Accepted: 11 July 2023
DOI: 10.1111/ecca.12490

ORIGINAL ARTICLE

Economica LSE

Productivity dispersion, wage dispersion and superstar firms

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Abstract
Using a rich sample of firms in 14 EU countries from 2000 to 2016, we confirm increases in productivity dispersion, wage dispersion and superstar firms. Beyond reaffirming an incomplete pass-through from productivity to wages, we present novel empirical evidence of an even weaker pass-through in industries dominated by superstar firms. This effect is observed in both the lower and upper parts of the productivity and wage distributions, and is stronger for tradable (versus non-tradable) sectors and markets with low (versus high) collective bargaining power. These findings point to different mechanisms, consistent with theoretical work and various underlying structural changes in the economy.

1 | INTRODUCTION

Although often studied separately,[1] productivity and wage dispersion are found to have notably similar evolutions (Dunne *et al.* 2004; Faggio *et al.* 2010; Barth *et al.* 2016).[2] This positive relationship arises under a range of models based on various theoretical foundations (Lentz and Mortensen 2010; Manning 2011).[3] Overall, changes in productivity and wage dispersion are shown to be closely linked.[4] As such, a host of structural factors and policies are expected to impact the wage distribution not only directly,[5] but also indirectly through the link between productivity and wage dispersion, that is, the extent to which the distribution of productivity gains are passed on to wages. In line with the above, such structural factors and policies range from globalization and technological change to minimum wage and labour unions (for an empirical exploration of a range of factors, see Berlingieri *et al.* 2017).

While each of these factors is a compelling explanation, they jointly appear to have contributed to the emergence of a global secular trend: the rise of 'superstar firms'. Superstar firms refer to a handful of large entities that dominate product market shares in their industries (Autor *et al.* 2020). These firms are known to be the most productive, technologically advanced and globally engaged (Mayer and Ottaviano 2008; Andrews *et al.* 2015); they set higher markups

(Autor *et al.* 2020), and have a lower firm-specific labour share despite paying above-average wages (Gouin-Bonenfant 2022). The rise of superstar firms is a global phenomenon already used to interpret emerging trends such as declining labour share (Abraham and Bormans 2020; Autor *et al.* 2020) and rising markups (De Loecker *et al.* 2020).

In a world where a handful of firms increasingly control the market, it is important to understand how this structural change might affect the extent to which productivity gains are passed on to wages. The importance of this question is underscored by recent anecdotal evidence from Amazon opening a warehouse in South Carolina. Despite creating approximately 4000 jobs, Amazon's dominance in the local labour market translated to a decrease in average annual wages by roughly 30% (*The Economist* 2018). This behaviour supports theoretical considerations proposed by Gouin-Bonenfant (2022) about the link between productivity and wage dispersion. In particular, as productivity dispersion increases, high-productivity firms enjoy increased profit margins while being shielded from local wage competition. Therefore increased monopsony power of firms at the top of the distribution leads to a gradual moderating effect in workers' wages—to levels below their marginal value of revenue. Such effects, however, are not limited to the top of the distribution. They could also arise at the bottom of the distribution through structural changes in the labour market due to increased concentration, as evidenced in the case of Amazon. Overall, a rise in market concentration is expected to weaken the link between productivity and wage dispersion, which we examine empirically in this paper.

The contribution of this paper is twofold. First, using a rich firm-level dataset for 14 EU countries between 2000 and 2016, we complement evidence of the increasing evolution of productivity and wage dispersion. A key difference between our analysis and others is the time period covered, with most previous studies ending around 2012. While we confirm increases in productivity and wage dispersion throughout the sample period, we also observe a moderating effect in more recent years. This novel evidence posits that trends in productivity and wage dispersion might be non-secular. Moreover, these evolutions are driven primarily by changes at the bottom of the distribution. In the case of productivity dispersion, these findings are consistent with increases in misallocation of resources towards the least productive firms.[6] In the case of wage dispersion, results support the presence of increased downward pressure on labour and wages at lower parts of the distribution.[7]

Further, we confirm a rather incomplete link between productivity and wage dispersion. Otherwise stated, while we find that industries with higher productivity dispersion are associated with higher wage dispersion, the correlation is less than 1. Unpacking these results, we show that this link is considerably stronger at the bottom of the distribution. Intuitively, firms at the bottom seem to transfer a relatively larger share of their productivity gains to wages compared to firms at the top. This finding can be reconciled with theoretical considerations of firms' differential levels of labour market power, where larger and more productive firms have more labour market power markdowns, and thus put relatively more downward pressure on wages (Berger *et al.* 2022).

Second, we explore the emergence of superstar firms and their potential impact on the link between productivity and wage dispersion. In doing so, we establish a rise of superstar firms in our sample, in line with Autor *et al.* (2020). In turn, we provide novel evidence that high market concentration industries—a proxy for superstar firms—are associated with a weaker link between productivity and wage dispersion. As such, superstar firms appear to induce a larger disconnect between productivity and wages, and hence a more incomplete pass-through.

Interestingly, this effect holds at both the top and bottom parts of the distribution, pointing to possibly different mechanisms at play. At the top part of the distribution, such effects provide positive affirmation of the mechanism referred to above: highly productive firms enjoy increased profit margins from access to globalization while being shielded from local wage competition through increased domestic labour market power. This allows them to pass a smaller share of their productivity gains to wages (Gouin-Bonenfant 2022). At the bottom part of the distribution, such effects might be present through the overall impact on the market structure.

Specifically, the emergence of superstar firms reduces competitive pressure in the labour market, which allows even the least productive firms to have some monopsony power, which translates to low wages (Azkarate-Askasua and Zerecero 2022; Berger *et al.* 2022). To help to contextualize the above results, we also provide a case study for the manufacturing industry of leather and related products in Spain.

Upon deeper examination of underlying heterogeneity, we provide additional support to these mechanisms. In particular, we find that the baseline results are prominent in: (a) output markets that are more open to internationalization, that is, tradable sectors; and (b) labour markets with limited regulations in place, that is, countries with low collective bargaining power. Intuitively, the first result suggests that firms in tradable sectors reap the benefits of internationalization more intensively, thus allowing them to occupy a dominant position in both domestic output and labour market. Furthermore, the latter finding supports the presence of higher labour market power in countries with lower employment protection, which allows for stronger mediating effects of superstar firms on the pass-through from productivity to wages.

Our analysis relies on firm-level data from Orbis Global, which allows us to construct measures for productivity dispersion, wage dispersion and market concentration at the country–industry–year level. The broad set of 14 European countries considered differs across various dimensions—geography, economic development, institutions, trade openness/integration, etc. Such variation lends itself to strong external validity of our main analysis. On the other hand, limitations on the coverage of this database for smaller-sized firms are well-known. We thus provide a series of cross-validation checks in terms of the data at hand to overcome these constraints and implement a set of robustness checks on the construction of our measures of interest. In all cases, results remain robust, reaffirming the main conclusions from our baseline analysis. Finally, while all interpretations are based on conditional correlations, our findings remain robust against a rich set of fixed effects that guard against potential unobserved heterogeneity along various dimensions.

