Multinational Enterprises and Between-Firm Wage Inequality Across European Regions

Juan Duran [*1, 2] and Iulia Siedschlag [†1, 2]

[1]The Economic and Social Research Institute (ESRI)
[2]Department of Economics, Trinity College Dublin

Abstract

This paper examines the causal effect of multinational enterprises (MNEs) on between-firm wage inequality across European regions, utilizing firm-level data from the Orbis Europe dataset (2012–2021). Employing measures such as Gini coefficients and wage percentile ratios and addressing endogeneity through regional FDI shocks, the findings demonstrate that the regional presence of MNEs significantly contributed to increased wage inequality between firms across European regions. The effects are more pronounced for MNE parent firms and top-performing affiliates, underscoring the role of international superstar firms in driving regional disparities. This research advances the understanding of FDI's distributional impacts and its implications for regional inequalities.

Keywords— Foreign direct investment; Multinational firms; Market power; Wage inequality.

JEL Codes— F23, R12, R15

[*]Whitaker Square Sir John Rogerson's Quay, Dublin, Ireland. Email: juan.duranvanegas@esri.ie.
[†]Whitaker Square Sir John Rogerson's Quay, Dublin, Ireland. Email: iulia.siedschlag@esri.ie.

I. Introduction

A well-established literature has examined the effects of foreign direct investment (FDI) flows on a range of outcomes in the host economies, including economic growth (Paul & Feliciano-Cestero, 2021; Alfaro et al., 2010; Chakraborty & Nunnenkamp, 2008; Alfaro et al., 2004a; Borensztein et al., 1998), productivity gains (Amiti et al., 2024; Fons-Rosen et al., 2021; Stojčić & Orlić, 2020; Newman et al., 2015; Suyanto et al., 2009), and the adoption of new technologies (Ambos et al., 2006; Lee & Rugman, 2012). Nonetheless, and despite a growing literature on trade-induced wage inequality, there is scarce evidence on the effects of FDI on wage inequality in the host economies. While the existing literature tends to focus on the effects of FDI on wage inequality between workers at the industry or firm-level in specific countries (Feenstra & Hanson, 1995, 1997; Figini & Görg, 1999; Taylor & Driffield, 2005; Girma & Görg, 2007b; Chen et al., 2011), recent studies have pointed at international investments as a driver of regional inequalities (Buchholz & Bathelt, 2024; Bathelt et al., 2024) and between-firm inequality as the main driver of overall wage inequality (Akerman et al., 2013; Card et al., 2013; Helpman et al., 2016; Sampson, 2014; Song et al., 2019). Incorporating these two elements in the analysis of the wage inequality effects is of particular importance. On the one hand, international investment is highly unevenly distributed across regions, with disparities in FDI shown to surpass those in Gross Domestic Product (GDP) or productivity (OECD, 2022), making it challenging to grasp its economic effects without considering this regional dimension. On the other hand, FDI can affect wages by increasing firms' revenue in a similar fashion as the exporter revenue premium mechanism studied in the international trade literature (Akerman et al., 2013), thus becoming a source of between-firm and overall wage inequality.

Against this background, this paper examines the causal effect of the presence of multinational enterprises (MNEs) on between-firm wage inequality across European regions. MNEs are identified using firm-level data from the Orbis Europe data set over 2012-2021.[1] Among MNEs, we distinguish those holding dominant market shares (i.e. the international superstar firms).

We begin by documenting two empirical trends over the analysed period: i) between-firm wage dispersion has increased and has been driven by average wages in the top 90th and 95th percentiles; ii) the regional presence of MNEs shows an upward trend, which is stronger for the top-performing foreign affiliates, both in terms of labour and turnover shares. We then study the effect of the presence of MNEs across European NUTS-2 regions[2] on regional between-firm wage inequality using measurements of such as Gini coefficients and wage percentile ratios. To account for potential

[1] Access to the Orbis Europe data set is provided by under a Licence Agreement from Bureau van Dijk-Moody's.

[2] NUTS-2 regions are defined using the Nomenclature of Territorial Units for Statistics, the Eurostat's classification of geographical units in European countries.

endogeneity, we instrument MNEs' presence at the regional level with regional FDI shocks by exploiting the regional variation in pre-sample industry labour shares interacted with the aggregated change in Europe-wide inward FDI stocks. Moreover, we control for region-specific determinants of wage inequality identified in the literature, such as technological change and innovation capacity.

To the best of our knowledge, the effects of MNEs and international superstar firms on between-firm wage inequality across regions and countries have not been analysed so far. The novelties of our contribution to the literature are threefold. First, we focus on the dispersion of average wages (wage bill per employee) between firms, which allows us to go beyond existing analyses of wage inequality between industries. Our approach using average wages (computed using data from the Orbis dataset) follows De Loecker et al. (2022) and is motivated by recent research pointing to the rising dispersion of wages between firms as the main driver of rising overall wage inequality (Zwysen, 2022; Song et al., 2019; Akerman et al., 2013; Helpman et al., 2016, 2010). However, a limitation of our analysis is that we cannot observe differences in workforce composition across firms and thus empirically determine the role of the within-firm component in addition to the between-firm component of wage inequality. Despite this limitation and given the absence of available linked employer-employee data at region-year level, we believe that our approach is justified by the abundant evidence on the role of the between-firm component in accounting for the rise in wage inequality.[3]

Second, by exploiting data on firm-level characteristics, we distinguish between different types of MNEs, such as parent firms, foreign-owned firms, and foreign-owned firms with dominant market shares (i.e., market power), to determine whether the effects are stronger for these top-performing foreign affiliates. In that regard, our findings point at the parent MNEs and top-performing foreign affiliates as superstar firms which are considerably larger than domestic firms in terms of fixed assets and number of employees, have substantial wage premia, and which regional presence has sizable effects on between-firm wage inequality.

Third, our paper adds to the literature on the effects of FDI on host economies, particularly on host regions. Specifically, we generate new knowledge on the effects of the presence of MNEs and international superstar firms on between-firm wage inequality across European regions. The regional and the cross-country approach is also a novelty in the emerging literature on between-firm wage inequality. In that regard, our work relates to the literature on the regional impacts of FDI, which has focused on economic growth and technology spillovers (Stojčić & Orlić, 2020; Carbonell

[3]In particular, Zwysen (2022) documents that the increase in earnings inequality across EU member states between 2005-2018 is disproportionately driven by rising variation between establishments using data from the Structure of Earnings Survey (SES). Using the SES database as an alternative input to compute wage dispersion is not feasible in our setting since it is carried out every four years and it is only available at the NUTS1 level.

& Werner, 2018; Y. Wang et al., 2016; Oscar Bajo-Rubio & Díaz-Roldán, 2010). Understanding the causal impact of FDI on wage inequality in host regions is also important given increasing evidence on rising regional inequalities (Iammarino et al., 2018; Rosés & Wolf, 2021; Bathelt et al., 2024) and increasing concerns about the distributional effects of globalisation that have materialised in a political 'globalisation backlash' (Colantone et al., 2022).

We find that increases in the regional presence of MNEs significantly rise between-firm wage inequality. On average, over and above other factors, a 10 percent increase in the foreign affiliates' employment share increases the Gini coefficient of between-firm wage inequality by 0.49 percent, while an equivalent increase in the labour share of MNEs parents increases the Gini coefficient by 0.65 percent. These findings are robust to several model specifications using alternative measures of regional MNE presence, data sources, and additional control variables. Importantly, we also find that the effects increase in magnitude when comparing the overall presence of foreign-owned companies to the presence of top-performing foreign-owned companies measured as those in the top quartile and percentile of revenue by region and year.

The remainder of this paper is organized as follows. Section II. discusses existing related literature. Section III. presents our empirical approach. Next, Section IV. describes the data and measures used for the analysis and discusses trends of between-firm wage inequality and of foreign affiliates and international superstar firms across European regions. Section V. discusses our empirical results. Section VI. summarises the key findings and policy implications.

II. Related Literature

Our work relates to several literatures. Existing studies on the impact of FDI on wage inequality at the industry or firm-level are country-specific (Feenstra & Hanson, 1995, 1997; Figini & Görg, 1999; Taylor & Driffield, 2005; Girma & Görg, 2007b; Chen et al., 2011), while cross-country studies have focused on differences at the macroeconomic level (Pan-Long, 1995). Country studies have focused on impacts of FDI on relative wages and wage inequality between skilled and unskilled workers: Feenstra & Hanson (1997) for Mexico; Figini & Görg (2011) for Ireland; Taylor & Driffield (2005) and Girma & Görg (2007a) for the United Kingdom; Chen et al. (2011) for China. In a cross-country study, Figini & Görg (1999) examine the effects of inward FDI on wage inequality between sectors and workers. They find that inward FDI initially increases wage inequality in developing countries, but this effect diminishes over time while in developed countries inward FDI decreases wage inequality.

