX refers to the value added of foreign goods and services that are used as intermediates to produce goods and services for exports. Further, we use two measures for offshoring and, following Feenstra and Hanson (1999), distinguish between narrow (N) and broad (B) offshoring. The former

[6] In order to mitigate the potential impact of outliers, we exclude observations +/- two times the standard deviation around the mean gross hourly wage in each country for each year.

considers imported intermediates in a given industry from the same industry only while the latter considers imported intermediates from all industries but its own (for their definitions, see equation (A.1) in Annex A). Value-added levels for each industry are also taken from the WIOD. Furthermore, we employ data on inward and outward FDI stocks in each industry provided by Eurostat and OECD. For migration we use the European Union Labour Force Survey (EU-LFS) and compute the share of foreign employees (with reported country of origin different from the country of residence) as the share of migrant workers in the total number of employees in each industry. Business enterprise R&D stocks are generated based on real business enterprise R&D expenditure (BERD, PPS-adjusted, at 2005 prices) obtained from Eurostat, applying the perpetual inventory method (PIM) (for further details, see equations (A.2) and (A.3) in Annex A).

Since the variables pertaining to trade and FDI tend to be highly correlated, we conduct a principle component analysis (PCA) which allows us to extract the common explanatory power for each of the two dimensions. In doing so, we take only one component from trade and FDI each in order to minimise the number of explanatory variables.[7] Moreover, this allows us to consider the general exposure to trade and FDI, and not only to rely on a particular direction thereof (that is either outward or inward).

Table 1 / Variable overview

Level	Name	Definition
Individual	Wage	(lhs-transformed) gross hourly wage
Individual	Gender	Female, dummy
	Age	Age, age^2
	Education	Primary (ISCED 0-1, reference group), secondary (ISCED 2-4), tertiary (ISCED 5), dummies
	Occupation	Low (ISCO 90-99, reference group), medium (ISCO 40-89), high (ISCO 11-39), dummies
	Contract type	Temporary contract, dummy
	Urbanisation	Rural (reference group), intermediate, urban, dummies
	Firm size	Small (<6 employees, reference group), medium (6-12 employees), large (>12 employees), dummies
Industry[8]	Migration	Share of foreign-born employees (in total employment)
	Trade	Domestic VAX-VA-ratio, foreign VAX-VA-ratio, narrow offshoring, broad offshoring
	FDI	Inward and outward FDI stocks
	SBTC	Business R&D stock per employee
	Productivity	Value added per employee

However, due to some specific features of the data we employ in our analysis, we tend to underestimate the effect of globalisation on inequality. On the one hand, as a result of the rather crude industry classification available in the EU-SILC data, we can use the three measures of globalisation only at the 1-digit industry level. Therefore, the level of variation is rather low which will lead to lower estimated effects in the regressions. On the other hand, since each individual has to be ascribed to an industry, unemployed individuals cannot be included in the analysis which makes it impossible to consider labour market participation decisions in our analysis. However, if globalisation also affects labour market participation decisions (e.g. unemployment due to offshoring activities), it is likely that owing to the associated selection bias we underestimate the true effect of globalisation. Hence, in view of these restrictions, our results can be considered the lower bound of the overall effect.

7 Since combinations of variables increase exponentially with an additional variable, we have to rely on a smaller set of explanatory variables.

8 The correlation between industry explanatory variables generally does not raise concern about multicollinearity. With around 0.65, correlation is highest between productivity and SBTC.

5. Results

In order to provide a first insight into the wage inequality situation across the selected EU countries, Table 2 reports three different inequality measures (Gini index, GE(0) and GE(2)) for the crisis period (2008-2010) and the post-crisis period (2011-2013). In principle, the three inequality measures differ in their emphasis on different parts of the wage distribution. For instance, the Gini index puts more emphasis on the centre of the wage distribution, where medium-wage earners are located. In contrast, the Generalised Entropy index (GE) is more sensitive to changes at the tails of the wage distribution. While the GE(0) is bottom sensitive, and therefore representative of low-wage earners, the GE(2) is top sensitive, and therefore representative of high-wage earners. In general, the higher the respective inequality measure, the higher the wage inequality.

Overall, the extent of wage inequality differs across EU Member States in our sample. Table 2 demonstrates that during the crisis period, wage inequality – as captured by the Gini index – was relatively high and of similar magnitude in the OMS Austria, Germany, Spain, and the UK, while it was highest in the NMS Lithuania, Latvia and Poland, with the two Baltic countries showing by far the highest level of wage inequality in our sample of EU countries considered. In contrast, wage inequality was lowest in Belgium and Denmark, followed by France and Italy. Among NMS, inequality was lowest in Romania and with 0.249 just slightly higher than in Italy (with 0.239).

Table 2 / Income inequality measures

	2008-2010			2011-2013		
	Gini	GE(0)	GE(2)	Gini	GE(0)	GE(2)
OMS						
AT	0.287	0.169	0.140	0.270	0.151	0.120
BE	0.194	0.067	0.062	0.199	0.070	0.069
DE	0.292	0.176	0.135	0.297	0.176	0.142
DK	0.199	0.095	0.066	0.192	0.073	0.064
EL	0.279	0.130	0.135	0.227	0.084	0.088
ES	0.298	0.163	0.149	0.281	0.149	0.129
FR	0.224	0.108	0.086	0.227	0.110	0.092
IT	0.236	0.108	0.091	0.242	0.118	0.095
UK	0.295	0.147	0.172	0.290	0.141	0.162
NMS						
HU	0.276	0.124	0.145	0.245	0.097	0.105
LT	0.321	0.188	0.175	0.309	0.182	0.156
LV	0.320	0.179	0.172	0.310	0.166	0.166
PL	0.291	0.143	0.147	0.276	0.126	0.132
RO	0.249	0.104	0.104	0.237	0.091	0.094

Note: Numbers based on period averages.
Source: EU-SILC, own calculations.

Between crisis and post-crisis periods wage inequality declined in almost all countries. Interestingly, irrespective of the inequality measure considered, wage inequality fell in all NMS but most strongly in

Hungary, where wage inequality declined the most in the middle and at the top of the wage distribution. Similarly, among OMS, wage inequality declined in Austria, Spain and the UK (particularly at the top of the wage distribution) and in Denmark (almost exclusively driven by improvements at the bottom of the wage distribution). In contrast, wage inequality increased in Belgium, France and Italy. In general, however, observable increases in wage inequality in this set of countries were rather modest and, except for Italy, more strongly driven by a deterioration in the middle and at the top of the wage distribution. In Italy, the increase in wage inequality was the result of a deterioration at the bottom of the wage distribution. Overall, as concerns changes in inequality across periods, Greece and Germany stand out, for different reasons though: Greece not only experienced the most pronounced drop among all EU countries considered in the Gini-based inequality measure but saw all its inequality measures fall substantially. In contrast, Germany saw a rise in the wage dispersion which was solely driven by changes around the middle and the upper tail of the distribution (as captured by the GE(2) index).

5.1. RESULTS FROM MINCER WAGE REGRESSIONS

The estimates of the multilevel wage regression are generated by means of a maximum likelihood estimation. Table B.2 in Annex B shows the regression results for the crisis period 2008-2010 while Table B.3 in Annex B shows the results for the post-crisis period 2011-2013. The first section in each Table reports estimation results for all individual-level explanatory variables while the second section reports results for all industry-level explanatory variables. Since we specify a two-level model, there are separate random effects for the individual and the industry level. In both Tables, the random effects are generally significant which indicates that our defined hierarchy is appropriate.