The remainder of this paper is structured as follows. Section 2 discusses the construction of the main variables of interest and the choice of empirical specifications. Section 3 describes the dataset used in the empirical analysis. Section 4 presents results, Section 5 explores the potential mechanisms in place, and Section 6 provides robustness checks. Section 7 concludes.

2 | EMPIRICAL METHODOLOGY

This section discusses the construction of our main variables and empirical strategy used in the paper. We first describe how we measure productivity and wages at the firm level as well as the construction of measures that capture productivity and wage dispersion at the country–industry–year level. This leads to an examination of the evolution of these measures over time. Subsequently, we provide a theoretical background that supports the introduction of the empirical specification that links productivity dispersion to wage dispersion. Finally, we elaborate on the construction of proxies that reflect the evolution of superstar firms. With these at hand, and in line with the theoretical background, we present the empirical specification used to assess (a) the direct effect of superstar firms on wage dispersion, and (b) the mediating effect of superstar firms on the link between productivity and wage dispersion.

2.1 | Measuring productivity and wages

Productivity reflects how efficient firms are in transforming inputs into output. For our baseline analysis, we use labour productivity P defined as

$$P_{jcit} = \frac{VA_{jcit}}{L_{jcit}}, \tag{1}$$

where VA_{jcit} is value-added, and L_{jcit} is employment (in full-time equivalents) for firm j in country c, industry i, and year t. This measure is advantageous because it is straightforward to compute and interpret, and information on value-added and employment—necessary to calculate the measure—are well reported in the financial statements of firms. The main drawback of this measure is that it attributes all changes in labour productivity to a single factor of production, namely labour.[8]

For wages, we rely on the average firm wage W, calculated as

$$W_{jcit} = \frac{TLC_{jcit}}{L_{jcit}}, \tag{2}$$

where TLC_{jcit} captures the total labour cost for firm j in country c and industry i at time t. This measure is well reported in firms' financial statements across sectors and countries; however, by construction, it assumes that all employees earn the same wage within the firm.[9] Nonetheless, using average firm wages still captures a sizeable part of the wage dispersion both at the cross-section and over time.[10] As such, results in this paper focus on between-firm wage differentials, which remain meaningful in understanding the evolution of overall wage dispersion (for an in-depth discussion, see Berlingieri *et al.* 2017).

2.2 | The evolution of productivity and wage dispersion

To proxy productivity dispersion for each country–industry–year group of firms (cit), we use the natural logarithm of the ratio of the 90th over the 10th percentile of the firm-level productivity distribution, denoted by $PD_{cit}^{90/10} = \ln(PD_{cit}^{90}/PD_{cit}^{10})$. This ratio tells us how many times more productive the firm at the 90th percentile is relative to the firm at the 10th percentile of the distribution.

To capture the evolution of productivity dispersion, we estimate

$$PD_{cit}^{90/10} = D_t\beta_t + FE_{ci} + \varepsilon_{cit}, \tag{3}$$

where D_t is a vector of year dummies, FE_{ci} is a set of country–industry fixed effects, and ε_{cit} is an independent and identically distributed error term. Country–industry fixed effects eliminate all cross-sectional variation and thus account for any compositional differences in dispersion between countries and industries. As such, β_t captures intertemporal changes within each country–industry pair. Specifically, β_t is the parameter vector of interest measuring the average dispersion in each year t relative to the reference year at the start of the sample. We weigh the regression by the natural logarithm of total value-added at the country–industry–year level.

Analogously, wage dispersion is computed as $WD_{cit}^{90/10} = \ln\left(WD_{cit}^{90}/WD_{cit}^{10}\right)$, and its evolution is estimated as

$$WD_{cit}^{90/10} = D_t\beta_t + FE_{ci} + \varepsilon_{cit}, \tag{4}$$

where now β_t captures the estimated changes of wage dispersion in each year relative to the reference year. All other controls and the regression weighting approach remain the same as in equation (3). To uncover potential underlying heterogeneity, we repeat the analysis by focusing on different subsections of the entire distribution (see the first subsection of Section 4).

2.3 | The link between productivity and wage dispersion

To focus ideas, we start by introducing the theoretical background on how (labour) productivity translates into wages. Specifically, we rely on the model introduced by Wong (2021), which has two key ingredients: labour market frictions and firm heterogeneity.[11] This framework allows us to structurally decompose firm-specific wages into four components:

$$w_{jcit} = P_{jcit} * LEO_{jcit} * \frac{\eta_{jcit}}{\mu_{jcit}}, \tag{5}$$

where P_{jcit} is labour productivity (defined as before), $LEO_{jcit} \equiv \partial \ln VA_{jcit} / \partial \ln L_{jcit}$ is the labour elasticity of output, $\eta_{jcit} \equiv \varepsilon^{L}_{jcit} / \left(1 + \varepsilon^{L}_{jcit}\right)$ is the markdown (with ε^{L}_{jcit} being the labour supply elasticity), and $\mu_{jcit} \equiv \varepsilon^{D}_{jcit} / \left(\varepsilon^{D}_{jcit} - 1\right)$ is the markup (with ε^{D}_{jcit} capturing the price elasticity of demand).

These components can be interpreted as follows. First, *ceteris paribus*, more productive firms pay higher wages, as shown by the productivity term. Second, the labour elasticity of output shows the percentage increase in value-added resulting from a one percentage point increase in employment. Firms with a high labour elasticity of output pay higher wages, all else equal, because they have higher labour demand. Third, firms in a monopsonistic environment have upward-sloping labour supply curves, creating a wedge between the workers' wage and their marginal value of production. The lower the labour supply elasticity, the less competition a firm faces on the labour market. Fourth, firms might have price-setting power in the product market, which disappears as the price elasticity of demand goes to infinity. Such a markup allows us to set prices above marginal costs. Wong (2021) shows that the labour supply elasticity and the price elasticity of demand might depend on the firms' market share, with more dominant firms having more labour and product market power.

This structural framework does not require defining the specific microeconomic foundations for the price elasticity of demand or the labour supply elasticity, and nests various settings of frictions that lead to upward-sloping labour supply curves. For example, labour markets might be characterized by a random search wage-bargaining framework in which search frictions are present and wages are set via bargaining over the surplus.[12] In turn, the labour supply elasticity is a function of relative bargaining power and workers' value of outside options. Other possibilities that could generate an upward-sloping labour supply curve include a random search wage-posting framework, a directed search wage-posting framework or a monopsonistic model with workplace differentiation.[13]

To look into the link between productivity and wage dispersion, we consider a high-productivity firm (H) and a low-productivity firm (L), and express the logarithmic ratios of their firm-specific wages in equation (5) as

$$WD^{H/L}_{cit} = PD^{H/L}_{cit} + \ln\left(\frac{LEO_{Hcit}}{LEO_{Lcit}}\right) + \ln\left(\frac{\eta_{Hcit}/\mu_{Hcit}}{\eta_{Lcit}/\mu_{Lcit}}\right). \tag{6}$$

Under the assumptions of homogeneous markups and markdowns, and the same labour elasticity of output at the country–industry–year cells, we look at the ratio of the 90th over the 10th percentile of the productivity and wage distribution to obtain the following empirical specification (also used in Berlingieri *et al.* 2017):

$$WD^{90/10}_{cit} = \beta PD^{90/10}_{cit} + FE_{ci,ct,it} + \varepsilon_{cit}, \tag{7}$$

where all components are as defined previously, but now with $FE_{ci,ct,it}$ also accounting for a set of country–year (ct) and industry–year (it) fixed effects. These controls capture any unobserved country- and industry-specific growth rates, such as business cycle variation across countries and industrial technological progress. Here, β identifies the conditional correlation between productivity dispersion and wage dispersion. The regression is weighted by the natural logarithm of total value-added at the country–industry–year level.