Several recent studies provide evidence on rising regional inequalities (Iammarino et al., 2018;

Kemeny & Storper, 2020; Feldman et al., 2020; Rosés & Wolf, 2021; Kemeny et al., 2022; Bathelt et al., 2024). Some of these studies point to technological change and globalisation as main drivers of the rising regional inequalities without a specific focus on regional wage inequality (Iammarino et al., 2018; Kemeny et al., 2022). Buchholz & Bathelt (2024) argue that international investment can enhance intra-regional inequalities given that the benefits of global connectivity are not equally distributed across workers and space. To support their argument, they cite evidence provided by Boschken (2023) who finds that some of the most globally connected cities in the US have the highest levels of inequality. Crescenzi & Iammarino (2017) point out that that openness and global connectivity impact on regional development and they put forward a new analytical framework to understand regional development trajectories in this context. Rosés & Wolf (2018) provide evidence on increasing income inequality across EU NUTS-2 regions. Existing studies on increasing wage inequalities within countries over the past decades (Card et al., 2013; De Loecker et al., 2022; Guvenen et al., 2022; Deb et al., 2024) do not relate these inequalities to FDI.

An emerging literature strand focuses on firm heterogeneity as a driver of within country wage inequality across firms and workers. A key outcome of this literature is that the rise in overall wage inequalities has been driven mainly by increased between-firm inequality (Akerman et al., 2013; Card et al., 2013; Helpman et al., 2016; Sampson, 2014; Song et al., 2019). Song et al. (2019) estimate that the increased dispersion of average firm earnings explains two-thirds of overall earnings inequality in the US. Card et al. (2013) finds that the rise in the dispersion of firm-level pay premiums has contributed to the increased wage inequality in Germany. This literature has built on previous studies showing that some firms pay higher wages for same skills (Van Reenen, 1996) and that controlling for differences in the composition of observed and unobserved worker characteristics, differences in average firm-level pay between firms has contributed significantly to wage inequality (Abowd et al., 1999; Goux & Maurin, 1999). Firm heterogeneity has also been uncovered as a channel through which international trade enhances the dispersion of revenues across firms and increases wage inequality (Akerman et al., 2013; Amiti & Davis, 2012; Sampson, 2014).

More generally, our paper relates to an extensive literature on the sources of wage inequality. As discussed by Helpman et al. (2016), research in this area highlights differences in workforce composition and labour market frictions as the main sources of wage dispersion across firms. Assuming competitive labour markets, several studies examine wage variation as a consequence of the sorting of workers across firms with different labour demand. Another set of studies introduces labour market imperfections such as search and matching frictions or efficiency or fair wages, leading to wage variation across firms for workers with similar characteristics. Empirically, there is increasing evidence of the between-firm component (i.e. earning variation within sector and occupation) accounting for most of the overall wage inequality (Akerman et al., 2013; Helpman et al., 2016; Song et al., 2019), although recent research also highlights the role of compositional

changes in the workforce such as sorting and segregation of high-skilled workers in explaining wage variation across firms (Song et al., 2019).

Most closely related to our paper is a growing literature on firm heterogeneity, international trade and wage inequality. This literature strand studies international trade as a source of dispersion of revenues across firms that contributes to the between-firm component of wage inequality (Akerman et al., 2013). At the core of this trade-related inequality mechanism is the fact that exporters are larger, more productive, and pay higher wages than non-exporters. Hence, the exporter premium occurs due to the selection of larger and more productive firms into exporting (selection effect) and the increased market access of the exporters (market access effect) (Helpman et al., 2016). In this paper, we explore a related channel by focusing on foreign-owned companies belonging to multinational firms, which have been documented to be larger and more productive than non-multinational exporters and domestic firms, which allows them to succeed in an external environment (Amiti et al., 2024; Keller, 2021; Taylor & Driffield, 2005; Driffield & Taylor, 2000). In that regard, the main channel leading to increased between-firm wage dispersion is the presence of larger firms paying higher wages and additionally benefiting from increased market access.

Our paper is also related to recent literature studying the consequences of the rise of large and dominant companies known as "superstar firms" (Autor et al., 2020). While superstars are usually defined as the largest firms by industry (Autor et al., 2020), Amiti et al. (2024) extends the definition to exporters and multinational firms. We build and extend these definitions by identifying the top-performing foreign affiliates at the regional level. In line with the FDI wage premium mechanism described above, we expect the presence of these dominant foreign affiliates to have a larger effect on local between-firm wage inequality.

III. Empirical Approach

To quantify the relationship between the presence of MNEs and between-firm wage inequality across regions, we use the following model specification:

$$Inq_{jt} = \beta MNE_{jt} + \Gamma \mathbf{X}_{jct} + \alpha_t + \epsilon_{jt}, \tag{1}$$

where Inq_{jt} is a measure of between-firm wage inequality in region j and year t; MNE_{jt} is a measure of the presence of foreign affiliates or parent MNEs in region j at time t; X_{jt} is a vector of regional characteristics that control for other potential determinants of local wage inequality; α_t denote year fixed effects; and ϵ_{jt} is an error term.

Our coefficient of interest is β and it quantifies the contemporary effect of the presence of MNEs

on between-firm wage inequality across regions once we account for other determinants of wage inequality. Year fixed effects α_t absorb unobserved time-specific shocks affecting between-firm wage inequality across all regions.

We measure the outcome variable in Eq. 1 in different ways using Gini coefficients, 90/10, and 90/50 wage percentile ratios. To measure MNE_{jt} we first use regional labour shares of all foreign-owned firms and parent MNEs. In the case of the foreign affiliates, we also look at the regional labour shares of the firms with the top quartile and top percentile revenue in each region and year. The vector of regional characteristics controls for different groups of wage inequality determinants and includes the third-level education attainment (the share of the population aged 25-64 with third level education) capturing the sorting of high-skilled workers across regions, the share of employment in knowledge-intensive sectors, productivity proxied with the regional Gross Domestic product (GDP) per worker, and the number of employees in Human Resources in Science & Technology per inhabitant as a proxy for the innovation capacity of a given region (Berkes & Gaetani, 2023).

For β to capture the causal effect of MNE presence on between-firm wage inequality across regions, we require MNE_{jt} to be unrelated with unobserved determinants of wage inequality. Therefore, the main potential identification concern would be given by regional economic shocks related to MNE presence and affecting between-firm wage inequality. To address this identification concern, we use an instrumental variable approach. An ideal instrument would be highly related to regional MNE presence but unrelated to unobserved determinants of wage inequality. While the literature has typically used lagged values as instruments (D. Wang et al., 2013; Taylor & Driffield, 2005; Alfaro et al., 2004b), recent research has highlighted that using these instruments requires additional and equally untestable identifying assumptions (Bellemare et al., 2017). Therefore, we use an alternative shift-share instrument that interacts Europe-wide changes in FDI stocks across industries with initial regional industry composition. Intuitively, the instrument predicts regional MNE presence by exploiting Europe-wide variation in FDI stocks with each region's industry mix at baseline, thus isolating any local characteristics potentially related to between-firm wage inequality across regions that could have determined the presence of foreign affiliates. More precisely, the shift-share instrument is defined as follows:

$$\tilde{MNE}_{jt} = \sum_{k} \eta_{kjt^0} \cdot \Delta FDI_{kt} \tag{2}$$

where η_{kjt^0} is the employment share of industry k in region j at a reference year t^0; and ΔFDI_{kt} is the log change in the FDI stock in the Europe-wide in industry k between the reference year t^0 and year t. We set t^0 as 2008 and source the local employment structure by industry from the Eurostat's Structural Business Statistics and the FDI stock from the OECD's International Direct Investment

Statistics. When instrumenting the regional presence of foreign affiliates, the direction principle of the FDI stocks is inward, while the instrument is constructed with the outward FDI stocks in the case of the regional presence of parent MNEs.

As pointed out by Goldsmith-Pinkham et al. (2020), the identification assumption when using this shift-share instrument is that the region-industry shares are uncorrelated with the error term in Eq. 1, which implies that the regions' industry mix is, in turn, uncorrelated with unobserved factors explaining between-firm wage inequality given the vector of controls. We find this assumption convincing since our controls include local factors such as third-level education attainment, productivity, and the importance of knowledge-intensive sectors.

Our approach follows a growing literature using shift-share instrumental variables to identify causal effects in different settings as migration (Jaeger et al., 2018), trade competition (Dell et al., 2019; D. Autor et al., 2013), and labour demand (Bartik, 1991). Very close to our approach is the shift-share instrument used by Ascani & Gagliardi (2015), where initial employment shares interact with inward FDI inflows by industry. Compared to the shift-share applications in the labour market or migration settings, the interpretation and expected direction of the shift-share instrument in the context of regional FDI presence is not straightforward. For instance, a positive relationship between the shift-share instrument and the actual FDI presence could reflect coexistence with foreign industry peers motivated by existing production complementarities and relevant inputs availability, while a negative relationship can be explained by existing established industry peers deterring the location of new foreign firms through input costs or market dominance. For instance, Ascani & Gagliardi (2015) find a positive coefficient in the first stage in the case of inward FDI across Italian provinces. Because we use a cross-country setting at the regional level, our instrument could reflect both within-country coexistence based on production complementarities or division due to cost-reduction or new market-seeking strategies. Therefore, we consider the sign of the coefficient of the shift-share instrument in the first stage an empirical question.