In general, the results of the individual explanatory variables exhibit the expected signs. For instance, the female dummy is consistently negative significant. This is in line with rich empirical evidence on gender wage gaps and demonstrates that, even after controlling for other individual and job characteristics, native women earn lower gross hourly wages, on average, than native men. In particular, irrespective of the period considered, gender wage gaps are highest in the NMS, particularly in Lithuania, Latvia and Romania, where native women earn on average between 25 per cent and 14 per cent less per hour than native men. In the OMS, gender wage gaps are particularly pronounced in Spain and the UK. In contrast, gender wage gaps are lowest in Belgium and Denmark, where native women only earn between 5 per cent and 8 per cent less per hour than native men. For age, with the exception of Latvia during the crisis period, we find the expected concave earnings profile captured by the positive main effect and the negative squared term. Hence, in principle, gross hourly wages increase with age up to a maximum and then decline. We find a maximum at between 40 years (in Germany, Italy and Lithuania) and 60 years (in France and Greece). Furthermore, the results for education highlight the expected positive returns to education and capture that the higher the level of education, the higher the gross hourly wages on average. While returns to education are particularly high in Germany, there is some evidence of no or partly negative returns to education in Austria, Denmark, the UK or Lithuania. Similarly, our results point to earnings differences across occupations and reveal that higher (i.e. more skill-intensive) occupations tend to earn higher gross hourly wages on average. In general, occupational earnings differences vary across the countries considered and are highest in Germany, where native workers in medium and high occupations earn between 21 per cent to 31 per cent and 51 per cent, respectively, higher gross hourly wages on average than native workers in low occupations. Similarly, occupational earnings differences are also high in all NMS, particularly in Lithuania, where native workers in high occupations earn around 44 per cent higher gross hourly wages than native workers in low occupations. Furthermore, in line with related empirical evidence, our results emphasise that native workers on temporary contracts earn significantly lower gross hourly wages than those on permanent contracts. The only exceptions are found in the UK (for the post-crisis period only) and Lithuania (for both periods considered). The penalty associated with temporary contracts is particularly high in Spain, where native workers on temporary contracts earn between 25 per cent and 30 per cent lower gross hourly wages than native workers on permanent contracts. In contrast, with only about 10 per cent, the penalty associated with temporary contracts is lowest in Denmark (for the post-crisis period), Hungary (also for the crisis period only) and Romania (for both periods). We also find some evidence that the degree of urbanisation of a native worker's residential area is associated with higher gross hourly wages. As expected, our results also consistently point to non-negligible firm-size premia and indicate that firm-size premia are highest in France and Spain but lowest in Greece and Romania.

Contrary to the unambiguous results for the individual explanatory variables, results for industry-level variables are mixed and less consistent. As concerns immigration, coefficients are generally negative but only significant also for Denmark or France (for the crisis period only) as well as for Greece, Spain, Italy and Lithuania (all for the post-crisis period). This indicates that native workers in industries with a higher share of migrants are paid lower gross hourly wages. This negative effect might simply reflect the self-selection of migrants into industries with lower productivity and wage levels. However, since we also control for differences in labour productivity across industries, the potentially underlying selectivity effect should be limited. Therefore, our results suggest that native workers suffer from stronger immigration in terms of lower gross hourly wages. In particular, our results suggest that an increase in the migrant share by one percentage point is associated, on average, with around 1 per cent lower gross hourly wages of natives in Denmark, France Greece, Italy and Spain but around 2 per cent lower gross hourly wages in Lithuania. Furthermore, our results are rather mixed for trade and differ across country groups. Among OMS, coefficients are generally negative and also significant for Austria and France, for the crisis period only, as well as Italy and Spain, for the post-crisis period only. Hence, in these countries, native workers in industries more strongly exposed to and integrated into VC trade receive lower gross hourly wages. In contrast, in the group of NMS, positive coefficients tend to dominate. For Hungary, the effect is positive significant for the post-crisis period which suggests that a stronger exposure to VC trade is associated with higher wages for native workers. Conversely, for Latvia, a negative significant effect of VC trade is observable, but only for the crisis period. In contrast, our results are more consistent for the effects of FDI on native workers' wages. While positive coefficients dominate, among OMS positive significant effects are observable for Spain (for both periods) but also Italy (only for the crisis period) and Austria, Belgium, France (only for the post-crisis period). Among NMS, positive significant effects are observable for Lithuania and Romania, for the post-crisis period only. Hence, native workers in these countries seem to profit from more FDI in terms of higher gross hourly wages. As concerns value added per capita, which serves as a proxy for labour productivity and industry-specific business cycle effects, coefficients generally show the expected positive sign (except for Germany, France and Lithuania) and are significant also for Austria, the UK and Hungary for both periods, but also for Spain and Poland (for the crisis period only) and for Latvia (for the post-crisis period only). Finally, with respect to the R&D stock per capita, which we use to capture SBTC, negative coefficients seem to dominate in general. Negative significant results are found for all NMS but Latvia and Lithuania as well as for Spain. This indicates that workers employed in industries characterised by higher SBTC receive lower gross hourly wages, on average. In contrast, in Germany (for the post-crisis period) and France (for the crisis period), SBTC exerts a positive effect which implies that German and French workers in higher SBTC industries earn higher wages, on average, than those employed in lower SBTC industries.

5.2. RESULTS FROM THE SHAPLEY VALUE DECOMPOSITION

Based on the estimated coefficients of the multilevel wage regressions, we assess the contribution of variables to wage inequality by means of the Shapley value decomposition technique. While section 5.2.1 discusses results for the Gini index, section 5.2.2 focuses on results for the two Generalised Entropy indexes GE(0) and GE(2).

Since this approach considers all possible combinations of variables in assessing the contribution of variables to wage inequality, the number of variable combinations increases exponentially with each additional explanatory variable considered. In order to minimise the variable combinations and keep the computational time feasible, in Table 3 we define the following sets of variable groups:

Table 3 / Variable overview

	Variable group	Variable
Globalisation measures:	Migration	Migration share
	Trade	Trade PC
	FDI	FDI PC
Other industry characteristics:	Add Var	Productivity, SBTC
Worker characteristics:	Individual	Gender, age, age², urbanisation
	Education	Education
	Occupation	Occupation
	Contract	Contract type
Firm characteristics:	Firm size	Firm size

As discussed in section 5.1., we also obtained insignificant results – assessed at conventional levels of significance – particularly for industry-level explanatory variables. In the Shapley value decomposition we consider all explanatory variables (as listed in Table 3) irrespective of the significance of the respective estimated coefficient.[9] We therefore also include variables in this analysis with levels of significance lower than 10 per cent. However, since insignificant coefficients tend to be close to zero, these variables are less influential for the predicted individual gross hourly wage and eventually for wage inequality. This further implies that significant coefficients tend to have higher contributions to wage inequality.

5.2.1. Gini index

Figure B.1 in Annex B depicts the decomposition results for the Gini index for the crisis period (2008-2010) in Panel A and the post-crisis period (2011-2013) in Panel B. It shows that the set of variables considered in the analysis explains around two thirds of the Gini index, while the rest remains

9 Moreover, the highly aggregated industry level is associated with a relatively low level of variation. We therefore also argue for considering even weakly significant results in our analysis.

unexplained. In Greece and the UK but also Latvia, Lithuania and Poland the explained part is somewhat smaller.

To make contributions of variable groups (as defined in Table 3) comparable across countries and periods, we focus on the explained part of the Gini index and compute relative contributions of each variable group. The relative contributions are depicted in Figure 1 below for each country and period separately. Generally, Figure 1 shows that immigration, trade and FDI enhance wage inequality. For immigration, this finding is in line with expectations and empirical evidence (e.g., Dustmann et al., 2013). For trade and FDI, this is consistent with predictions from the Feenstra and Hanson models (1996, 1997) in which the shift/outsourcing of intermediate input production from the skill-abundant North to the unskill-abundant South increases inequality in both regions. In general, however, we find that immigration, trade and FDI contribute little to wage inequality which is also consistent with the small contributions of either immigration, trade or FDI to inequality found in the literature (see section 2). All three measures of globalisation taken together explain between 1 per cent (in Hungary) and 20 per cent (in Spain) of overall wage inequality among native workers. Furthermore, their roles as a source of wage inequality differ across countries and periods – and are often even zero – which underscores the heterogeneous role played by globalisation for wage inequality across countries.

As concerns the *relative* importance of the three measures of globalisation, interesting differences emerge across country groups and periods. During the crisis period, FDI and migration contributed the most to wage inequality among OMS while trade mattered little, except for Germany where around 4 per cent of wage inequality can be assigned to trade. In particular, migration contributed the most to wage inequality in France (with around 5 per cent), followed by Greece (with around 3 per cent). FDI contributed the most to wage inequality in Spain (with around 8 per cent), Italy, Denmark and Austria. By and large, for the group of OMS, a similar pattern also emerges for the post-crisis period, with some exceptions, however. In France, instead of migration, FDI becomes the key source of wage inequality. In contrast, migration becomes the most important cause of wage inequality in Italy.