Moving from equation (6) to equation (7) implies the existence of a monotonic relationship between the productivity and wage ranking. In Online Appendix Figure B.1, we rank the average productivity by percentile and plot it against the corresponding average wage to show that a positive monotonic relationship holds in the data. Specifically, percentiles with higher labour productivity are characterized by higher average wages.[14]

Under the maintained assumptions, we expect a complete pass-through from productivity to wages, that is, $\beta = 1$. However, this setting is rather unrealistic in practice, and based on equation (6), we expect β to be smaller than 1 in the presence of market inefficiencies or frictions (Van Biesebroeck 2015).

In particular, there is a host of potential mechanisms that could drive this incomplete pass-through. To demonstrate, we focus on two of the most important contemporaneous economic aspects. First, De Loecker *et al.* (2020) document an increase in aggregate markups coupled with diverging markups between the top and bottom firms over time. This implies that in equation (6), $\ln(\mu_{Lcit}/\mu_{Hcit})$ is a negative term that drives a wedge between PD and WD. In turn, this is reflected in the estimates of β from equation (7). Second, Berger *et al.* (2022) document considerable labour market power in the USA due to imperfectly competitive labour markets. Similarly, if high-productivity firms have more labour market power compared to low-productivity firms, then $\eta_{Hcit} < \eta_{Lcit}$, thus $\ln(\eta_{Hcit}/\eta_{Lcit}) < 0$. In the simple setting of equation (7), this would appear as an incomplete pass-through of productivity to wages.

While various other frictions and/or inefficiencies might be equally relevant, we do not take a stance on their relative importance since it would require additional assumptions and more granular data. Hence, as a next step, we test whether $\beta = 1$ under the null hypothesis, or $\beta < 1$ under the alternative. In line with the above, we expect a statistically significant value less than 1, which would suggest incomplete pass-through.[15]

2.4 | Superstar firms and their mediating role

Although many factors might be driving this incomplete pass-through, it appears that the emergence of superstar firms is directly or indirectly intertwined with these factors. In particular, superstar firms are known to be more productive, have larger product and labour market power (i.e. set lower markdowns and higher markups), and have lower labour shares (Autor *et al.* 2020; Wong 2021). Therefore the presence of superstar firms in a sector can be seen as a good proxy for the remaining unobserved factors shown in equation (6).

To proxy the evolution of superstar firms, we rely on the evolution of market concentration, in line with Autor *et al.* (2020). The gist of the argument is that superstar firms are becoming increasingly dominant within their industries, thereby controlling a larger share of the product market. Therefore we use an index of market concentration, CNn_{cit}, calculated as the market share of the n largest firms within a country–industry–year combination. For the baseline specifications, we consider $CN4_{cit}$, and for robustness we use $CN10_{cit}$, $CN20_{cit}$ and the Herfindahl–Hirschman Index (HHI_{cit}). Market shares are in terms of value-added in line with productivity dispersion measures.

To examine the overall evolution of superstar firms in the economy, we construct an aggregate measure of market concentration at the yearly level by regressing the country–industry–year market shares on a full set of year dummies, and use total value-added as weights. The estimated coefficients represent the aggregate weighted market concentration at the yearly level.

Finally, we explore whether superstar firms affect wage dispersion by augmenting specification (7):

$$WD^{90/10}_{cit} = \beta PD^{90/10}_{cit} + \gamma\ CN4_{cit} + \delta\left(PD^{90/10}_{cit} * CN4_{cit}\right) + FE_{ci,ct,it} + \varepsilon_{cit}, \tag{8}$$

where γ captures the direct effect that estimates whether superstar firms increase ($\gamma > 0$) or decrease ($\gamma < 0$) wage dispersion. Here, δ captures the indirect effect on wage dispersion, which indicates whether superstar firms strengthen ($\delta > 0$) or weaken ($\delta < 0$) the link between productivity and wage dispersion captured in β. All other components are defined as before, and regressions are weighted by the natural logarithm of total value-added at the country–industry–year level.

3 | DATA

We source data from Orbis Global, a product of Bureau van Dijk Electronic Publishing (2020a). Orbis Global collects firms' financial statements from national sources and standardizes them for cross-country comparability and time consistency related to survivorship bias, that is, firm exit (Bureau van Dijk Electronic Publishing 2020b). We use the balance sheet information of firms that file unconsolidated accounts from 2000 to 2016 in 14 European countries: Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, Sweden and the UK.[16] For each firm identifier, we retain firm–year observations that report strictly positive values of value-added, number of employees, and total cost of employees. For the country–industry-level analysis, we group firms by their NACE Rev.2 2-digit production industries.[17]

Cross-country comparability—a large advantage of this dataset (Kalemli-Ozcan *et al.* 2015; Merlevede *et al.* 2015)—comes at the expense of reduced coverage for smaller-sized firms for which there are simplified reporting obligations (European Commission 2020). Nonetheless, the sample captures on average 67% of total private employment across the 14 EU countries considered.[18] The firm-level dataset includes 20,210,495 observations, which represent an unbalanced panel of 3,601,418 firms used to compute the country–industry–year-level measures of interest. Online Appendix A provides a detailed discussion of the steps followed to construct the firm-level sample, and its representativeness across countries and industries, and over time. Overall, we find that the average firm in our sample produces value-added of approximately €2.2 million, employs 31 workers, and pays average wage €33,359 (see Online Appendix Table A.4).[19]

Importantly, we thoroughly check against the data limitations discussed above through a battery of robustness checks. In short, these include: (1) comparing the trends in productivity and wage dispersion with those reported in Berlingieri *et al.* (2017) under a representative sample; (2) using a balanced sample to ensure that results are not driven by the entry and exit of country–industry combinations; (3) using a sample that excludes country–industry groups with irregular changes in the number of reported firms between years to account for issues related to the time-varying coverage of our sample; and (4) implementing the suggestions in Bajgar *et al.* (2020) to further improve the representativeness of Orbis Global. All of these exercises are detailed in Section 6.