With our shift-share instrument in hand, we estimate the regression model described in Eq. 1 using the instrumental variables two-stage least squares (IV-2SLS) estimator.

IV. Data and Descriptive Statistics

Our analysis uses firm-level data from the Orbis Europe dataset (2012–2021), including firm-level information on ownership, number of employees, wage bill, turnover, total fixed assets, and incorporation year for all active firms in 21 EU countries and the UK. Aggregated at the NUTS2 regional level, our dataset comprises 206 regions. Orbis, provided by Bureau van Dijk-Moody's, covers over

200 million companies and includes firms' location details, enabling geographic analysis used in prior studies on economic issues (Stavropoulos et al., 2020; Cortinovis & Van Oort, 2015; Temouri, 2012).

Nonetheless, there are different data limitations related to Orbis such as the variation in coverage across counties that have been previously identified in the literature (Kalemli-Ozcan et al., 2015). This setback can be amplified when focusing on sub-national level geographic units. To mitigate concerns about coverage variation over space and time, we focus on regions with at least 30 firms after imposing the conditions of non-missing data on employment, wage bill, and location. This constraint prevents us from constructing wage inequality measures in regions with a very low number of firms and is in line with research quantifying regional outcomes such as total factor productivity taking firm-level as an input (Moretti, 2011).[4] Moreover, we look at the sample average share of regional employment from Eurostat's Structural and Business Statistics (SBS) accounted by Orbis and further restrict the sample by dropping countries with very low average coverage, such as Iceland, Luxembourg, and Malta. As a robustness check, we also show that our results hold when restricting the sample to countries with at least 50% employment coverage as identified by Kalemli-Ozcan et al. (2015). Additionally, we weigh all regression models by SBS employment to further alleviate concerns about our results being altered by uneven coverage. Finally, as a robustness check, we construct our dependent variable using CompNet average labour costs per employee aggregated at the NUTS2 level. CompNet provides micro-aggregated indicators at industry-level computed based on confidential firm-level data by national data providers for 14 European countries in our sample.

The outcome variable of interest in the empirical analysis is the between-firm inequality of mean wages (i.e. wage bill per employee) at the region level, which we measure using Gini coefficients, 90/10, and 90/50 wage percentile ratios. To construct these regional inequality measures, we adjust firm-level observed wages with firms' observable characteristics such as size and age. While this approach is conservative in that part of the wage premium between MNEs and domestic firms can be due to differences in these observable characteristics, it allows to account for potential differences that can directly arise from variation of these factors across sectors of activity or regional industry concentration. More precisely, we adjust wages per employee by using a firm-level regression with the following specification:

$$W_{ijt} = F_{ijt}\gamma + e_{ijt} \tag{3}$$

[4] Moretti (2011), for instance, restricts the sample to regions with 10 or more manufacturing plants when estimating total factor productivity. We increase the threshold to 30 firms since our dataset includes all market sectors. This number of firms maximizes the number of firm-year observations, given the imposed restriction on non-missing data. Our results are robust to increasing this threshold (e.g. 50 or 70 firms).

where W_{ijt} are observed mean wages per employee for firm i located in region j in year t, F_{ijt} is a vector of individual characteristics including size, age, and age squared, and e_{ijt} is an error term. We refer to the residuals of this regression as the residualised wages and use them to construct the measures of between-firm wage inequality in each region j and time t.[5] When using CompNet, since we cannot observe firm-level characteristics, we use the 10, 50, and 90 percentiles in observed wages to construct 90/10 and 90/50 observed wage percentile ratios.

The main explanatory variable is the regional presence of MNEs. For the baseline estimates, following a common approach in the literature, we define foreign affiliates as firms with at least ten percent of foreign direct ultimate ownership and with ten or more employees, excluding those in health, education, and government sectors.[6] Similarly, parent MNEs are defined as shareholders with more than ten percent ultimate ownership and at least ten employees. In the case of foreign affiliates, we further define superstar foreign-owned firms as those with revenues in the top quartile and decile by region and year, respectively. Since the ownership status could have changed over the studied period, we use the Orbis M&A dataset to update the status to domestic/foreign before the M&A transaction occurs whenever the firm identifier can be traced. At the region level, we use labour shares of these MNEs in regional employment as a measure of FDI local presence. Since superstar firms can display lower employment shares (Autor et al., 2020), we also substitute them with regional turnover shares as a robustness exercise.

Regarding our regional control variables, we obtain mean productivity (GDP per worker), the share of employment in high technology sectors, and the number of employees in Human Resources in Science & Technology (ST) per inhabitant from the Eurostat Regional database.[7] Detailed definitions of variables and data sources are given in Table A1 in Appendix A.

In Table 1, we report summary statistics for individual firm characteristics by distinguishing between domestic, foreign affiliates, and parent MNEs. On average, foreign affiliates are two times larger than domestic firms in terms of number of employees and fixed assets, and they pay about 15 per cent higher wages. Among these foreign affiliates, those in the top quartile of revenue reported in column 3 are nearly three times larger and pay 30 per cent higher wages than the average foreign-owned firms. Additionally, these foreign affiliates have a higher average regional labour share than the domestic firms. The last column reports the average outcomes for parent MNEs and documents that these firms are substantially larger than and their mean wages nearly double those paid by foreign affiliates.

[5]The estimation results of this regression are shown in Table A4 in the Appendix.

[6]Restricting the analysis to firms with more than ten employees also helps to alleviate concerns related to non-productive inward FDI with non-physical presence in the destination region. Our results are robust to including all foreign affiliates.

[7]Productivity data for the UK comes from the Office of National Statistics.

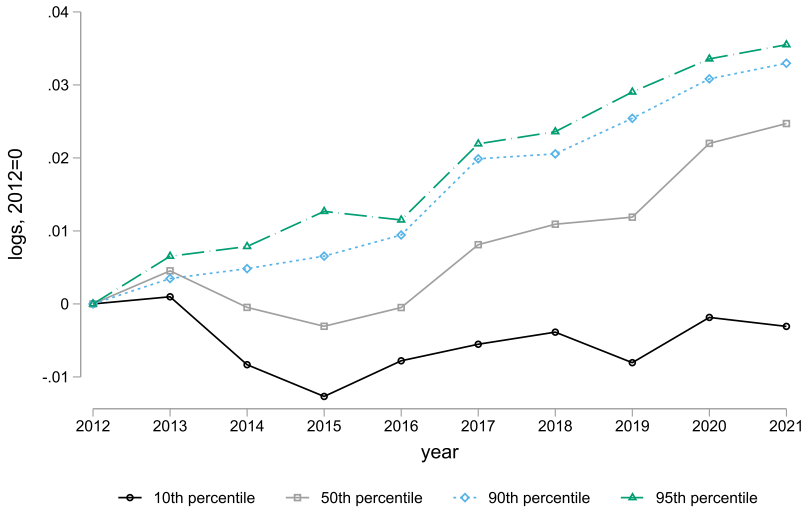
Table 1: Firm-level Summary Statistics

	Domestic	Foreign Affiliates	Foreign Affiliates top performers	Parent MNEs
Employees	28.15	56.24	86.26	497.91
	(320.48)	(541.79)	(761.32)	(2,724.84)
Fixed assets (euro mn)	6.59	12.16	20.49	199.47
	(213.74)	(227.34)	(326.97)	(1,483.55)
Log average wages	4.22	4.37	4.53	5.29
	(0.96)	(0.74)	(0.67)	(0.61)
Turnover (euro mn)	5.20	11.12	19.57	149.42
	(77.03)	(225.57)	(307.06)	(1,408.40)
Regional labour share (%)	0.09	0.15	0.17	1.06
	(0.82)	(1.25)	(1.14)	(4.47)
Observations	1,752,467	92,835	41,422	32,403

Notes: Standard deviations in parentheses. Monetary values are in constant 2018 prices calculated using the Eurostat harmonised CPIs. Wages are adjusted using Eq. 3.