As for the NMS, however, among the three measures of globalisation considered, trade and migration were the key contributors to wage inequality during the crisis period. Particularly, trade was the key driver behind wage inequality in Lithuania and Latvia (with around 6 per cent), while migration contributed the most to wage inequality in Poland and Hungary. During the post-crisis period, however, trade and FDI are the key sources of wage inequality among NMS whereas migration hardly matters. While trade is the most important inequality-enhancing globalisation force in Hungary, Poland and Romania, FDI contributes the most to wage inequality in the Baltic countries.

As concerns R&D and value added per capita, we find contributions in the range of 2 per cent (in Belgium) and 13 per cent (in France) in the crisis period and between 2 per cent (in Belgium and Spain) and around 11 per cent (in Austria and the UK) in the post-crisis period. Thus, differences in SBTC and labour productivity across industries exacerbate differences in gross hourly wages of native employees.

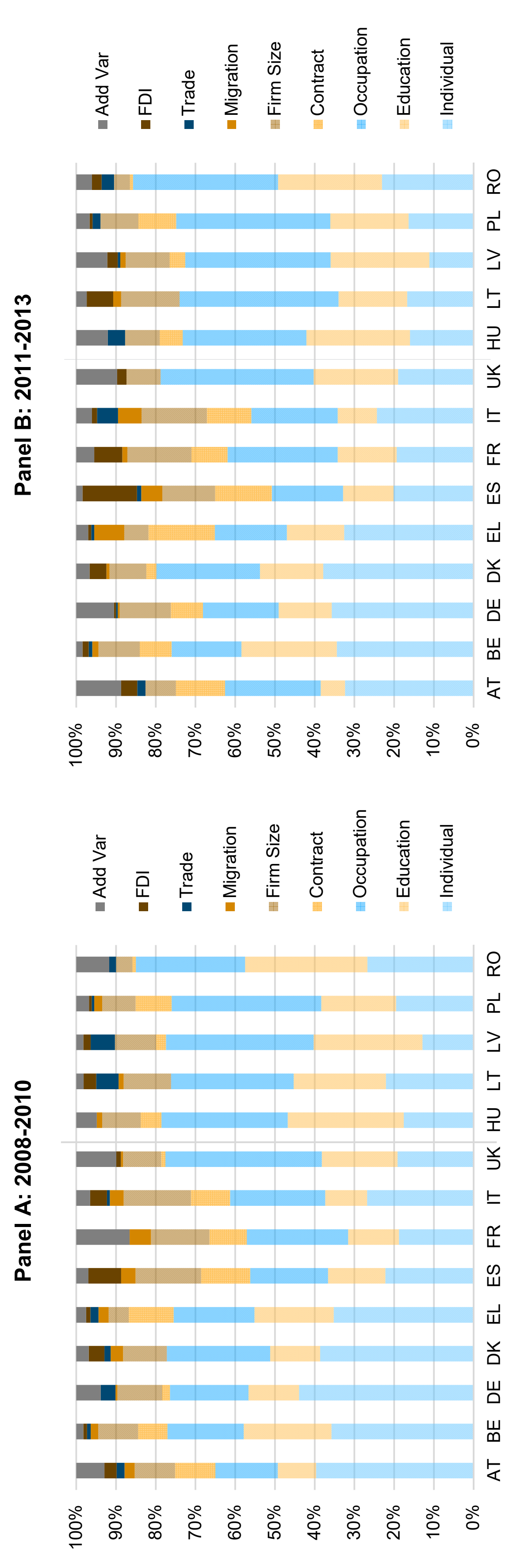
In contrast, the lion's share (around 80 per cent on average) of the explained wage inequality can be ascribed to individual worker characteristics. In some countries, such as Spain, France and Italy, the importance of individual worker characteristics is somewhat lower with around 65 per cent to 70 per cent. In this context, individual characteristics, such as gender, age and urbanisation, are the key determinants of wage inequality in the group of OMS (except for France and the UK). In contrast, among

NMS, occupation is the key contributor to wage inequality of all worker characteristics considered. Furthermore, as concerns changes across periods, worker characteristics remain the key source of wage inequality but become less important in Greece, Italy and Hungary (by around 5 ppts) but more important in Denmark and France (also by around 5 ppts). In the latter case, this is predominantly driven by the higher contribution of differences in education and occupation to wage inequality.

In contrast, firm size contributes very little to wage inequality: between around 5 per cent (in Greece or Romania) and 16 per cent (in France, Spain and Italy).

As highlighted above, the relatively low explanatory power of globalisation in our results is related to some specific features of the data we employ in our analysis, such as the high level of aggregation of the globalisation measures and the absence of any industry affiliation for unemployed persons which makes it impossible to account for the labour market participation decision of individuals. Moreover, the small contribution might also be related to the chosen inequality measure. The Gini index is sensitive to changes around the centre of the wage distribution. If globalisation has a different impact at the tails of the wage distribution, the Gini index is unable to capture this appropriately. In view of the last shortcoming, we now turn to the decomposition of the two Entropy class indexes GE(0) and GE(2), which more strongly focus on and capture changes at the tails of the wage distribution.

Figure 1 / Relative contributions to Gini index



Source: EU-SILC; WIOD; Eurostat; EU-KLEMS; EU-LFS, own calculations.

5.2.2. Generalised Entropy indexes

Figure B.2 in Annex B shows the absolute contributions of the various variable groups of interest to the GE(0) index for the crisis and the post-crisis period. As a bottom-sensitive measure, the GE(0) index is better able to reflect the effects of the various variable groups on native low-wage earners. In general, our variables can only explain a relatively small part of this inequality measure. While approximately two thirds of the Gini index could be ascribed to our variable groups, we can only explain around one third of this inequality measure in most cases. For Austria, Germany and Romania the explained part is somewhat larger.

In order to make the results comparable, we again focus on the explained part. Figure 2 below illustrates the corresponding relative contributions to the GE(0) index. It shows that the share explained by all industry characteristics is smaller compared to the Gini index, particularly in the NMS. Furthermore, in Belgium, industry characteristics have no effect whatsoever for the group of low-wage earners whose wage differences are solely determined by worker and firm characteristics. As concerns the *relative* importance of the three globalisation measures of interest, important differences are observable between the results for the Gini index and the GE(0) index. First, the three globalisation measures taken together generally contribute less to the GE(0) index. This means that low-wage earners are less strongly affected by globalisation than medium-wage earners. Second, in the NMS, above all in Hungary, Poland and Romania, none of the three globalisation measures matters for the GE(0) index, irrespective of the period considered. This indicates that native low-wage earners in these countries were completely unaffected by the three forces of globalisation. Third, in all NMS, migration has no effect on low-wage earners. Finally, particularly for trade but also for FDI, we observe sporadic negative contributions in a number of OMS. For instance, in the case of trade, negative contributions exist for Spain and France, in both periods, but also for Germany, in the post-crisis period, whereas in the case of FDI, negative contributions exist for Germany and France, but only for the crisis period. These findings indicate that, in these countries, low-wage earners actually profit from trade and FDI activities in terms of lower wage inequality. In contrast, if at all, immigration has an inequality-enhancing effect, also for low-wage earners.

Nevertheless, as concerns the relative roles of immigration, trade and FDI for wage inequality, we also observe similarities between the results for the Gini index and the GE(0) index which indicates that globalisation affects both medium- and low-wage earners. For instance, immigration has the strongest inequality-enhancing effect for low-wage earners in the Southern European countries Greece and Italy (in both periods) but also in France (in the crisis period only). The inequality-enhancing effect of trade was strongest for native low-wage earners in Latvia, Lithuania and Germany, but only in the crisis period. FDI has the strongest inequality-enhancing effect for low-wage earners in Spain and Denmark (in both periods) as well as France, Lithuania, Austria and the UK (in the post-crisis period). However, the consistently lower contributions to the GE(0) index than the Gini index suggest that low-wage earners are less affected, in general, than medium-wage earners.

Furthermore, concerning the remaining worker and firm characteristics, we observe similarities – but also some important differences – to the findings for the Gini index. For instance, individual worker characteristics also contribute the most to wage inequality, as measured by the GE(0) index. However, with somewhat higher contributions in the range of 72 per cent (in Spain and France) and 92 per cent (in Romania), differences in individual worker characteristics matter more for low- than medium-wage earners. Similarly, of all individual worker characteristics considered, individual characteristics (such as gender, age and urbanisation) are again the key contributors to wage inequality among OMS, while occupation is the key driver of wage inequality among NMS. However, the somewhat higher contributions to the GE(0) index indicate that differences in individual characteristics and occupations are more important for low- than medium-wage earners.