With the sample of selected firm-level variables, we can now compute the country–industry–year-level measures of productivity dispersion, wage dispersion and market concentration. Table 1 provides summary statistics of these variables. In panel A, we see that, on average across all countries, industries and years in the sample, a firm in the 90th percentile of the productivity distribution is approximately exp(1.74) = 5.7 times more productive than the 10th percentile firm. We observe that dispersion is larger for the top part of the productivity

TABLE 1 Summary Statistics

	Mean	S.D.	Min	Percentile 25th	50th	75th	Max
Panel A							
$PD_{cit}^{90/10}$	1.74	0.72	0.37	1.27	1.56	2.01	7.68
$PD_{cit}^{90/50}$	0.96	0.53	0.21	0.65	0.81	1.07	6.95
$PD_{cit}^{50/10}$	0.78	0.30	0.14	0.56	0.73	0.94	3.10
Panel B							
$WD_{cit}^{90/10}$	1.20	0.52	0.13	0.85	1.10	1.44	7.24
$WD_{cit}^{90/50}$	0.54	0.25	0.05	0.39	0.50	0.64	3.55
$WD_{cit}^{50/10}$	0.66	0.36	0.03	0.43	0.59	0.81	5.14
Panel C							
$CN4_{cit}$	0.38	0.23	0.02	0.19	0.34	0.51	1.00
$CN10_{cit}$	0.51	0.25	0.03	0.31	0.50	0.71	1.00
$CN20_{cit}$	0.62	0.25	0.05	0.41	0.62	0.84	1.00

Notes: Productivity dispersion (PD), wage dispersion (WD) and market concentration (CN) measures are computed across 10,280 country–industry–year (*cit*) combinations. For PD and WD, measures capturing the entire (90/10), upper (90/50) and bottom (50/10) parts of the distribution are presented. For CN, measures capturing the market concentration of the largest 4, 10 or 20 firms in each *cit* are presented.

distribution $\left(PD_{cit}^{90/50}\right)$ than the bottom $\left(PD_{cit}^{50/10}\right)$. In particular, the top firm is on average 2.6 times more productive than the median firm, while the median firm is 2.2 times more productive than the bottom firm.

Next, in panel B of Table 1, we observe that the wage dispersion is smaller compared to the productivity dispersion, on average. The average wage in the top firm is 3.3 times larger than the average wage in the bottom firm ($WD_{cit}^{90/10}$). Interestingly, in contrast to productivity dispersion, wage dispersion is more pronounced at the bottom part of the distribution. The wage in a top firm is 1.7 times larger than the wage of the median firm $\left(WD_{cit}^{90/50}\right)$, while the wage of the median firm is almost twice as large than the wage of the bottom firm $\left(WD_{cit}^{50/10}\right)$.

Finally, in panel C of Table 1, we show that $CN4$ market concentration in the 'average industry' is 0.38. This implies that, on average, the four largest firms in a country–industry–year group capture 38% of the total value-added in the sample. Some industries are less concentrated, while others are dominated by a few firms. For example, at the 25th percentile, market concentration is 0.19; at the 75th percentile, it is 0.51. This suggests that the degree of competition varies across industries that appear to be monopolies/oligopolies versus those that exhibit more competitive behaviour. Finally, market concentration becomes larger by construction when we consider more firms in the concentration index. In particular, it is on average 0.51 for $CN10$ and 0.62 for $CN20$.

4 | RESULTS

This section describes the main findings of our analysis. First, we present results on the evolution of aggregate productivity and wage dispersion. We then split these evolutions for the top and bottom parts of the distribution. Next, we examine the extent to which the pass-through of productivity dispersion into wage dispersion is incomplete. Finally, we document the evolution of market concentration as a proxy for superstar firms and how they impact the link between productivity and wage dispersion.

4.1 | The rise and fall of productivity and wage dispersion

4.1.1 | Productivity dispersion

To examine the evolution of productivity dispersion, we estimate equation (3). Figure 1 plots the estimated parameters for each year (β_t) for the period 2000–2016. The top left panel shows that the average country–industry productivity dispersion $\left(PD_{cit}^{90/10}\right)$ has increased statistically significantly between 2004 and 2012. Specifically, frontier firms at the top of the productivity distribution are, on average, increasing the productivity gap with laggard firms at the bottom.[20] These results complement existing findings in the literature of increasing productivity dispersion by providing additional external validity for a broader set of countries. For the most recent years, 2013–16, we observe a reversal of this pattern. The increase in productivity dispersion weakens, yet remains significantly larger relative to 2000. Notwithstanding the short period that this decline is observed, results remain intriguing given their coincidence with the European debt crisis recovery period. However, additional information on later years is needed to examine further whether this is a temporary trough or a more persistent downward trend.

To guard against concerns about the representativeness of our sample, which is skewed towards larger-sized firms, we compare our findings with those from Berlingieri *et al.* (2017)

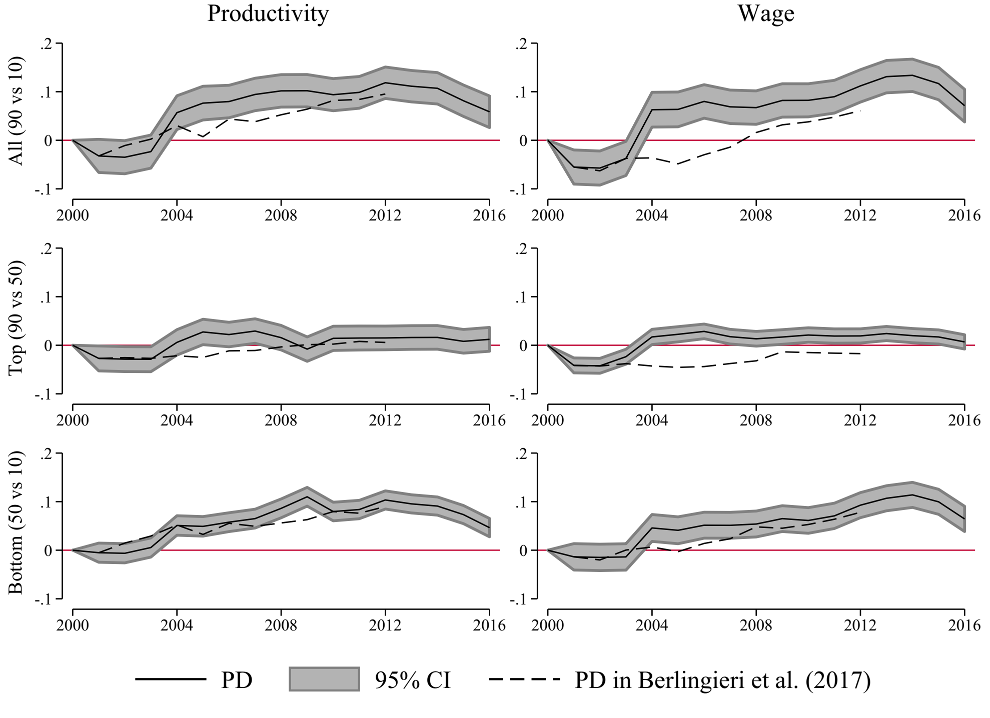

FIGURE 1 Evolution of productivity dispersion (PD) and wage dispersion (WD). *Notes*: The solid line connects the estimated coefficients from regressing productivity dispersion (PD_{cit}) in the first column and wage dispersion (WD_{cit}) in the second column on a set of year dummies, respectively, i.e. parameter set β_t in equation (3). The chosen base year is 2000. All regressions include country–industry (*ci*) fixed effects and are weighted by the logarithm of total value-added at the country–industry–year (*cit*) level. The dispersion measures considered in the top, middle and bottom row panels capture the entire 'All (90 vs 10)', upper 'Top (90 vs 50)' and bottom 'Bottom (50 vs 10)' parts of the distributions, respectively. The shaded area represents the clustered at the country–industry (*ci*) level 95% confidence interval. The dashed line in each panel corresponds to the respective dispersion measure found in Berlingieri *et al.* (2017). Source: Authors' estimations using Orbis Global database.