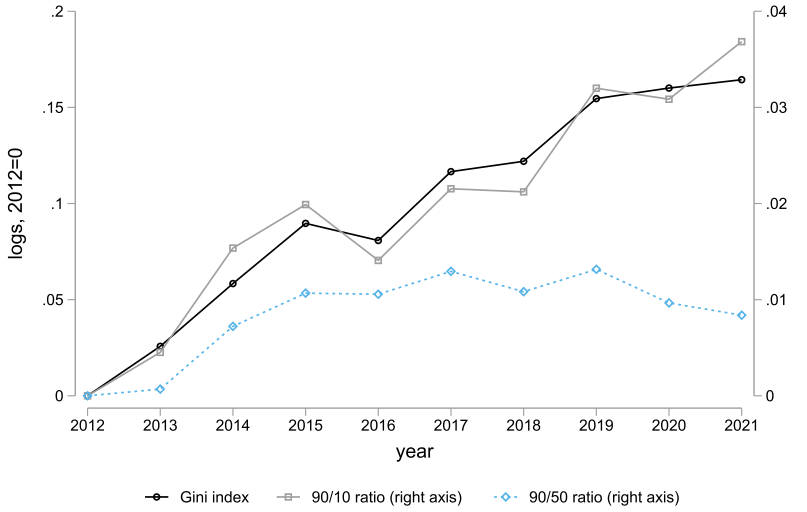
We next document trends in between-firm wage dispersion and MNE presence across regions over time. Figure 1 plots the average of different wage percentiles across NUTS2 regions weighted by regional employment and shows that between-firm wage dispersion has increased over the analysed period. Mean wages in the 90th and 95th percentiles have persistently increased, while those in the 50th percentile have remained stagnant after 2013. This increase in wage inequality between firms is also captured by increasing trends in mean regional Gini coefficients and the mean 90/10 wage percentile ratio (Figure 2). Finally, we report the trends in the employment shares of MNEs in Figure 3 which documents that the mean regional employment share of both foreign affiliates and parent MNEs has consistently increased during the studied period.

Figure 1: Wage Percentiles across Regions



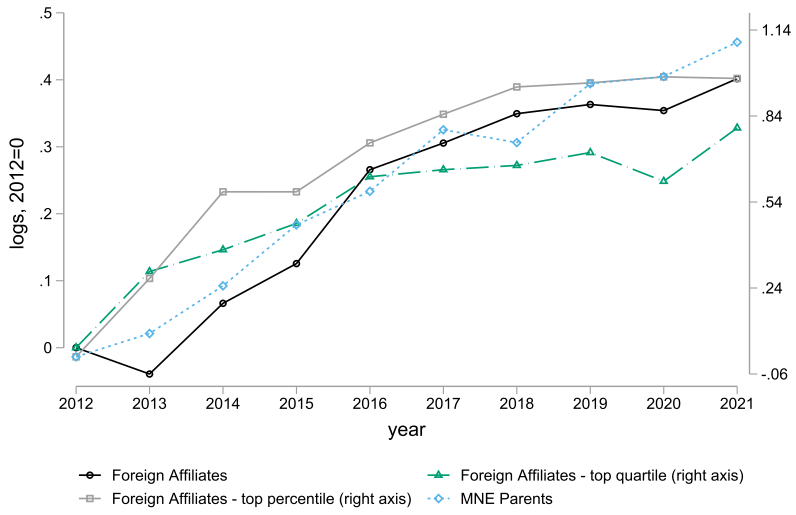
Source: Authors' calculations using data from the Orbis Europe.
Weighted average firm wages across NUTS2 regions in 21 EU countries and the UK. Series are winsorized at the 5th and 95th percentiles by year.

Figure 2: Between-firm Wage Inequality across Regions



Source: Authors' calculations using data from the Orbis Europe.
Weighted average firm wages across NUTS2 regions in 21 EU countries and the UK. Series are winsorized at the 5th and 95th percentiles by year.

Figure 3: MNE Regional Labour Shares across Regions



Notes: Weighted average firm wages across NUTS2 regions in 21 EU countries and the UK. Series are winsorized at the 5th and 99th percentiles by year. Foreign affiliates and parent MNEs defined with a $> 10\%$ threshold for direct ownership.
Top performers foreign affiliates are defined given revenue shares by region and year.
Source: Authors' calculations using data from the Orbis Europe and Eurostat.

V. Estimation Results

A. *Baseline Estimates*

We start by presenting the results when measuring regional between-firm wage inequality using the Orbis Europe database. Table 2 presents the results when the explanatory variable of interest is the regional labour share of foreign-owned firms and parent MNEs. The outcome variable is the regional Gini coefficient in models (1)-(2), the 90/10 wage percentile ratio in models (3)-(4), and the 90/50 wage percentile ratio in models (5)-(6). All models include the full set of controls, although we omit the control estimates in the first stage (Panel A) and the OLS estimates (Panel C) for ease of presentation and interpretation. Panel A documents that the shift-share instruments are strong predictors of the regional labour shares of both types of international firms. This is further corroborated by the heteroskedasticity-robust Kleibergen-Paap F statistics reported in Panel B which exceed the cutoff of ten proposed by Staiger & Stock (1997).

According to the IV estimates reported in Panel B of Table 2, regions with higher presence of foreign affiliates and parent MNEs experienced, on average, over and above other factors, higher between-firm wage inequality. Across models, the coefficients of interest are positive and statistically significant at the 10 percent level. For instance, a 10 per cent increase in the foreign affiliates' employment share increases the Gini coefficient of between-firm wage inequality by 0.49 percent, while an equivalent increase in the labour share of parent MNEs increases the Gini coefficient by 0.65 percent. Comparing these estimates with the OLS results reported in Panel C implies similar findings in terms of the statistical significance and direction of the effects. Nonetheless, the magnitude of the IV coefficients is relatively higher for the foreign affiliates' employment shares and relatively lower for the parent MNEs employment shares.

The estimated effects are economically large. In the case of foreign affiliates, a one standard deviation increase in the regional employment share leads to a 1.3 standard deviations increase in the Gini coefficient and between 0.6 to 1 standard-deviations in the wage percentile rations. When considering the parent MNEs, the effects to a one-standard deviation increase in the regional employment share vary between 0.5 and 0.9 standard deviations increase in the indices of between-firm wage inequality

Table 2: Regional MNE Presence and Between-firm Wage Inequality

Outcome variable:	*Panel A. First Stage* MNE regional employment shares					
	(1)	(2)	(3)	(4)	(5)	(6)
First stage coefficient	0.026***	0.033***	0.045***	0.033***	0.045***	0.033***
	(0.0058)	(0.0065)	(0.0132)	(0.0065)	(0.0132)	(0.0065)
Outcome variable:	*Panel B. IV Estimates* Gini index		90/10 ratio		90/50 ratio	
	(1)	(2)	(3)	(4)	(5)	(6)
Foreign aff. employment share	0.490***		1.320*		0.552***	
	(0.1703)		(0.7718)		(0.2070)	
Parent MNEs employment share		0.646**		1.412*		1.664***
		(0.2525)		(0.6890)		(0.4465)
Third level education	-0.076	-0.139**	-0.361	0.229	0.086	-0.248*
	(0.0575)	(0.0692)	(0.2232)	(0.4887)	(0.0731)	(0.1328)
HR in ST per capita	-0.197**	0.077	0.009	-0.768	-0.505***	0.323
	(0.0780)	(0.1331)	(0.3743)	(0.8594)	(0.0946)	(0.2590)
High tech employment share	0.024***	0.020***	0.032	0.030*	0.037***	0.031***
	(0.0044)	(0.0024)	(0.0232)	(0.0155)	(0.0055)	(0.0040)
GDP per worker	-0.090	0.344***	0.109	1.156***	0.008	0.536***
	(0.1316)	(0.0405)	(0.6143)	(0.1613)	(0.1609)	(0.0743)
Kleibergen-Paap F stat	11.397	25.647	11.397	25.647	11.397	25.647
Outcome variable:	*Panel C. OLS Estimates* Gini index		90/10 ratio		90/50 ratio	
	(1)	(2)	(3)	(4)	(5)	(6)
Foreign aff. employment share	0.381***		1.058		0.218***	
	(0.1342)		(0.7793)		(0.1944)	
Parent MNEs employment share		0.708***		1.312*		1.611***
		(0.2134)		(0.6890)		(0.4865)
R-squared	1.340	0.161	0.180	0.290	0.146	0.245

Notes: N=1,589 region-year observations. All variables are transformed to logs. All models are weighted by regional employment and include year fixed effects. Inequality indices are calculated using adjusted wages following Eq. 3. * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors are shown in parentheses.

We next investigate whether the effects differ when considering the regional presence of foreign affiliates with dominant market shares. Table 3 presents the results when we focus on the labour shares of the foreign-owned firms within the top quartile and percentile of revenue by year and region, respectively. We find that the IV estimates are larger than the ones obtained with the overall labour share of foreign-owned firms, suggesting that the effects are driven by the presence of these superstar international firms. Namely, a 10 percent increase in the regional labour share of the

foreign affiliates with the top 25% revenue increases the Gini coefficient by 0.62 percent, while the effect increases to 0.74 percent when considering the employment share of the foreign affiliates within the top 10% revenue.