As compared to the findings for the Gini index, firm characteristics matter less so that differences in firm size affect low-wage earners less than medium wage earners, particularly in NMS.

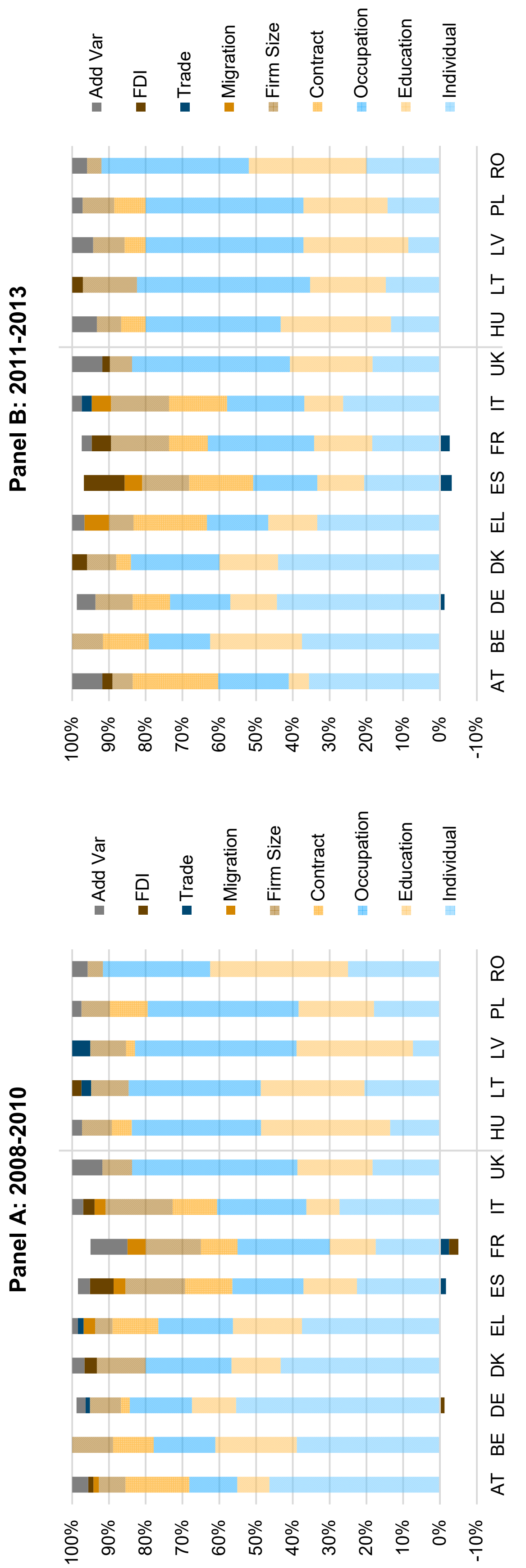
As concerns the top-sensitive GE(2) index (see Figure B.3 in Annex B), which better captures the effects of the various variable groups on native high-wage earners, similar patterns emerge as for the bottom-sensitive GE(0) index (depicted in Figure B.2). In this respect, our variables can only explain a relatively small part (about one third) of this inequality measure. Furthermore, the relative contributions to the GE(2) index (see Figure 3 below) are also of similar magnitude (Figure 2) which implies that both low- and high-wage earners are subject to similar forces.

With regard to the relative role of all industry characteristics, in general, and the three globalisation measures of interest, in particular, very similar patterns emerge for the two GE measures in terms of: (i) the relatively lower contribution of globalisation to wage inequality, (ii) the prevalence of zero contributions of globalisation to wage inequality in some countries (such as Belgium, the UK, Latvia, Poland and Romania), (iii) the prevalence of negative contributions of trade and FDI to wage inequality in some countries, and (iv) the relative importance of migration, trade and FDI in individual countries.

However, at the same time, interesting differences are observable between the two GE measures. Most importantly, the magnitudes of the calculated positive and negative contributions to wage inequality differ across country groups. For OMS, contributions to wage inequality are generally higher for the GE(2) than the GE(0) index, while for NMS, the opposite is true. Together with findings for the Gini index, our results therefore show that in the group of OMS, immigration, trade and FDI predominantly affect medium- and high-wage earners while in the group of NMS, they mainly affect medium- and low-wage earners.

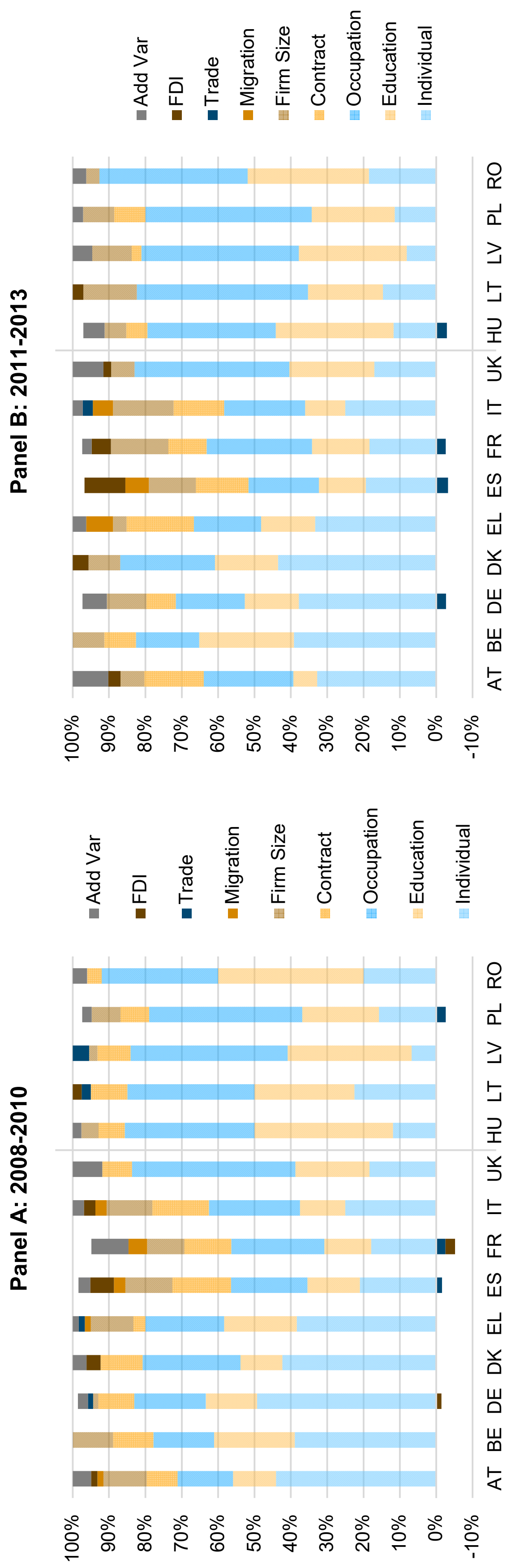
Furthermore, some country-specific differences are observable as concerns the relative role of immigration, trade and FDI. In particular, for Greece, immigration exerts a relatively weaker inequality-enhancing effect at the top of the wage distribution. Hence, immigration less strongly increases wage differences of Greek native high- than low-wage earners. In a similar vein, in contrast to the findings for the GE(0) index, trade also has an inequality-reducing effect in Poland (in the crisis period) and Hungary (in the post-crisis period).

Figure 2 / Relative contributions to GE(0) index



Source: EU-SILC; WIOD; Eurostat; EU-KLEMS; EU-LFS, own calculations.

Figure 3 / Relative contributions to GE(2) index



Source: EU-SILC; WIOD; Eurostat; EU-KLEMS; EU-LFS, own calculations.

6. Summary and conclusion

In this analysis we have used the regression-based Shapley value decomposition approach of Shorrocks (2013) to calculate the relative contributions of three key forces of globalisation, namely trade, FDI and immigration, to wage inequality among native workers in a sample of OMS and NMS. We analysed each country individually, for both the crisis period (2008-2010) and the post-crisis period (2011-2013). This allowed us to better bring out differences across countries and time, the latter particularly in view of the effects of the global financial crisis. We employed three different inequality measures (Gini index, GE(0) and GE(2)) which place different weights on different segments of the wage distribution to identify the wage segment which is more strongly affected by each of the three forces of globalisation.