(dashed line in Figure 1). Their dataset is representative of the population of firms in 14 OECD countries[21]—some of which are included in our sample—and available for the period 2001–12.[22] For the overlapping years, the evolution of productivity dispersion moves roughly in parallel in all panels. This provides further assurance that our selected sample generates aggregate trends similar to those presented in the literature to date.

Next, we explore whether this increase happens at the top or bottom of the productivity distribution. In line with the analysis above, we thus estimate the yearly coefficients β_t for the upper $\left(PD_{cit}^{90/50}\right)$ and lower $\left(PD_{cit}^{50/10}\right)$ parts of the productivity distribution. Results are plotted in the second and third rows of the first column in Figure 1, respectively. We find that the widening of productivity dispersion occurs at the bottom of the distribution rather than the top. Specifically, the evolution of productivity dispersion at the top hovers around zero, but remains statistically insignificant in nearly all years (middle left panel). In contrast, large and statistically significant increases in productivity dispersion at the bottom take place between 2004 and 2012 (bottom left panel). Despite a moderating effect in more recent years, we still find a significant and positive increase for the period 2013–16. Overall, the evolution of productivity dispersion for the entire distribution is driven by changes at the bottom, where firms appear to diverge over time from the median firm.

These findings are consistent with a host of mechanisms proposed in the literature that support mounting evidence of increased misallocation of resources towards the least productive firms. Such mechanisms include: a decline in business dynamism that results in a limited degree of churning in the economy (Decker *et al.* 2016); falling real interest rates that cause misallocation of capital inflows towards relatively unproductive firms (Gopinath *et al.* 2017); zombie firms that hoard productive inputs and prevent their optimal allocation (Andrews and Petroulakis 2019); and stalling technological diffusion/adoption that prevents laggard firms from catching up (Andrews *et al.* 2016).

4.1.2 | Wage dispersion

To document the evolution of wage dispersion $\left(WD_{cit}^{90/10}\right)$, we follow the same road map. Specifically, we estimate the set of parameters β_t from equation (4) that capture the average wage dispersion in each year t relative to 2000. Results are plotted in the right column of Figure 1. The top right panel shows that the initial fall of wage dispersion between 2000 and 2002 is dominated by a subsequent rise until 2014. Similar to the productivity dispersion, this pattern weakens towards the end of our sample, but remains significantly higher compared to its 2000 level.[23] Reassuringly, the upward evolution in wage dispersion is similar to that in Berlingieri *et al.* (2017) under the same representative sample considered in their productivity dispersion measures discussed above (dashed line). Results are also in line with Cortes and Tschopp (2020), who document a rise in wage inequality in a broad set of countries over recent decades.[24]

We now examine how the evolution of wage dispersion emerges in different segments of the distribution. In Figure 1, the middle right and bottom right panels repeat the analysis for the top $\left(WD_{cit}^{90/50}\right)$ and bottom $\left(WD_{cit}^{50/10}\right)$ parts of the wage distribution, respectively. On the one hand, wage dispersion at the top hovers above zero and remains weakly statistically significant (at the 95% level) from 2004 onwards. On the other hand, wage dispersion at the bottom increases significantly between 2004 and 2014, after which it diminishes slightly (but remains higher compared to 2000). These findings suggest that while the gap between high- and median-wage firms has increased only modestly since 2000, low-wage firms were unable to offer more competitive salaries that would mitigate increases in wage inequality.

These findings might be explained by changes in firms' operating environment that place downward pressure on labour and wages. This is especially true for low-wage firms, which are typically more labour-intensive (Abowd *et al.* 1999), likely to exit the market (Bossavie *et al.* 2019), financially constrained (Babina *et al.* 2018), vulnerable to increased competition (Autor *et al.* 2014), and less productive (Bernard *et al.* 2012) overall. Changes in firms' operating environment could include increased import competition from low-wage countries (Autor *et al.* 2013; Dauth *et al.* 2014), top firms exploiting their monopsony power (Burdett and Mortensen 1998), increasing openness in capital markets (Huber *et al.* 2020), and increasing automation in production (Acemoglu and Restrepo 2019), among others.

4.2 | The link between productivity and wage dispersion

To examine the link between productivity and wage dispersion, we estimate equation (7) and present results in Table 2. The parameter of interest, β, captures the correlation between productivity and wage dispersion after controlling for unobserved heterogeneity at the country–industry, country–time and industry–time dimensions. Column (1) shows this estimate, while columns (2) and (3) repeat the analysis for the top and bottom parts of the productivity and wage dispersion, respectively. Additionally, we test whether each estimated coefficient is significantly smaller than 1, and present the corresponding test p-values at the bottom of the table.[25]

In column (1) of Table 2, we find that industries with higher productivity dispersion are associated with higher wage dispersion. However, the pass-through is incomplete as it is significantly smaller than 1. Wage dispersion is thus linked positively to productivity dispersion, but not perfectly. These findings complement other existing empirical evidence (Berlingieri *et al.* 2017) and point to the presence of imperfect labour markets (Pissarides 2011; Van Biesebroeck 2015).[26]

Columns (2) and (3) of Table 2 suggest that the link between productivity and wage dispersion is considerably stronger at the bottom of the distribution than at the top. Intuitively, firms at the bottom transfer a relatively larger share of their productivity gains to wages, compared to firms

TABLE 2 The Link Between Wage and Productivity Dispersion

	$WD^{90/10}_{cit}$ (1)	$WD^{90/50}_{cit}$ (2)	$WD^{50/10}_{cit}$ (3)
$PD^{90/10}_{cit}$	0.399***		
	(0.030)		
$PD^{90/50}_{cit}$		0.262***	
		(0.028)	
$PD^{50/10}_{cit}$			0.574***
			(0.045)
$H_0 : \beta = 1$	0.000	0.000	0.000
R^2	0.892	0.881	0.851
Observations	10,268	10,268	10,268

Notes: This table presents point estimates from regressing wage dispersion (WD_{cit}) on productivity dispersion (PD_{cit}), i.e. the β parameter in equation (7). The dispersion measures considered capture the entire (90/10), upper (90/50) and bottom (50/10) parts of the respective distributions. All regressions include country–industry (ci), country–year (ct) and industry–year (it) fixed effects, and are weighted by the logarithm of total value-added at the country–industry–year (cit) level. Standard errors are clustered at the country–industry (ci) level and reported in parentheses below point estimates. $H_0 : \beta = 1$ presents the p-value from testing whether the estimated coefficient is significantly smaller than 1.