Table 3: Top Performing Foreign Affiliates and Between-firm Wage Inequality across Regions - IV Estimates

Outcome variable:	Gini index		90/10 ratio		90/50 ratio	
	(1)	(2)	(3)	(4)	(5)	(6)
Foreign aff. - top q1 emp. share	0.619***		1.668*		0.697***	
	(0.2201)		(0.9877)		(0.2637)	
Foreign aff. - top p1 emp. share		0.744***		2.003*		0.838***
		(0.2074)		(1.0954)		(0.2609)
Third level education	-0.169**	-0.236***	-0.612*	-0.793*	-0.019	-0.094
	(0.0844)	(0.0828)	(0.3515)	(0.4141)	(0.1045)	(0.1074)
HR in ST per capita	-0.007	0.147	0.519	0.935	-0.292**	-0.118
	(0.1130)	(0.1270)	(0.5337)	(0.6875)	(0.1367)	(0.1599)
High tech employment share	0.013***	0.004	0.003	-0.022	0.025***	0.015**
	(0.0045)	(0.0058)	(0.0254)	(0.0334)	(0.0058)	(0.0075)
GDP per worker	-0.099	-0.045	0.084	0.230	-0.003	0.059
	(0.1364)	(0.0916)	(0.6320)	(0.5099)	(0.1659)	(0.1186)
Kleibergen-Paap F stat	11.598	23.714	11.598	23.714	11.598	23.714

Notes: N=1,589 region-year observations. All variables are transformed to logs. All models are weighted by regional employment and include year fixed effects. * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors are shown in parentheses.

B. *Robustness*

We conduct several robustness checks. First, to check the robustness of our results to the choice of our data, we use the CompNet database to obtain wage percentile ratios instead of aggregating firm-level wages from the Orbis dataset. CompNet provides micro-aggregated indicators computed on the basis of firm-level data by national data providers for 14 countries in our sample. Although the sample size is smaller given the number of countries which are covered, CompNet indicators are constructed using national representative firm-level datasets and allow us to further control for additional regional determinants of between-firm wage inequality. In our case, we use the 10, 50, and 90 percentiles to construct comparable 90/10 and 90/50 wage percentile ratios. Results in Table 4 imply that there is a positive and significant effect of the regional presence of multinational firms and between-firm wage inequality. Moreover, using CompNet data, we also control for aver-

age regional labour markdowns to proxy for employer market power, defined as the ratio between firms' marginal revenue product of labour and its wage (Yeh et al., 2022). Table A5 shows that our main results are robust and, interestingly, the coefficient of the regional markdown variable tends to be positive and significant, implying relative employer market power also exhibit is correlated with between-firm wage inequality at the regional level.

Table 4: Regional MNE Presence and Between-firm Wage Inequality - IV Estimates Using CompNet Data

Outcome variable:	90/10 ratio				90/50 ratio			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Foreign aff. employment share	1.735**				0.187			
	(0.8244)				(0.2526)			
Parent MNEs employment share		4.054				3.796***		
		(2.6784)				(1.2395)		
Foreign aff. - top q1 emp. share			2.352**				0.253	
			(1.1278)				(0.3445)	
Foreign aff. - top p1 emp. share				3.185**				0.343
				(1.5141)				(0.4692)
Third level education	0.048	-0.790	-0.333	-0.573	0.135	-0.916**	0.094	0.068
	(0.2912)	(0.8184)	(0.4412)	(0.5476)	(0.0892)	(0.3801)	(0.1356)	(0.1676)
HR in ST per capita	-1.552***	0.753	-0.871	-0.383	-0.377***	1.814**	-0.304*	-0.252
	(0.3627)	(1.5726)	(0.5400)	(0.7361)	(0.1144)	(0.7444)	(0.1674)	(0.2250)
High tech employment share	0.221***	0.137***	0.187***	0.152***	0.037***	0.009	0.034***	0.030***
	(0.0335)	(0.0265)	(0.0244)	(0.0253)	(0.0126)	(0.0153)	(0.0099)	(0.0093)
GDP per worker	0.418	2.662***	0.391	0.722	0.664**	0.990***	0.662**	0.697**
	(1.0411)	(0.3302)	(1.0679)	(0.9066)	(0.3195)	(0.1631)	(0.3257)	(0.2828)
Kleibergen-Paap F stat	21.969	24.791	20.999	23.256	21.969	24.791	20.999	23.256

Notes: N=1,029 region-year observations. All variables are transformed to logs. All models are weighted by regional employment and include year fixed effects. * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors are shown in parentheses.

Second, we define the ownership link with a 50% ownership instead of 10% as a threshold, another common cutoff used in the literature (Fons-Rosen et al., 2021) and using turnover regional shares instead of labour shares since superstar firms' labour shares can decline over time (Autor et al., 2020). Estimates reported in Table A7 and Table A6 confirm our findings are robust to these alternative measures.

Finally, we restrict our sample to countries with at least 50% employment coverage as identified by Kalemli-Ozcan et al. (2015) in order to address potential concerns related to the uneven coverage of Orbis. Estimation results reported in Table A8 show that the estimates are similar in magnitude and more precisely estimated when we restrict the sample to the regions in these countries.

VI. Conclusions

In this paper, we examined between-firm wage inequality across European regions, focusing on the role of foreign direct investment and international top firms with dominant market shares within the region where they are located. For this purpose, we used firm-level data from the Orbis Europe and CompNet datasets combined with economic and social data for European regions from 2012 to 2021. In terms of empirical methodology, to identify causal effects, we use a shift-share instrumental variables empirical approach.

We document that between-firm wage dispersion has increased over the analysed period, and it has been driven by average wages in the top 90th and 95th percentiles. Consequently, we observe increased wage inequality between firms, as shown by upward trends in the 90/10 wage percentiles ratio and Gini coefficients across regions. Furthermore, we document that mean regional employment shares of foreign-owned companies have consistently increased between 2012 and 2021.

Our estimates indicate that, on average, over and above other factors, a 10 per cent increase in the foreign affiliates' employment share increases the Gini coefficient of between-firm wage inequality by 0.49 percent, while an equivalent increase in the labour share of parent MNEs increases the Gini coefficient by 0.65 percent. The effects increase in magnitude when considering other indices of between-firm wage inequality and the regional presence of superstar firms among those with foreign ownership.

Taken together, the key findings of this paper suggest that FDI and international superstar firms have contributed to increased wage inequality between firms across European regions over the period 2012-2021. While increased wage inequality between firms might appear to be less of a concern (see, for example, De Loecker et al. 2022), as discussed in the Introduction, international evidence indicates that it can lead to increased overall income inequality (see, for example, Song et al. 2019). As documented in a large literature, overall income inequality is negatively correlated with health outcomes and life expectancy, access to education and equal opportunities, and it can also adversely affect economic performance, social cohesion and political stability (OECD, 2015a,b). To mitigate such potential unfavourable economic, social and political effects associated

with increased between-firm wage inequality, we suggest that policy measures aimed at enhancing spillovers from highly innovative and productive international superstar firms to domestic firms could foster productivity and wages and thus help achieve a more equal income distribution across firms. Such policy measures include strengthening the absorptive capacity of domestic firms (Cohen & Levinthal, 1989; Barrios et al., 2005; Girma & Görg, 2007b) and enabling supply chain linkages between superstar firms and domestic firms (Havranek & Irsova, 2011; Di Ubaldo et al., 2018; Alfaro-Ureña et al., 2022; Amiti et al., 2024).

Funding

This research paper is part of the ESSPIN project funded under the Horizon Europe Programme Grant Agreement No. 101061104.

Data Availability

This study used third-party data made available under a licence that the authors do not have permission to share. Requests to access the data should be directed to Bureau van Dijk-Moody's for the Orbis Europe data sets and to the CompNet Secretariat for the CompNet data set.

Acknowledgements

We acknowledge financial support from the Horizon Europe project ESSPIN (grant 101061104) funded by the European Union. Views and opinions expressed are however those of the authors only and do not necessarily reflect those of the European Union or the granting authority. Neither the European Union nor the granting authority can be held responsible for them. We thank all data-providing institutions within the CompNet network and the CompNet team for granting us access to the CompNet data set. We gratefully acknowledge helpful comments and suggestions from Eckhardt Bode, Roberta Capello, Riccardo Crescenzi, Daniela Constantin, and John Curtis and participants at research presentations at the 2023 RSA Annual Conference, the 62nd ERSA Congress, the 2024 CITP Annual Academic Conference 2024, the 2024 RSA Annual Conference, the 63rd ERSA Congress, and the ETSG 25th Annual Conference.

References

Abowd, J. M., Kramarz, F., & Margolis, D. N. (1999). High wage workers and high wage firms. *Econometrica*, *67*(2), 251–333.

Akerman, A., Helpman, E., Itskhoki, O., Muendler, M.-A., & Redding, S. (2013). Sources of wage inequality. *American Economic Review*, *103*(3), 214–219.