Our results highlight that immigration, trade and FDI have very heterogeneous and country-specific effects on wage inequality among native workers which is in line with and partly explains the mixed results found in the empirical literature. In general, however, they contribute little to wage inequality: in the range of between 1 per cent and 20 per cent. In light of some data limitations, the calculated contributions can be understood as lower bounds of the total expected effect. Among all three globalisation measures considered, immigration and FDI contribute the most to wage inequality in the OMS while trade and, to a lesser degree, also immigration (in Poland and Hungary) and FDI (in the Baltic countries) are key drivers of wage inequality in the NMS.

However, immigration, trade and FDI have different effects across the wage distribution, though they generally affect medium-wage earners the most. Immigration is felt across the entire wage distribution and increases inequality in all wage segments, but the immigration-induced increase in wage inequality is strongest at the centre and the top of the wage distribution. This effect is dominant in the Southern EU countries, which have become important countries of immigration. For NMS, which are traditionally countries of emigration not immigration, any inequality-enhancing effects of immigration are solely concentrated at the centre of the wage distribution. Trade and FDI contribute to inequality in both OMS and NMS, which is consistent with predictions from the Feenstra and Hanson models (1996, 1997) of offshoring and international outsourcing of intermediate input production from the North to the South. Among more skill-abundant OMS, the effects of trade and FDI are predominantly felt at the centre and top of the wage distribution. In contrast, among more unskill-abundant NMS, trade and FDI mainly affect the centre but also the bottom of the wage distribution, if at all. Furthermore, in some OMS (sporadically also in some NMS), trade and, to a lesser degree, also FDI have inequality-reducing effects as well which solely operate at the tails of the wage distribution and are strongest at its top.

All in all, our analysis highlights that globalisation forces predominantly affect wage earners at the centre of the wage distribution. Globalisation therefore appears to be associated with a squeeze of the medium-wage class. Job polarisation and thus a shift away from medium-wage jobs (IMF, 2011) will result in a concentration of wage earners at the bottom and the top of the distribution. From a policy point of view, one way to mitigate observable polarisation tendencies in the wage distribution is to encourage investments in human capital. This also includes guided pathways to link students more directly to career paths and to expand the support and advising of students, which would reduce the risk of mismatch. In particular, in the NMS, education explains a large share of the wage inequality. Selective investments in human capital could enhance individuals' competitiveness and lower wage inequality, which might help to counteract the medium-wage squeeze caused by globalisation and guarantee a more egalitarian distribution of wages.

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Annex A: Technical Annex

› Offshoring

Following Feenstra and Hanson (1999), narrow (N) and broad (B) offshoring are defined as follows:

$$IIM_{j,c}^{N} = \frac{O_{k=j,c}}{V_{j,c}} \quad \text{and} \quad IIM_{j,c}^{B} = \frac{\sum_{k=1,k\neq j}^{K} O_{k,c}}{V_{j,c}}. \tag{A.1}$$

› Business enterprise R&D stock

Business enterprise R&D stocks $\boldsymbol{S_{jt}}$ (in industry $\boldsymbol{j}$ at time $\boldsymbol{t}$) are calculated based on real business enterprise R&D expenditure (BERD, PPS-adjusted, at 2005 prices) by means of the perpetual inventory method (PIM) as follows:

$$\boldsymbol{S_{jt} = (1-\delta)S_{j,t-1} + R_{jt}}, \tag{A.2}$$

where $\boldsymbol{\delta}$ is the depreciation rate of knowledge obsolescence set at 15 per cent and $\boldsymbol{R_{jt}}$ refers to real business R&D expenditure. The initial value of real BERD stock $\boldsymbol{S_{j0}}$ is calculated as follows:

$$\boldsymbol{S_{j0} = \frac{R_{jt}}{\delta + \varphi_j}}, \tag{A.3}$$

with $\boldsymbol{\varphi_j}$ as the average growth rate of real BERD for industry $\boldsymbol{j}$ over the entire period (2005-2013).

Annex B: Tables and figures

Table B.1 / List of industries (NACE Rev. 2)

Industry	Description
A	Agriculture, forestry and fishing
B-E	Mining and quarrying; manufacturing; electricity, gas, steam and air conditioning supply; water supply, sewerage, waste management and remediation activities
F	Construction
G	Wholesale and retail trade, repair of motor vehicles and motorcycles
H	Transportation and storage
I	Accommodation and food service activities
J	Information and communication
K	Financial and insurance activities
L-N	Real estate activities; professional, scientific and technical activities; administrative and support service activities
O	Public administration and defence, compulsory social security
P	Education
Q	Human health and social work activities
R-U	Arts, entertainment and recreation; other service activities; activities of household; activities of extraterritorial organisations and bodies