*, **, *** indicate $p < 0.05$, $p < 0.01$, $p < 0.001$, respectively.

at the top. This finding can be reconciled with the labour market power of firms. Specifically, firms at the top of the productivity distribution have larger markdowns compared to firms at the bottom and thus gradually pay wages that are relatively lower than the marginal revenue product of labour (Berger *et al.* 2022).

4.3 | The rise of superstar firms

We proceed by documenting the evolution of superstar firms, proxied by the three concentration measures described in Section 2. Figure 2 shows their evolution for the total economy. We find that market concentration is rising in Europe, irrespective of the number of firms considered. For example, $CN4$ increased from 28% in 2000 to 35.5% in 2016; the four largest firms' market share grew by 7.5 percentage points (pp) on average. The evolution of $CN10$ and $CN20$ exhibits the same pattern, indicating that the four largest firms are driving the overall evolution of the measures. In particular, $CN10$ increased from 38.7% in 2000 to 47.3% in 2016. Since the four largest firms increased their market share by 7.5 pp, the remaining 'top six' increased their market share by 1.1 pp only. Similarly, $CN20$ rose from 47.1% in 2000 to 56.2% in 2016. Thus the additional 'top 10' capture only 0.5 pp.

Overall, we find that a handful of firms dominate the economy, which is in line with the recent literature on superstar firms and increasing market concentration in the product market (Autor *et al.* 2020).[27] Although increases in EU market concentration might be less pronounced compared to those in the USA, the rise of superstar firms remains a relevant and significant trend to consider for the EU economy (Gutiérrez and Philippon 2018; Bajgar *et al.* 2019; Bighelli *et al.* 2023). In the same spirit, Gutiérrez and Philippon (2019a) show that while superstar firms in the USA did not necessarily become larger or more productive over time, they have become more profitable. This latter finding relates closely to our focus of interest on market competition and superstar firms in the EU, and thus the extent to which firms pass on their productivity advantages to wages as shown in equation (6).

It is noteworthy that these results are accompanied by a lively discussion in the literature on the causes/correct interpretation of superstar firms—for example, whether this is about the rise of technologically superior firms (Autor *et al.* 2020), or about monopolies under loose antitrust enforcement (Gutiérrez and Philippon 2018, 2019b). To that end, since EU institutions are known to enforce pro-competition policies more strongly than any other economy (Gutiérrez and Philippon 2018), we conjecture that findings for the EU would be seen as a lower bound compared to what one would observe in countries with looser antitrust policies, such as the USA

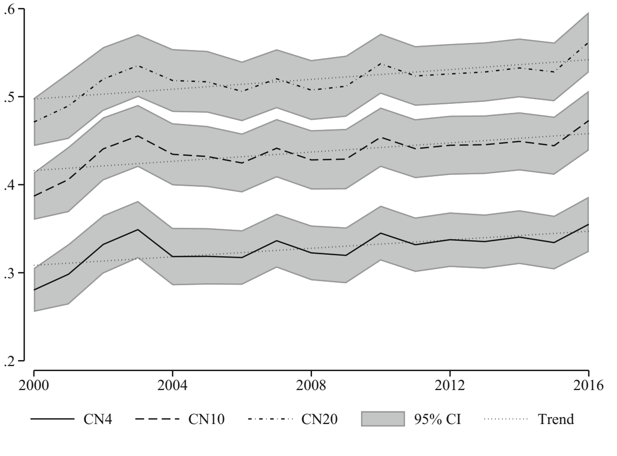

FIGURE 2 Evolution of market concentration (CN). *Notes*: The lines connect the estimated coefficients from regressing the market concentration measures ($CN4$, $CN10$, $CN20$) on a set of year dummies. All regressions are weighted by the logarithm of total value-added at the country–industry–year (*cit*) level. Source: Authors' estimations using Orbis Global database.

(Gutiérrez and Philippon 2019b). However, given the design of our empirical strategy and the focus of interest, we cannot take a stance to identify the exact drivers of the emergence of superstar firms.

4.4 | The mediating role of superstar firms

We estimate equation (8) to unpack how the rise of superstar firms impacts the link between productivity and wage dispersion. Table 3 presents the results, where our main variables of interest are the direct effect of superstar firms—proxied by market concentration—on wage dispersion, and the mediating effect of superstar firms on the link between productivity and wage dispersion. The latter is captured by the interaction between productivity dispersion and market concentration. Column (1) shows the estimates for the entire distribution, while columns (2) and (3) repeat the analysis for the top and bottom parts, respectively.[28]

Two key findings emerge from column (1) of Table 3. First, the positive and significant point estimate on our market concentration proxy ($CN4$) suggests that industries with a larger dominance of superstar firms exhibit higher wage dispersion, on average. This is consistent with various models, such as fair-wage models (Egger and Kreickemeier 2012). As superstar firms become more dominant in terms of market share and profitability, workers demand fair wages that are proportional to profits. Similarly, results are also in line with the literature on rent sharing (Card *et al.* 2013, 2014). As top firms accumulate rents because of increasing market shares, they

TABLE 3 Superstar Firms and the Link Between Productivity and Wage Dispersion

	$WD_{cit}^{90/10}$ (1)	$WD_{cit}^{90/50}$ (2)	$WD_{cit}^{50/10}$ (3)
$PD_{cit}^{90/10}$	0.518***		
	(0.042)		
$PD_{cit}^{90/50}$		0.312***	
		(0.042)	
$PD_{cit}^{50/10}$			0.792***
			(0.079)
$CN4_{cit}$	0.357***	0.061	0.328***
	(0.090)	(0.041)	(0.093)
$PD_{cit}^{90/10} * CN4_{cit}$	−0.196***		
	(0.050)		
$PD_{cit}^{90/50} * CN4_{cit}$		−0.079**	
		(0.038)	
$PD_{cit}^{50/10} * CN4_{cit}$			−0.388***
			(0.120)
R^2	0.893	0.882	0.853
Observations	10,268	10,268	10,268

Notes: This table presents point estimates from regressing wage dispersion (WD_{cit}) on productivity dispersion (PD_{cit}), market concentration ($CN4_{cit}$) and their interaction ($PD_{cit} * CN4_{cit}$), i.e. β, γ and δ parameters in equation (8), respectively. The dispersion measures considered capture the entire (90/10), upper (90/50) and bottom (50/10) parts of the respective distributions. $CN4_{cit}$ captures the market shares of the 4 largest firms in each country–industry–year (cit) group. All regressions include country–industry (ci), country–year (ct) and industry–year (it) fixed effects, and are weighted by the logarithm of total value-added at the country–industry–year (cit) level. Standard errors are clustered at the country–industry (ci) level and reported in parentheses below point estimates.
*, **, *** indicate $p < 0.05$, $p < 0.01$, $p < 0.001$, respectively.

are also able to partially transfer those gains to their employees in the form of increased wages. Both explanations support a positive link between market concentration and wage dispersion. An alternative explanation could be that top firms screen and search for additional and better workers more intensively to meet increased production needs. This, in turn, could lead to an increase in employment and wages relative to firms at the bottom of the distribution that have limited production and profits (Cortes and Tschopp 2020). Therefore we conclude that between-firm wage inequality increases with concentration of production within industries.