Alfaro, L., Chanda, A., Kalemli-Ozcan, S., & Sayek, S. (2004a). Fdi and economic growth: the role of local financial markets. *Journal of International Economics*, *64*(1), 89-112.

Alfaro, L., Chanda, A., Kalemli-Ozcan, S., & Sayek, S. (2004b). FDI and economic growth: the role of local financial markets. *Journal of International Economics*, *64*(1), 89-112.

Alfaro, L., Chanda, A., Kalemli-Ozcan, S., & Sayek, S. (2010). Does foreign direct investment promote growth? exploring the role of financial markets on linkages. *Journal of Development Economics*, *91*(2), 242-256.

Alfaro-Ureña, A., Manelici, I., & Vasquez, J. P. (2022). The Effects of Joining Multinational Supply Chains: New Evidence from Firm-to-Firm Linkages. *The Quarterly Journal of Economics*, *137*(3), 1495-1552.

Ambos, T. C., Ambos, B., & Schlegelmilch, B. B. (2006). Learning from foreign subsidiaries: An empirical investigation of headquarters' benefits from reverse knowledge transfers. *International Business Review*, *15*(3), 294–312.

Amiti, M., & Davis, D. R. (2012). Trade, firms, and wages: Theory and evidence. *The Review of economic studies*, *79*(1), 1–36.

Amiti, M., Duprez, C., Konings, J., & Van Reenen, J. (2024). FDI and superstar spillovers: Evidence from firm-to-firm transactions. *Journal of International Economics*, *152*, 103972.

Ascani, A., & Gagliardi, L. (2015). Inward FDI and local innovative performance. An empirical investigation on Italian provinces. *Review of Regional Research*, *35*, 29–47.

Autor, Dorn, D., Katz, L. F., Patterson, C., & Van Reenen, J. (2020). The Fall of the Labor Share and the Rise of Superstar Firms. *The Quarterly Journal of Economics*, *135*(2), 645-709.

Autor, D., Dorn, D., & Hanson, G. H. (2013). The China Syndrome: Local Labor Market Effects of Import Competition in the United States. *American Economic Review*, *103*(6), 2121-68.

Barrios, S., Görg, H., & Strobl, E. (2005). Foreign direct investment, competition and industrial development in the host country. *European Economic Review*, *49*(7), 1761-1784.

Bartik, T. (1991). *Who benefits from state and local economic development policies?* W.E. Upjohn Institute.

Bathelt, H., Buchholz, M., & Storper, M. (2024). The nature, causes, and consequences of inter-regional inequality. *Journal of Economic Geography*, *24*(3), 353-374.

Bellemare, M. F., Masaki, T., & Pepinsky, T. B. (2017). Lagged Explanatory Variables and the Estimation of Causal Effect. *The Journal of Politics*, *79*(3), 949-963.

Berkes, E., & Gaetani, R. (2023). Income segregation and the rise of the knowledge economy. *American Economic Journal: Applied Economics*, *15*(2), 69–102.

Borensztein, E., De Gregorio, J., & Lee, J.-W. (1998). How does foreign direct investment affect economic growth? *Journal of International Economics*, *45*(1), 115-135.

Boschken, H. L. (2023). Economic inequality in US global cities. *Journal of Urban Affairs*, *45*(10), 1785–1803.

Buchholz, M., & Bathelt, H. (2024). Relational hinterlands in the USA have become disconnected from major global centres. *Cambridge Journal of Regions, Economy and Society*, *17*(1), 219–234.

Carbonell, J. B., & Werner, R. A. (2018). Does Foreign Direct Investment Generate Economic Growth? A New Empirical Approach Applied to Spain. *Economic Geography*, *94*(4), 425-456.

Card, D., Heining, J., & Kline, P. (2013). Workplace heterogeneity and the rise of West German wage inequality. *The Quarterly journal of economics*, *128*(3), 967–1015.

Chakraborty, C., & Nunnenkamp, P. (2008). Economic Reforms, FDI, and Economic Growth in India: A Sector Level Analysis. *World Development*, *36*(7), 1192-1212.

Chen, Z., Ge, Y., & Lai, H. (2011). Foreign Direct Investment and Wage Inequality: Evidence from China. *World Development*, *39*(8), 1322-1332.

Cohen, W. M., & Levinthal, D. A. (1989). Innovation and Learning: The Two Faces of R & D. *The Economic Journal*, *99*(397), 569–596.

Colantone, I., Ottaviano, G., & Stanig, P. (2022). Chapter 7 - the backlash of globalization. In G. Gopinath, E. Helpman, & K. Rogoff (Eds.), *Handbook of international economics: International trade, volume 5* (Vol. 5, p. 405-477). Elsevier.

Cortinovis, N., & Van Oort, F. (2015). Variety, economic growth and knowledge intensity of European regions: a spatial panel analysis. *The Annals of Regional Science*, *55*(1), 7–32.

Crescenzi, R., & Iammarino, S. (2017). Global investments and regional development trajectories: the missing links. *Regional Studies*, *51*(1), 97–115.

Deb, S., Eeckhout, J., Patel, A., & Warren, L. (2024). Walras–Bowley Lecture: Market Power and Wage Inequality. *Econometrica*, *92*(3), 603–636.

Dell, M., Feigenberg, B., & Teshima, K. (2019). The Violent Consequences of Trade-Induced Worker Displacement in Mexico. *American Economic Review: Insights*, *1*(1), 43–58.

De Loecker, J., Obermeier, T., & Van Reenen, J. (2022). Firms and inequalities. *Institute for Fiscal Studies*, *1*, 1–41.

Di Ubaldo, M., Lawless, M., & Siedschlag, I. (2018). Productivity spillovers from multinational activity to local firms in Ireland. *OECD Productivity Working Papers*, *16*.

Driffield, N., & Taylor, K. (2000). FDI and the labour market: a review of the evidence and policy implications. *Oxford Review of Economic Policy*, *16*(3), 90–103.

Feenstra, R. C., & Hanson, G. H. (1995). Foreign investment, outsourcing and relative wages. *NBER Working Paper Series*, *5121*.

Feenstra, R. C., & Hanson, G. H. (1997). Foreign direct investment and relative wages: Evidence from Mexico's maquiladoras. *Journal of International Economics*, *42*(3), 371-393.

Feldman, M., Guy, F., & Iammarino, S. (2020). Regional income disparities, monopoly and finance. *Cambridge Journal of Regions, Economy and Society*, *14*(1), 25-49.

Figini, P., & Görg, H. (1999). Multinational Companies and Wage Inequality in the Host Country: The Case of Ireland. *Weltwirtschaftliches Archiv*, *135*(4), 594–612.

Figini, P., & Görg, H. (2011). Does foreign direct investment affect wage inequality? an empirical investigation. *The World Economy*, *34*(9), 1455-1475.

Fons-Rosen, C., Kalemli-Ozcan, S., Sørensen, B. E., Villegas-Sanchez, C., & Volosovych, V. (2021). Quantifying productivity gains from foreign investment. *Journal of International Economics*, *131*, 103456.

Girma, S., & Görg, H. (2007a). Evaluating the foreign ownership wage premium using a difference-in-differences matching approach. *Journal of International Economics*, *72*(1), 97–112.

Girma, S., & Görg, H. (2007b). Multinationals' Productivity Advantage: Scale or Technology? *Economic Inquiry*, *45*(2), 350-362.

Goldsmith-Pinkham, P., Sorkin, I., & Swift, H. (2020). Bartik instruments: What, when, why, and how. *American Economic Review*, *110*(8), 2586–2624.

Goux, D., & Maurin, E. (1999). Persistence of interindustry wage differentials: a reexamination using matched worker-firm panel data. *Journal of labor Economics*, *17*(3), 492–533.

Guvenen, F., Pistaferri, L., & Violante, G. L. (2022). Global trends in income inequality and income dynamics: New insights from GRID. *Quantitative Economics*, *13*(4), 1321–1360.

Havranek, T., & Irsova, Z. (2011). Estimating vertical spillovers from FDI: Why results vary and what the true effect is. *Journal of International Economics*, *85*(2), 234-244.

Helpman, E., Itskhoki, O., Muendler, M.-A., & Redding, S. J. (2016). Trade and inequality: From theory to estimation. *The Review of Economic Studies*, *84*(1), 357–405.

Helpman, E., Itskhoki, O., & Redding, S. (2010). Inequality and unemployment in a global economy. *Econometrica*, *78*(4), 1239–1283.

Iammarino, S., Rodriguez-Pose, A., & Storper, M. (2018, 04). Regional inequality in Europe: evidence, theory and policy implications. *Journal of Economic Geography*, *19*(2), 273-298.

Jaeger, D. A., Ruist, J., & Stuhler, J. (2018). Shift-Share Instruments and the Impact of Immigration. *NBER Working Papers*, *24285*.

Kalemli-Ozcan, S., Sorensen, B., Villegas-Sanchez, C., Volosovych, V., & Yesiltas, S. (2015). How to Construct Nationally Representative Firm Level Data from the Orbis Global Database: New Facts and Aggregate Implications. *NBER Working Paper Series*, *21558*.