Table B.2 / Multilevel wage regression, 2008-2010

Dep.var.: ihs-transformed gross hourly wages	AT	BE	DE	DK	EL	ES	FR	IT	UK	HU	LT	LV	PL	RO
Individual														
Female	-0.163***	-0.0599***	-0.123***	-0.0546*	-0.138***	-0.143***	-0.0984***	-0.0728***	-0.145***	-0.129***	-0.247***	-0.187***	-0.124***	-0.151***
	(0.0180)	(0.0126)	(0.0228)	(0.0300)	(0.0305)	(0.0232)	(0.0123)	(0.0260)	(0.0204)	(0.0251)	(0.0245)	(0.0291)	(0.0242)	(0.0166)
Age	0.0642***	0.0377***	0.128***	0.0689***	0.0626***	0.0265***	0.0254***	0.0387***	0.0376***	0.0241***	0.0307***	0.00657	0.0394***	0.0235***
	(0.00683)	(0.00352)	(0.00502)	(0.0115)	(0.00585)	(0.00539)	(0.00522)	(0.00280)	(0.00610)	(0.00365)	(0.00534)	(0.00421)	(0.00362)	(0.00339)
Age²	-0.00060***	-0.00033***	-0.0013***	-0.00069***	-0.00052***	-0.00018***	-0.00021***	-0.00033***	-0.00039***	-0.00024***	-0.00032***	-7.91e-05*	-0.00040***	-0.00024***
	(9.47e-05)	(4.15e-05)	(6.41e-05)	(0.000132)	(6.00e-05)	(5.61e-05)	(5.90e-05)	(3.53e-05)	(7.26e-05)	(4.90e-05)	(6.84e-05)	(4.57e-05)	(4.52e-05)	(4.00e-05)
Secondary educ.	-0.235*	0.133***	0.532**	0.547	0.159***	0.112***	0.146***	0.143***	0.00769	0.194***	-0.0298	0.0785	0.0876***	0.153***
	(0.128)	(0.0167)	(0.251)	(0.417)	(0.0269)	(0.0163)	(0.0282)	(0.0125)	(0.0238)	(0.0380)	(0.0718)	(0.0608)	(0.0218)	(0.0421)
Tertiary educ.	-0.0443	0.270***	0.726***	0.653	0.348***	0.275***	0.272***	0.283***	0.216***	0.494***	0.220***	0.349***	0.272***	0.435***
	(0.124)	(0.0236)	(0.250)	(0.415)	(0.0421)	(0.0358)	(0.0314)	(0.0158)	(0.0230)	(0.0463)	(0.0734)	(0.0614)	(0.0307)	(0.0607)
Medium occup.	0.206***	0.0913***	0.301***	0.111***	0.199***	0.0823***	0.0401*	0.145***	0.110***	0.134***	0.170***	0.151***	0.130***	0.130***
	(0.0255)	(0.0255)	(0.0569)	(0.0401)	(0.0458)	(0.0177)	(0.0236)	(0.0378)	(0.0231)	(0.0146)	(0.0318)	(0.0183)	(0.0367)	(0.0229)
High occup.	0.373***	0.195***	0.509***	0.282***	0.393***	0.312***	0.259***	0.326***	0.429***	0.372***	0.432***	0.423***	0.400***	0.343***
	(0.0230)	(0.0259)	(0.0448)	(0.0570)	(0.0698)	(0.0312)	(0.0165)	(0.0397)	(0.0302)	(0.0312)	(0.0495)	(0.0369)	(0.0496)	(0.0246)
Temp. Contract	-0.278***	-0.181***	-0.142***	-	-0.214***	-0.253***	-0.212***	-0.235***	-0.128**	-0.110***	-0.00566	-0.160***	-0.128***	-0.108***
	(0.0351)	(0.0221)	(0.0198)	(-)	(0.0483)	(0.0192)	(0.0172)	(0.0186)	(0.0527)	(0.0232)	(0.0390)	(0.0248)	(0.0126)	(0.0213)
Intermed. region	0.0334**	0.0656**	0.0975***	0.0547***	-0.0516*	0.0170	0.0142	-0.0142	0.0263*	0.0475***	-	-	0.0365	-0.0118
	(0.0155)	(0.0283)	(0.00783)	(0.0102)	(0.0301)	(0.0137)	(0.0151)	(0.0160)	(0.0136)	(0.00619)	(-)	(-)	(0.0250)	(0.0401)
Urban region	0.0302*	0.0665**	0.129***	0.0677***	-0.0503**	0.0535**	0.0672***	0.00579	0.0259*	0.113***	0.102***	0.0847***	0.0878***	0.110***
	(0.0177)	(0.0274)	(0.0136)	(0.0125)	(0.0198)	(0.0250)	(0.0164)	(0.0212)	(0.0136)	(0.00814)	(0.0274)	(0.0115)	(0.0216)	(0.0114)
Medium-sized firms	0.143***	0.0917***	0.108***	0.0866*	0.0943***	0.156***	0.200***	0.126***	0.0906***	0.0956***	0.122***	0.0725***	0.0832**	0.0936***
	(0.0164)	(0.0220)	(0.0292)	(0.0456)	(0.0280)	(0.0225)	(0.0576)	(0.0149)	(0.0169)	(0.0148)	(0.0260)	(0.0200)	(0.0354)	(0.0185)
Large firms	0.259***	0.160***	0.289***	0.145***	0.141***	0.311***	0.285***	0.231***	0.204***	0.172***	0.269***	0.184***	0.162***	0.115***
	(0.0196)	(0.0246)	(0.0405)	(0.0352)	(0.0458)	(0.0302)	(0.0598)	(0.0171)	(0.0204)	(0.0113)	(0.0282)	(0.0249)	(0.0273)	(0.0261)
Indusrtry														
Migrant share	-0.00445	-0.00276	-0.00178	-0.0137**	-0.00209	-0.00302	-0.0115**	-0.00303	-0.00298	-0.0206	-0.0121	0.00105	-0.208	-0.00504
	(0.00297)	(0.00354)	(0.00459)	(0.00606)	(0.00291)	(0.00269)	(0.00584)	(0.00322)	(0.00410)	(0.0155)	(0.0122)	(0.00340)	(0.135)	(0.0606)
Trade PC	-0.0286**	-0.00405	-0.0241	0.0107	-0.0141	-0.0111	-0.0275*	-0.00815	0.00207	0.00319	0.0359	-0.0335**	0.0135	0.0146
	(0.0124)	(0.0125)	(0.0363)	(0.00715)	(0.0147)	(0.0152)	(0.0163)	(0.0138)	(0.0111)	(0.0104)	(0.0292)	(0.0163)	(0.0271)	(0.0134)
FDI PC	0.0281	0.00363	0.0131	0.0180	0.0237	0.0537**	-0.0183	0.0288**	0.00571	-0.00211	0.0254	-0.0171	-0.00540	-0.00232
	(0.0200)	(0.00479)	(0.0158)	(0.0122)	(0.0234)	(0.0224)	(0.0112)	(0.0139)	(0.0182)	(0.0124)	(0.0288)	(0.0171)	(0.0350)	(0.0112)
VA p.c.	0.171**	0.0279	-0.178*	0.0624	0.0693	0.106*	-0.0949	0.0729	0.187***	0.0800*	0.0209	0.0181	0.0676*	0.0726***
	(0.0782)	(0.0320)	(0.0975)	(0.0445)	(0.110)	(0.0632)	(0.112)	(0.0817)	(0.0486)	(0.0413)	(0.0481)	(0.0353)	(0.0376)	(0.0125)
R&D stock p.c.	0.00590	0.00125	-0.00259	-0.00102	-0.00840	-0.0128	0.0381***	5.32e-05	-0.00554	-0.00406	-0.0121	0.00749	-0.0155	-0.0206***
	(0.00551)	(0.00224)	(0.00420)	(0.00839)	(0.0105)	(0.0130)	(0.0139)	(0.0112)	(0.00641)	(0.00759)	(0.00803)	(0.00794)	(0.0107)	(0.00480)
Constant	-0.355	1.765***	1.322	0.639	0.100	0.583	3.233**	0.867	-0.0460	-0.110	0.482	1.069***	-0.0389	-0.465***
	(1.049)	(0.415)	(1.194)	(0.841)	(1.282)	(0.771)	(1.374)	(0.989)	(0.633)	(0.421)	(0.557)	(0.384)	(0.416)	(0.106)
Random effects														
Industry	-2.400***	-2.824***	-1.597***	-3.881	-2.265***	-2.342***	-2.273***	-2.448***	-2.799***	-2.654***	-2.254***	-2.305***	-2.830***	-3.421***
	(0.223)	(0.602)	(0.438)	(2.928)	(0.274)	(0.289)	(0.348)	(0.224)	(0.197)	(0.198)	(0.459)	(0.149)	(0.148)	(0.373)
Individual	-0.723***	-1.136***	-0.762***	-0.889***	-0.961***	-0.752***	-0.854***	-0.867***	-0.820***	-1.024***	-0.766***	-0.750***	-0.908***	-1.183***
	(0.0229)	(0.0383)	(0.0278)	(0.0739)	(0.0490)	(0.0326)	(0.0628)	(0.0360)	(0.0215)	(0.0267)	(0.0200)	(0.0293)	(0.0179)	(0.0186)
Observations	11,614	11,342	26,011	7,399	5,678	22,265	20,483	28,902	14,948	18,288	11,871	11,394	9,383	13,844
Number of groups	13	12	12	12	10	11	13	12	12	13	13	13	13	13

Note: Robust standard errors in parentheses, results of yearly dummies and 'NA'-categories not shown; random effects parameters are displayed in log of standard deviation; weighs are used in estimations; *** p<0.01, ** p<0.05, * p<0.1.
Source: EU-SILC; WIOD; Eurostat; EU-KLEMS; EU-LFS, own calculations.

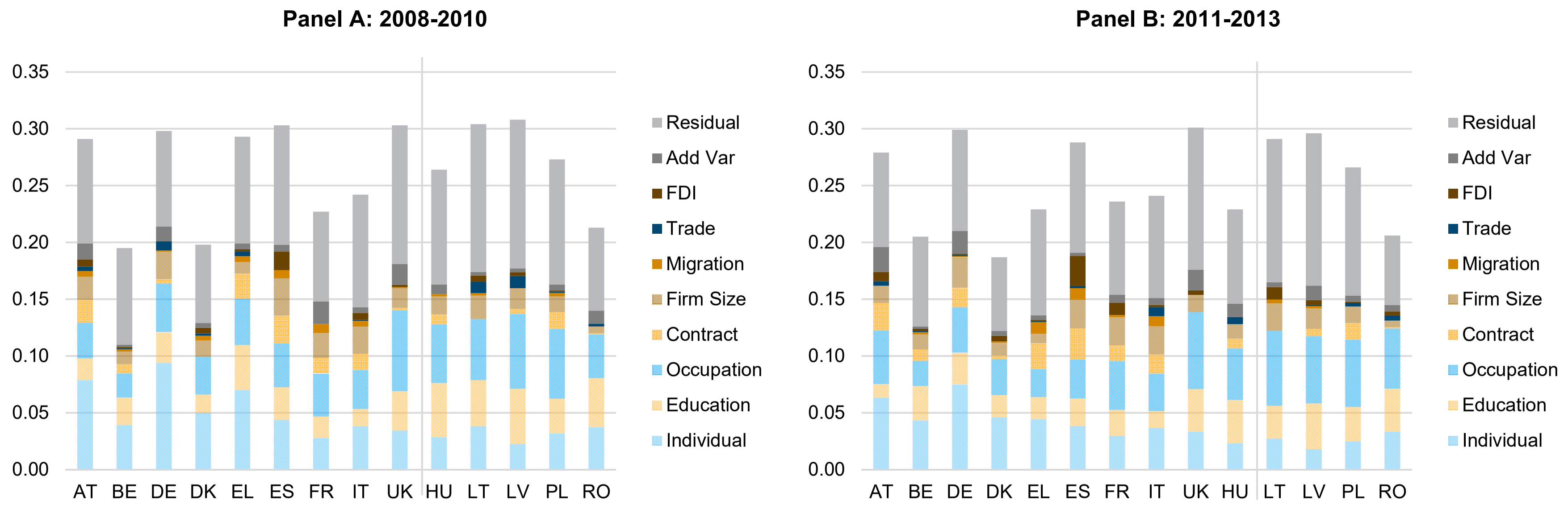
Table B.3 / Multilevel wage regression, 2011-2013