Next, we find a statistically significant negative effect from the interaction between market concentration and productivity dispersion. This result suggests a mediating effect of superstar firms on the link between productivity and wage dispersion. Specifically, industries with high market concentration—that is, industries that are likely dominated by superstar firms—are associated with a weaker link between productivity and wage dispersion. Overall, superstar firms appear to induce a larger disconnect between productivity and wages, hence a more incomplete pass-through, on average. This finding is in line with firms in more concentrated industries having larger markdowns due to higher labour market power and thus charging relatively lower wages,[29] while the opposite happens to firms in less concentrated industries (Berger *et al.* 2022).[30]

When considering different parts of the firm-level wage distribution in columns (2) and (3) of Table 3, results suggest that the rise of market concentration is associated with a statistically significant increase of wage dispersion at the bottom of the distribution only. A possible explanation could be an increased threat of offshoring and relocation, which becomes credible as firms grow and become more international, thus putting downward pressure on wages at the lower part of the distribution (Autor *et al.* 2013).

In addition, results suggest that superstar firms weaken the link between productivity and wages at both the top and bottom parts of the distribution. However, various different mechanisms might be at play in different parts of the distribution. For example, firms at the top part of the productivity distribution compete at a global level but might be shielded from wage competition that occurs primarily at the local level. Thus there is no motive to pass through a larger part of their productivity advantage to wages, since these firms already pay the highest wages in the domestic labour market (Gouin-Bonenfant 2022). At the bottom part of the distribution, the emergence of superstar firms reduces the overall competitive pressure in the labour market which allows even the least productive firms to have some monopsony power, i.e. large markdowns, and thus keep wages low (Azkarate-Askasua and Zerecero 2022; Berger *et al.* 2022).

4.5 | Case study

We next provide a mini case study to help contextualize the above results. We focus on the manufacturing industry of leather and related products (NACE Rev.2 code 15) in Spain. This is an interesting case for multiple reasons. First, Spain experienced continuous and sizeable reforms in employment protection, trade union density and collective bargaining coverage over the period of study (OECD 2021a,b,c). This has been coupled with extended periods of soaring youth and total unemployment that constrained the bargaining position of employees.[31] Second, this industry is highly tradable (Piton 2021) with increased access to foreign markets and intensified import competition. At the same time, as shown in Figure 3(a), market concentration increased by 26 pp between 2000 and 2016, which is in the top 5th percentile of $CN4$ increases in our sample. In sum, in this environment, firms could reap the benefits of access to globalized markets while competing only locally for workers. This has fostered the right conditions for superstar firms to arise and dominate in both the product and labour market.

Next, we assess qualitatively how this handful of firms relates to the extent to which they pass on their productivity advantages to wages. Therefore, in Figures 3(b)–3(d), we plot the evolution

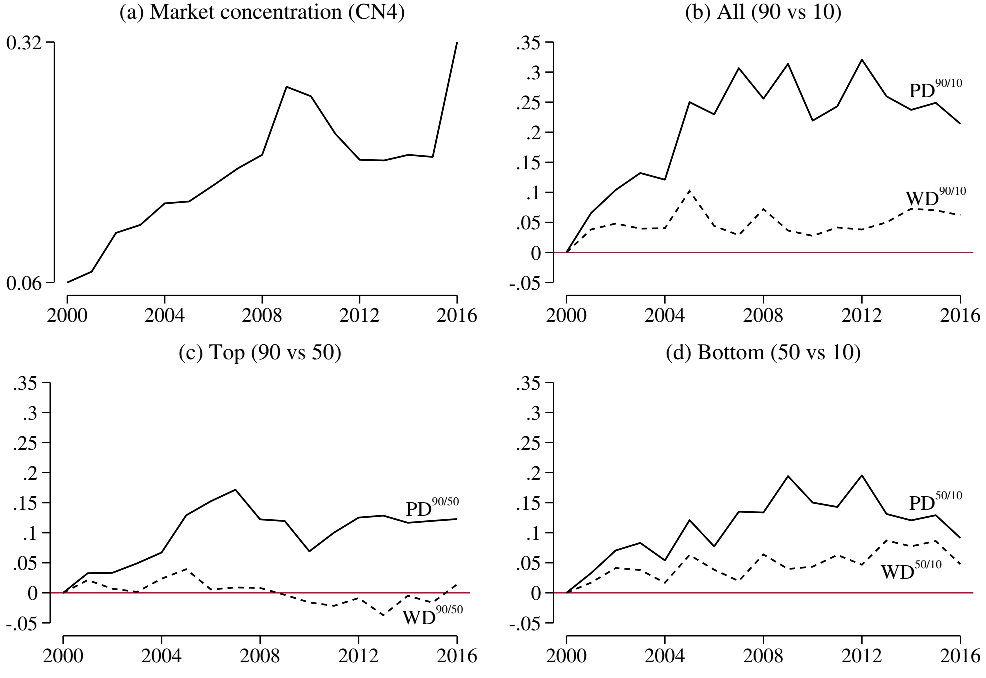

FIGURE 3 Evolution of market concentration, productivity dispersion (*PD*) and wage dispersion (*WD*) in the Spanish manufacture of leather and related products (NACE Rev.2 code 15). *Notes*: Panel (a) shows the evolution of market concentration *CN*4. Panels (b)–(d) show the evolution of productivity dispersion (*PD*) and wage dispersion (*WD*) relative to the base year 2000 across different parts of the distribution. The dispersion measures considered in panels (b), (c) and (d) capture the entire (90/10), upper (90/50) and bottom (50/10) parts of the distributions, respectively. The *y*-axis in panel (a) reflects market concentration between 0 and 1, while panels (b)–(d) reflect dispersion measures in logarithms. Source: Authors' estimations using Orbis Global database.

of *PD* and *WD* across different parts of the distribution. First, Figure 3(b) focuses on the entire distribution, that is, firms at the 90th versus the 10th percentile. We observe that both *PD* and *WD* increase across all years relative to 2000. However, the gap between the two widens steadily, and by 2016, the rise in *PD* is roughly three times that of *WD*. In other words, as superstar firms gradually dominate the market, the rate at which they pass on their productivity advantages to wages becomes smaller.

The same pattern holds when we zoom in on the top parts of the distribution. Specifically, in Figure 3(c), *PD* widens faster than *WD*, which hovers around zero. In words, over time, top firms become more productive (with respect to the median firm), but do not roll over this advantage to higher wages. Thus superstar firms appear to have managed to increase their product and labour market power over time, and thus effectively reduce the share of any productivity gains that they transfer to wages.

In the same spirit, in Figure 3(d), we find that the firms at the median and bottom parts of the distribution become more dispersed in terms of productivity and wages. However, the gap between the two widens over time, albeit with a moderating effect post-2012. This moderating effect coincides with the significant wage moderation after Spain's 2012 labour market reform, which promoted the internal flexibility of Spanish firms (OECD 2014). Thus even firms in the lower parts of the distribution succeed in driving a wedge between productivity and wage dispersion as the market became increasingly concentrated. Overall, we conjecture that superstar firms put downward pressure on wages that then impacted the rest of the industry, at both the upper and lower parts of the distribution.