Keller, W. (2021). Knowledge Spillovers, Trade, and FDI. *NBER Working Paper Series*, *28739*.

Kemeny, T., Petralia, S., & Storper, M. (2022). Disruptive innovation and spatial inequality. *Regional Studies*, *0*(0), 1–18.

Kemeny, T., & Storper, M. (2020). The Fall and Rise of Interregional Inequality: Explaining Shifts from Convergence to Divergence. *Scienze Regionali, Italian Journal of Regional Science*(2/2020), 175–198.

Lee, I. H., & Rugman, A. M. (2012). Firm-specific advantages, inward fdi origins, and performance of multinational enterprises. *Journal of International Management*, *18*(2), 132–146.

Moretti, E. (2011). Local Labor Markets. In D. Card & O. Ashenfelter (Eds.), (Vol. 4, p. 1237-1313). Elsevier.

Newman, C., Rand, J., Talbot, T., & Tarp, F. (2015). Technology transfers, foreign investment and productivity spillovers. *European Economic Review*, *76*, 168-187.

OECD. (2015a). *All on Board: Making Inclusive Growth Happen*. Paris: OECD Publishing.

OECD. (2015b). *In it together: Why less inequality benefits all*. Paris: OECD Publishing.

OECD. (2022). The geography of foreign investment in OECD member countries. *OECD Business and Finance Policy Papers*, *20*.

Oscar Bajo-Rubio, C. D.-M., & Díaz-Roldán, C. (2010). Foreign Direct Investment and Regional Growth: An Analysis of the Spanish Case. *Regional Studies*, *44*(3), 373-382.

Pan-Long, T. (1995). Foreign direct investment and income inequality: Further evidence. *World Development*, *23*(3), 469-483.

Paul, J., & Feliciano-Cestero, M. M. (2021). Five decades of research on foreign direct investment by mnes: An overview and research agenda. *Journal of Business Research*, *124*, 800-812.

Rosés, J. R., & Wolf, N. (2018). Regional economic development in Europe, 1900–2010: A description of the patterns. In *The Economic Development of Europe's Regions* (pp. 3–41). Routledge.

Rosés, J. R., & Wolf, N. (2021). Regional growth and inequality in the long-run: Europe, 1900–2015. *Oxford Review of Economic Policy*, *37*(1), 17-48.

Sampson, T. (2014). Selection into trade and wage inequality. *American Economic Journal: Microeconomics*, *6*(3), 157–202.

Song, J., Price, D. J., Guvenen, F., Bloom, N., & Von Wachter, T. (2019). Firming up inequality. *The Quarterly journal of economics*, *134*(1), 1–50.

Staiger, D., & Stock, J. H. (1997). Instrumental variables regression with weak instruments. *Econometrica*, *65*(3), 557–586.

Stavropoulos, S., van Oort, F., & Burger, M. (2020). Heterogeneous relatedness and firm productivity. *The Annals of Regional Science*, *65*, 403–437.

Stojčić, N., & Orlić, E. (2020). Spatial dependence, foreign investment and productivity spillovers in new EU member states. *Regional Studies*, *54*(8), 1057-1068.

Suyanto, Salim, R. A., & Bloch, H. (2009). Does Foreign Direct Investment Lead to Productivity Spillovers? Firm Level Evidence from Indonesia. *World Development*, *37*(12), 1861-1876.

Taylor, K., & Driffield, N. (2005). Wage inequality and the role of multinationals: Evidence from UK panel data. *Labour Economics*, *12*(2), 223–249.

Temouri, Y. (2012). The cluster scoreboard: Measuring the performance of local business clusters in the knowledge economy. *OECD Local Economic and Employment Development (LEED) Papers*.

Van Reenen, J. (1996). The creation and capture of rents: wages and innovation in a panel of UK companies. *The quarterly journal of economics*, *111*(1), 195–226.

Wang, D., Gu, F. F., David, K. T., & Yim, C. K. B. (2013). When does FDI matter? The roles of local institutions and ethnic origins of FDI. *International Business Review*, *22*(2), 450-465.

Wang, Y., Lutao Ning, J. L., & Prevezer, M. (2016). Foreign Direct Investment Spillovers and the Geography of Innovation in Chinese Regions: The Role of Regional Industrial Specialization and Diversity. *Regional Studies*, *50*(5), 805-822.

Yeh, C., Macaluso, C., & Hershbein, B. (2022, July). Monopsony in the US Labor Market. *American Economic Review*, *112*(7), 2099-2138.

Zwysen, W. (2022). Wage inequality within and between firms: Macroeconomic and institutional drivers in Europe. *ETUI Research Paper-Working Pape 2022.02*.

Appendix

Table A1: Variables Definitions and Data Sources

Variable	Description	Data Source
Regional units	Nomenclature of Territorial Units at the second level (NUTS2).	Eurostat
Wage per employee	Cost of employees over number of employees windsorized at the 5th and 95th percentiles in each region.	Own calculations based on Orbis Europe.
Wage inequality indices	Gini coefficients, 90/10, and 90/50 wage percentile ratios. Indices are constructed using wages adjusted using firm-level data from Orbis Europe. In the case of CompNet, 90/10 and 90/50 percentile ratios are available at the region level and correspond to observed wages.	CompNet and own calculations based on Orbis Europe.
Firms' age	Number of years between the date of incorporation and the reference year.	Own calculations based on Orbis Europe
Firms' size	Total assets in constant 2015 prices.	Own calculations based on Orbis Europe
Foreign affiliates	Firms with 10% (50%) or higher direct ultimate ownership.	Orbis Europe
Foreign affiliates - Top performers	Foreign-owned companies with the top percentile (quartile) revenues in each year and region.	Own calculations based on Orbis Europe
parent MNEs	Shareholders with more than 10% (50%) or higher ultimate foreign ownership.	Orbis Europe
Third-level education attainment	Share of population aged 25-64 with third level educational attainment	Eurostat regions database
Knowledge-intensive share	Share of employees in knowledge-intensive sectors	Eurostat regions database
Productivity	Gross Domestic Product per capita	Eurostat regions database, Office of National Statistics
HR in Science & Technology	Employees in Human Resources in Science & Technology per inhabitant	Eurostat regions database
Regional employment	Total number of individuals working or belonging to the corresponding NUTS2 region	Structural business statistics (SBS)

Table A2: Countries in the Sample

Country	Orbis	CompNet	Eurostat
Austria	✓		✓
Belgium	✓	✓	✓
Bulgaria	✓		✓
Germany	✓	✓	✓
Denmark	✓	✓	✓
Estonia	✓		✓
Finland	✓	✓	✓
France	✓	✓	✓
Croatia	✓	✓	✓
Hungary	✓	✓	✓
Ireland	✓		✓
Italy	✓	✓	✓
Netherlands	✓		✓
Norway	✓		✓
Poland	✓	✓	✓
Portugal	✓	✓	✓
Romania	✓	✓	✓
Slovakia	✓	✓	✓
Sweden	✓	✓	✓
Spain	✓	✓	✓
United Kingdom	✓		✓

Notes: CompNet data for Netherlands is not available at the NUTS2 level.

Table A3: Region-level Summary Statistics

	(1)		
	Mean	SD	Obs.
Gini coefficient	0.058	0.03	1,701
90-10 ratio	1.354	0.85	1,701
90-10 ratio CompNet	1.760	0.43	1,049
90-50 ratio	1.127	0.08	1,701
90-50 ratio CompNet	1.204	0.13	1,049
Foreign aff. employment share	0.068	0.08	1,701
Foreign aff. - top q1 emp. share	0.041	0.06	1,701
Foreign aff.- top p1 emp. share	0.021	0.04	1,701
Parent MNEs employment share	0.159	0.18	1,701
Third level education	0.311	0.10	1,637
High tech employment share	0.038	0.02	1,597
HR in ST per capita	0.242	0.07	1,631

.

Table A4: Individual Wage Estimations

Outcome variable: Log wage per employee	
	(1)
Size (total fixed assets)	0.209***
	(0.0004)
Age	-0.046***
	(0.0014)
Age squared	0.090***
	(0.0023)
Constant	1.476***
	(0.0029)
Obs.	1,436,926
R-squared	0.299

Notes: * p<0.1, ** p<0.05, *** p<0.01. Standard errors clustered at the region level are shown in parentheses.