Dep.var.: ihs-transformed gross hourly wages	AT	BE	DE	DK	EL	ES	FR	IT	UK	HU	LT	LV	PL	RO
Individual														
Female	-0.122***	-0.0784***	-0.135***	-0.0497**	-0.104***	-0.136***	-0.0731***	-0.0793***	-0.130***	-0.127***	-0.137***	-0.170***	-0.116***	-0.137***
	(0.0204)	(0.0164)	(0.0203)	(0.0207)	(0.0202)	(0.0239)	(0.0155)	(0.0305)	(0.0133)	(0.0228)	(0.0404)	(0.0257)	(0.0196)	(0.0141)
Age	0.0529***	0.0349***	0.100***	0.0714***	0.0466***	0.0362***	0.0271***	0.0427***	0.0386***	0.0191***	0.0246***	0.0154***	0.0301***	0.0185***
	(0.00941)	(0.00416)	(0.00429)	(0.00962)	(0.00523)	(0.00485)	(0.00813)	(0.00405)	(0.00446)	(0.00402)	(0.00470)	(0.00402)	(0.00366)	(0.00304)
Age²	-0.00049***	-0.00028***	-0.00103***	-0.00072***	-0.00042***	-0.00029***	-0.00022**	-0.00037***	-0.00040***	-0.00018***	-0.00022***	-0.00017***	-0.00030***	-0.00017***
	(0.000125)	(5.07e-05)	(5.42e-05)	(0.000108)	(5.44e-05)	(4.82e-05)	(9.08e-05)	(5.55e-05)	(4.77e-05)	(5.58e-05)	(5.72e-05)	(4.99e-05)	(4.07e-05)	(3.23e-05)
Secondary educ.	-0.0876*	0.114***	0.489**	0.165	0.137***	0.109***	0.144***	0.194***	-0.0888**	0.0983***	-0.133**	0.0952*	0.0716***	0.118***
	(0.0512)	(0.0188)	(0.197)	(0.119)	(0.0318)	(0.0232)	(0.0284)	(0.0285)	(0.0385)	(0.0322)	(0.0544)	(0.0551)	(0.0176)	(0.0388)
Tertiary educ.	0.0376	0.293***	0.696***	0.292***	0.241***	0.265***	0.290***	0.319***	0.135***	0.347***	0.0313	0.327***	0.254***	0.325***
	(0.0537)	(0.0238)	(0.204)	(0.113)	(0.0395)	(0.0368)	(0.0349)	(0.0316)	(0.0352)	(0.0383)	(0.0617)	(0.0586)	(0.0349)	(0.0491)
Medium occup.	0.200***	0.107***	0.205***	0.0624	0.0589	0.102***	0.0133	0.147***	0.0956***	0.142***	0.155***	0.156***	0.118***	0.122***
	(0.0417)	(0.0341)	(0.0401)	(0.0454)	(0.0559)	(0.0160)	(0.0342)	(0.0335)	(0.0281)	(0.0141)	(0.0198)	(0.0213)	(0.0256)	(0.0360)
High occup.	0.450***	0.224***	0.457***	0.224***	0.204***	0.314***	0.246***	0.315***	0.412***	0.351***	0.437***	0.409***	0.387***	0.352***
	(0.0411)	(0.0278)	(0.0472)	(0.0496)	(0.0740)	(0.0331)	(0.0194)	(0.0418)	(0.0245)	(0.0178)	(0.0539)	(0.0375)	(0.0406)	(0.0471)
Temp. contract	-0.168***	-0.210***	-0.296***	-0.0971***	-0.212***	-0.302***	-0.192***	-0.264***	0.0312	-0.169***	0.0407	-0.243***	-0.118***	-0.118***
	(0.0442)	(0.0262)	(0.0342)	(0.0354)	(0.0475)	(0.0234)	(0.0155)	(0.0231)	(0.0474)	(0.0313)	(0.0506)	(0.0433)	(0.0134)	(0.0281)
Intermed. region	0.0450**	-0.00122	0.0606***	0.0155	0.00880	0.0494***	0.0131	0.0308**	-0.00164	0.0399***	0.0606	-	0.0544***	0.0447***
	(0.0196)	(0.0129)	(0.00623)	(0.0213)	(0.0345)	(0.0176)	(0.0134)	(0.0129)	(0.0204)	(0.00791)	(0.0384)	(-)	(0.0146)	(0.0162)
Urban region	0.0440*	-0.00619	0.0926***	0.0372**	0.000449	0.0766***	0.0403***	0.0390**	0.00702	0.103***	0.121***	0.0313***	0.0817***	0.103***
	(0.0240)	(0.0139)	(0.00902)	(0.0158)	(0.0192)	(0.0263)	(0.00707)	(0.0170)	(0.0208)	(0.0110)	(0.0262)	(0.00679)	(0.0204)	(0.0150)
Medium-sized firm	0.0943***	0.106***	0.129***	0.0786***	0.0576***	0.127***	0.193**	0.163***	0.0952***	0.0765***	0.133***	0.107***	0.0685***	0.0616**
	(0.0237)	(0.0319)	(0.0247)	(0.0244)	(0.0130)	(0.0263)	(0.0966)	(0.0149)	(0.0324)	(0.0122)	(0.0378)	(0.0134)	(0.0214)	(0.0277)
Large firm	0.201***	0.179***	0.307***	0.131***	0.0959***	0.276***	0.284***	0.260***	0.195***	0.150***	0.306***	0.214***	0.156***	0.0902***
	(0.0229)	(0.0273)	(0.0410)	(0.0297)	(0.0159)	(0.0271)	(0.0944)	(0.0195)	(0.0364)	(0.0146)	(0.0448)	(0.0206)	(0.00910)	(0.0240)
Industry														
Migrant share	-0.000379	-0.00298	0.00339	-0.00327	-0.00516**	-0.00516**	-0.00344	-0.00444**	-0.000257	0.00922	-0.0227**	-0.00345	0.0385	0.0166
	(0.00598)	(0.00183)	(0.00576)	(0.00265)	(0.00233)	(0.00248)	(0.00317)	(0.00203)	(0.00466)	(0.00585)	(0.0101)	(0.00342)	(0.0443)	(0.0668)
Trade PC	-0.0225	0.00525	-0.0270	-0.00196	0.00776	-0.0531***	-0.0166	-0.0274*	0.000593	0.0316**	-0.00227	-0.00324	0.0227	0.0154
	(0.0163)	(0.00743)	(0.0356)	(0.00665)	(0.0125)	(0.0171)	(0.0138)	(0.0145)	(0.0129)	(0.0127)	(0.0181)	(0.0110)	(0.0169)	(0.0131)
FDI PC	0.0328*	0.00909**	-0.0118	0.0203	-0.00698	0.116***	0.0351**	0.0167	0.0134	-0.00537	0.0495*	0.0282	0.00595	0.0175***
	(0.0190)	(0.00390)	(0.0138)	(0.0131)	(0.00485)	(0.0262)	(0.0154)	(0.0236)	(0.0184)	(0.00943)	(0.0284)	(0.0371)	(0.0158)	(0.00532)
VA p.c.	0.288**	0.0471	-0.0453	0.0284	0.0515	0.0537	-0.0470	0.0734	0.219***	0.143***	-0.0696	0.125*	0.0477	0.0538***
	(0.131)	(0.0456)	(0.0818)	(0.0498)	(0.0693)	(0.0630)	(0.0646)	(0.0845)	(0.0772)	(0.0482)	(0.104)	(0.0655)	(0.0297)	(0.0105)
R&D stock p.c.	-0.00350	-0.00223	0.0390*	0.00319	-0.00237	-0.0252**	0.0160	0.00521	-0.0170	-0.0242***	0.00909	-0.00163	-0.0163*	-0.0140***
	(0.00668)	(0.00291)	(0.0227)	(0.00456)	(0.00891)	(0.0119)	(0.0116)	(0.0118)	(0.0162)	(0.00732)	(0.0202)	(0.00870)	(0.00970)	(0.00503)
Constant	-1.620	1.714***	0.200	1.487**	1.027	1.231*	2.626***	0.699	-0.380	-0.474	1.452	-0.221	0.472	-0.0370
	(1.622)	(0.529)	(0.871)	(0.607)	(0.757)	(0.665)	(0.730)	(0.994)	(0.795)	(0.500)	(1.025)	(0.738)	(0.327)	(0.178)
Random effects														
Industry	-2.124***	-3.319***	-2.134***	-3.463***	-2.398***	-2.890***	-2.854***	-2.661***	-3.037***	-3.062***	-2.247***	-2.289***	-2.889***	-3.221***
	(0.191)	(0.638)	(0.392)	(0.157)	(0.219)	(0.292)	(0.216)	(0.272)	(0.206)	(0.159)	(0.542)	(0.205)	(0.157)	(0.210)
Individual	-0.781***	-1.141***	-0.776***	-1.129***	-1.170***	-0.762***	-0.815***	-0.831***	-0.820***	-1.132***	-0.762***	-0.809***	-0.935***	-1.255***
	(0.0309)	(0.0329)	(0.0195)	(0.0436)	(0.0400)	(0.0307)	(0.0710)	(0.0323)	(0.0269)	(0.0239)	(0.0194)	(0.0321)	(0.00769)	(0.0132)
Observations	7,243	9,556	25,901	6,091	6,909	11,500	20,554	30,906	11,086	23,051	10,682	12,033	27,651	11,431
Number of groups	12	13	12	12	13	11	12	13	12	13	13	13	13	12