Table A5: Robustness Check - Regional Markdowns Using CompNet Data - IV Estimates

Outcome variable:	90/10 ratio				90/50 ratio			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Foreign aff. employment share	3.241**				0.404			
	(1.2971)				(0.3442)			
Parent MNEs employment share		4.179*				3.715***		
		(2.5022)				(1.2001)		
Foreign aff. - top q1 emp. share			4.533**				0.566	
			(1.9000)				(0.4924)	
Foreign aff. - top p1 emp. share				6.532**				0.815
				(2.7540)				(0.7268)
Third level education	-0.907*	-0.938	-1.704**	-2.380**	-0.003	-0.819**	-0.103	-0.187
	(0.5352)	(0.6662)	(0.8685)	(1.1941)	(0.1391)	(0.3228)	(0.2228)	(0.3007)
HR in ST per capita	-0.844	0.919	0.515	1.702	-0.275**	1.705**	-0.106	0.042
	(0.5854)	(1.3878)	(0.9884)	(1.5086)	(0.1372)	(0.6821)	(0.2490)	(0.3743)
High tech employment share	0.278***	0.139***	0.216***	0.147***	0.046***	0.008	0.038***	0.029***
	(0.0514)	(0.0271)	(0.0331)	(0.0313)	(0.0151)	(0.0159)	(0.0108)	(0.0097)
GDP per worker	-0.042	2.941***	-0.126	0.485	0.598*	0.806***	0.588	0.664**
	(1.2726)	(0.3838)	(1.3607)	(1.1083)	(0.3455)	(0.1795)	(0.3615)	(0.3062)
Regional mark-down	0.372***	0.070	0.397***	0.450***	0.054**	-0.046	0.057**	0.063*
	(0.1024)	(0.0705)	(0.1197)	(0.1442)	(0.0254)	(0.0346)	(0.0288)	(0.0357)
Kleibergen-Paap F stat	11.791	24.698	10.321	10.275	11.791	24.698	10.321	10.275

Notes: N=1,029 region-year observations. All variables are transformed to logs. All models are weighted by regional employment and include country-year fixed effects. * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors are shown in parentheses.

Table A6: Robustness Check - 50% Foreign Ownership Threshold - IV Estimates

Outcome variable:	Gini index				90/10 ratio				90/50 ratio			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Foreign aff. employment share	0.488***				1.313*				0.549***			
	(0.1688)				(0.7668)				(0.2053)			
Parent MNEs employment share		0.672**				0.943*				1.730***		
		(0.2654)				(0.4250)				(0.4746)		
Foreign aff. - top q1 emp. share			0.620***				1.668*				0.698***	
			(0.2203)				(0.9883)				(0.2640)	
Foreign aff. - top p1 emp. share				0.747***				2.011*				0.841***
				(0.2087)				(1.1005)				(0.2624)
Third level education	-0.074	-0.145**	-0.169**	-0.237***	-0.356	0.239	-0.612*	-0.794*	0.088	-0.266*	-0.019	-0.095
	(0.0569)	(0.0725)	(0.0844)	(0.0832)	(0.2209)	(0.5091)	(0.3513)	(0.4150)	(0.0724)	(0.1405)	(0.1045)	(0.1078)
HR in ST per capita	-0.198**	0.093	-0.008	0.148	0.006	-0.790	0.518	0.937	-0.506***	0.363	-0.292**	-0.117
	(0.0776)	(0.1408)	(0.1129)	(0.1274)	(0.3734)	(0.9067)	(0.5334)	(0.6886)	(0.0942)	(0.2759)	(0.1367)	(0.1604)
High tech employment share	0.024***	0.019***	0.013***	0.004	0.032	0.030**	0.003	-0.022	0.037***	0.030***	0.025***	0.015**
	(0.0044)	(0.0025)	(0.0045)	(0.0058)	(0.0232)	(0.0146)	(0.0254)	(0.0334)	(0.0055)	(0.0041)	(0.0058)	(0.0075)
Kleibergen-Paap F stat	11.530	23.239	11.588	23.549	11.530	23.239	11.588	23.549	11.530	23.239	11.588	23.549

Notes: N=1,589 region-year observations. All variables are transformed to logs. All models are weighted by regional employment and include year fixed effects. * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors are shown in parentheses.

Table A7: Robustness Check - Regional Turnover Shares - IV Estimates

Outcome variable:	Gini index				90/10 ratio				90/50 ratio			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Foreign aff. turnover share	0.561***				1.512*				0.632***			
	(0.2081)				(0.9067)				(0.2443)			
Parent MNEs turnover share		0.646**				1.311*				1.664***		
		(0.2525)				(0.6890)				(0.4465)		
Foreign aff. - top q1 turn. share			0.483***				1.300*				0.544***	
			(0.1494)				(0.7326)				(0.1807)	
Foreign aff. - top p1 turn. share				0.566***				1.523*				0.637***
				(0.1545)				(0.8278)				(0.1930)
Third level education	0.085	-0.139**	-0.047	-0.126**	0.073	0.229	-0.283	-0.494*	0.268***	-0.248*	0.119**	0.030
	(0.0543)	(0.0692)	(0.0457)	(0.0545)	(0.1887)	(0.4887)	(0.1789)	(0.2601)	(0.0629)	(0.1328)	(0.0574)	(0.0709)
HR in ST per capita	-0.397***	0.077	-0.127*	0.024	-0.529	-0.768	0.197	0.603	-0.730***	0.323	-0.426***	-0.257**
	(0.1022)	(0.1331)	(0.0761)	(0.0959)	(0.4454)	(0.8594)	(0.3968)	(0.5320)	(0.1169)	(0.2590)	(0.0919)	(0.1197)
High tech employment share	0.016***	0.020***	0.008*	0.005	0.012	0.030*	-0.010	-0.020	0.029***	0.031***	0.019***	0.015**
	(0.0047)	(0.0024)	(0.0049)	(0.0053)	(0.0242)	(0.0155)	(0.0289)	(0.0322)	(0.0058)	(0.0040)	(0.0063)	(0.0070)
GDP per worker	0.009	0.344***	-0.011	-0.046	0.376	1.156***	0.321	0.228	0.119	0.536***	0.096	0.057
	(0.1099)	(0.0405)	(0.0929)	(0.0909)	(0.4892)	(0.1613)	(0.4796)	(0.5097)	(0.1308)	(0.0743)	(0.1156)	(0.1165)
Kleibergen-Paap F stat	9.955	25.647	18.234	26.290	9.955	25.647	18.234	26.290	9.955	25.647	18.234	26.290

Notes: N=1,589 region-year observations. All variables are transformed to logs. All models are weighted by regional employment and include year fixed effects. * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors are shown in parentheses.

Table A8: Robustness Check - Orbis High Coverage Countries - IV Estimates

Outcome variable:	Gini index				90/10 ratio				90/50 ratio			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Foreign aff. employment share	0.426***				1.034***				0.373**			
	(0.1494)				(0.3768)				(0.1580)			
Parent MNEs employment share		0.547***				1.518***				0.343*		
		(0.1557)				(0.4488)				(0.2065)		
Foreign aff. - top q1 emp. share			0.579***				1.405**				0.507**	
			(0.2188)				(0.5490)				(0.2287)	
Foreign aff. - top p1 emp. share				0.842***				2.042***				0.737**
				(0.2715)				(0.6983)				(0.2958)
Third level education	-0.037	0.036	-0.156**	-0.280***	-0.110	0.067	-0.400**	-0.701***	0.097**	0.036	-0.008	-0.116
	(0.0433)	(0.0397)	(0.0691)	(0.0921)	(0.1088)	(0.1224)	(0.1715)	(0.2359)	(0.0470)	(0.0540)	(0.0763)	(0.1064)
HR in ST per capita	-0.374***	-0.356***	-0.138	0.086	-0.961***	-0.918***	-0.388*	0.155	-0.527***	-0.280***	-0.320***	-0.124
	(0.0956)	(0.0733)	(0.0849)	(0.1204)	(0.2391)	(0.2276)	(0.2110)	(0.3072)	(0.0965)	(0.1032)	(0.0933)	(0.1387)
High tech employment share	0.045***	0.029***	0.032***	0.022***	0.119***	0.080***	0.087***	0.062***	0.054***	0.040***	0.042***	0.033***
	(0.0078)	(0.0021)	(0.0044)	(0.0041)	(0.0199)	(0.0068)	(0.0119)	(0.0111)	(0.0082)	(0.0035)	(0.0054)	(0.0056)
GDP per worker	-0.114	0.273***	-0.146	-0.165	-0.197	0.742***	-0.273	-0.319	0.129	0.531***	0.101	0.084
	(0.1275)	(0.0341)	(0.1474)	(0.1280)	(0.3205)	(0.1108)	(0.3669)	(0.3250)	(0.1425)	(0.0609)	(0.1621)	(0.1515)
Kleibergen-Paap F stat	11.905	10.799	9.930	13.698	11.905	10.799	9.930	13.698	11.905	10.799	9.930	13.698

Notes: *N*=908 region-year observations. All variables are transformed to logs. All models are weighted by regional employment and include the full set of control variables and year fixed effects. The sample is restricted to Belgium, Finland, France, Germany, Spain, Italy, Norway, and Sweden.* p<0.1, ** p<0.05, *** p<0.01. Robust standard errors are shown in parentheses.