Note: Robust standard errors in parentheses; results for yearly dummies and 'NA'-categories not shown; random effects parameters are displayed in log of standard deviation; weighs are used in estimations; *** p<0.01, ** p<0.05, * p<0

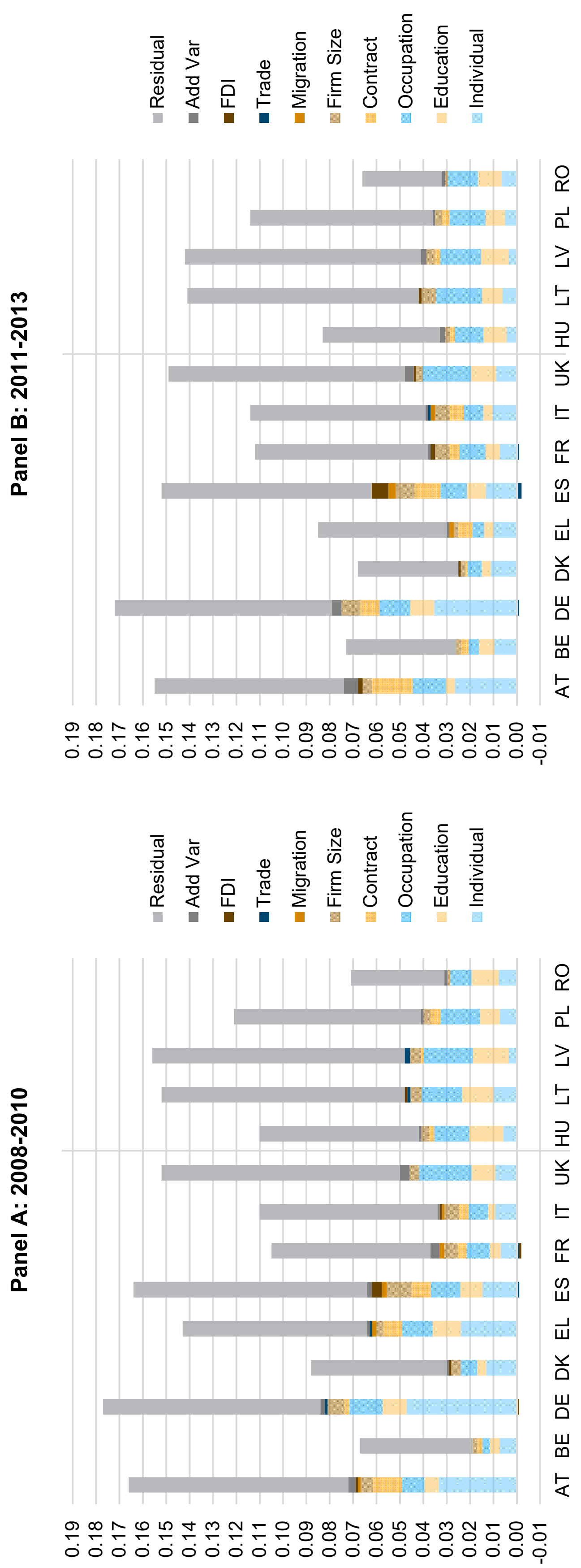
Source: EU-SILC; WIOD; Eurostat; EU-KLEMS; EU-LFS, own calculations.

Figure B.1 / Absolute contributions to Gini index



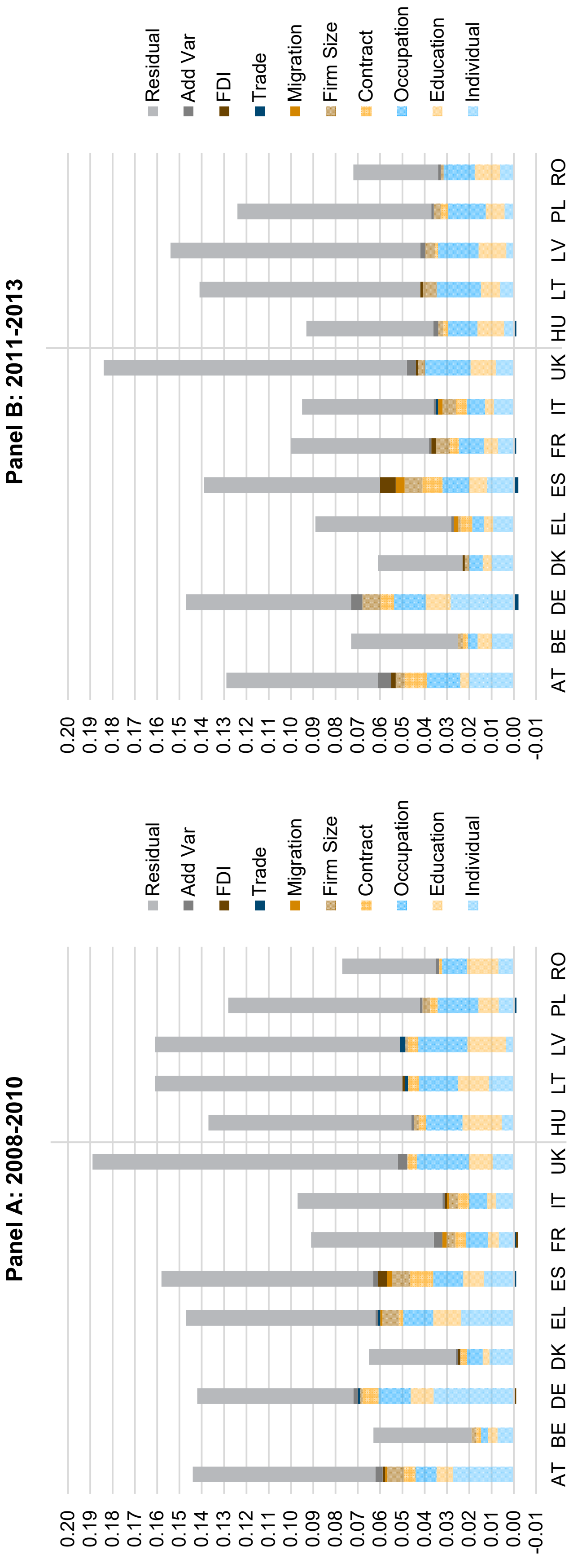
Source: EU-SILC; WIOD; Eurostat; EU-KLEMS; EU-LFS, own calculations.

Figure B.2 / Absolute contributions to GE(0) index



Source: EU-SILC; WIOD; Eurostat; EU-KLEMS; EU-LFS, own calculations.

Figure B.3 / Absolute contributions to GE(2) index



Source: EU-SILC; WIOD; Eurostat; EU-KLEMS; EU-LFS, own calculations.

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