5 EXPLORING POTENTIAL MECHANISMS

To understand the significance of the potential mechanisms discussed above, we explore underlying heterogeneity in output and labour market characteristics across sectors and countries. More specifically, we examine two different dimensions, one related to the structure of the output market—that is, tradability of sectors—and the other to the regulatory environment in the labour market—that is, the number of workers covered by collective agreements across countries.

The idea behind these subsamples is twofold. First, firms in tradable sectors are expected to enjoy higher profit margins due to globalization, relative to firms in non-tradable sectors, while competing only locally for workers. Second, firms in markets with low bargaining coverage are expected to have more labour market power relative to firms in markets with high bargaining coverage. Hence we expect to find a relatively more negative mediating effect in tradable (versus non-tradable) sectors and in markets with low (versus high) bargaining coverage.

In Table 4, we repeat the baseline analysis (columns (1)–(3)) by splitting the samples to tradable sectors (columns (4)–(6)) and non-tradable sectors (columns (7) and (8)).[32] When comparing results between columns (4) and (7), we find that both the direct and mediating effects of superstar firms remain strong and significant in tradable sectors (column (4)), while they become smaller in magnitude and insignificant in non-tradable sectors (column (7)). This finding holds for both the upper (columns (5) and (8)) and bottom (columns (6) and (9)) parts of the distributions. Intuitively, firms in tradable sectors reap the benefits of internationalization more intensively, allowing them to occupy a dominant position in both the domestic output and labour market. This is related conceptually to the empirical finding of unconditional convergence in labour productivity in manufacturing industries that are predominantly tradable and more integrated into global production (Rodrik 2012). Thus these industries are forced to converge to the productivity frontier due to heightened competitive pressure from abroad, but dot not necessarily need to compete globally for labour that is primarily local.

Further, in Table 5, we repeat the same analysis from above, but now split the sample into countries with high (columns (4)–(6)) versus low (columns (7)–(9)) collective bargaining power in the labour market.[33] When comparing results between columns (4) and (7), we find that both the direct and mediating effects of superstar firms remain larger in magnitude and strongly statistically significant in countries with low collective bargaining power (column (7)), while they become smaller in magnitude and weakly statistically significant in countries with high collective bargaining power (column (4)). This finding suggests the presence of higher labour market power in countries with lower employment protection. Results also hold when looking at the upper parts of the distributions (columns (5) and (8)), but differ when looking at the lower parts (columns (6) and (9)). In this case, we also find a strongly statistically significant effect that is larger in magnitude for countries with lower collective bargaining power (column (6)). However, the latter result is not surprising since it is plausible that median firms apply larger markdowns compared to the bottom firms, especially if one thinks that firms at the bottom might be constrained by other labour market regulations (e.g. minimum wage).

Overall, the mediating effect of superstar firms on the pass-through from productivity to wages is stronger in tradable sectors and countries with low collective bargaining power. This finding provides further support to the mechanisms that we have in mind, whereby highly productive firms enjoy increased profit margins from access to globalization while being shielded from local wage competition through increased domestic labour market power. However, further research is needed to fully understand these differential impacts in a causal way across various market policies and endogenous structural changes in the economy.

TABLE 4 Superstar Firms and the Link Between Productivity and Wage Dispersion in Tradable and Non-tradable Sectors

	All sectors			Tradable			Non-tradable		
	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$PD_{cit}^{90/10}$	0.518***			0.546***			0.442***		
	(0.042)			(0.041)			(0.119)		
$PD_{cit}^{90/50}$		0.312***			0.365***			0.147***	
		(0.042)			(0.052)			(0.029)	
$PD_{cit}^{50/10}$			0.792***			0.779***			0.933***
			(0.079)			(0.055)			(0.313)
$CN4_{cit}$	0.357***	0.061	0.328***	0.424***	0.108**	0.317***	0.183	−0.040	0.457
	(0.090)	(0.041)	(0.093)	(0.083)	(0.048)	(0.080)	(0.343)	(0.070)	(0.344)
$PD_{cit}^{90/10} * CN4_{cit}$	−0.196***			−0.227***			−0.143		
	(0.050)			(0.046)			(0.184)		
$PD_{cit}^{90/50} * CN4_{cit}$		−0.079**			−0.126***			0.025	
		(0.038)			(0.047)			(0.048)	
$PD_{cit}^{50/10} * CN4_{cit}$			−0.388***			−0.359***			−0.650
			(0.120)			(0.098)			(0.475)
R^2	0.893	0.882	0.853	0.908	0.886	0.872	0.848	0.887	0.816
Observations	10,268	10,268	10,268	8304	8304	8304	1950	1950	1950

Notes: This table presents point estimates from regressing wage dispersion (WD_{cit}) on productivity dispersion (PD_{cit}), market concentration ($CN4_{cit}$) and their interaction ($PD_{cit} * CN4_{cit}$), i.e. β, γ and δ parameters in equation (8), respectively. The dispersion measures considered capture the entire (90/10), upper (90/50) and bottom (50/10) parts of the respective distributions. $CN4_{cit}$ captures the market shares of the 4 largest firms in each country–industry–year (*cit*) group. All regressions include country–industry (*ci*), country–year (*ct*) and industry–year (*it*) fixed effects, and are weighted by the logarithm of total value-added at the country–industry–year (*cit*) level. Standard errors are clustered at the country–industry (*ci*) level and reported in parentheses below point estimates. Columns (1)–(3), (4)–(6) and (7)–(9) use data for all sectors (NACE 10–82), tradable sectors (NACE 10–33, 49-66, 69–82) and non-tradable sectors (NACE 35–47, 68), respectively.
*, **, *** indicate $p < 0.05$, $p < 0.01$, $p < 0.001$, respectively.

TABLE 5 Superstar Firms and the Link Between Productivity and Wage Dispersion in Countries with High Versus Low Collective Bargaining Power

	All sectors			High bargaining			Low bargaining		
	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$PD_{cit}^{90/10}$	0.518***			0.606***			0.439***		
	(0.042)			(0.066)			(0.036)		
$PD_{cit}^{90/50}$		0.312***			0.368***			0.251***	
		(0.042)			(0.067)			(0.037)	
$PD_{cit}^{50/10}$			0.792***			0.996***			0.593***
			(0.079)			(0.121)			(0.065)
$CN4_{cit}$	0.357***	0.061	0.328***	0.199	0.029	0.330**	0.574***	0.138***	0.320**
	(0.090)	(0.041)	(0.093)	(0.147)	(0.059)	(0.130)	(0.113)	(0.053)	(0.126)
$PD_{cit}^{90/10} * CN4_{cit}$	−0.196***			−0.151*			−0.262***		
	(0.050)			(0.089)			(0.053)		
$PD_{cit}^{90/50} * CN4_{cit}$		−0.079**			−0.056			−0.127***	
		(0.038)			(0.062)			(0.043)	
$PD_{cit}^{50/10} * CN4_{cit}$			−0.388***			−0.486***			−0.305**
			(0.120)			(0.184)			(0.138)
R^2	0.893	0.882	0.853	0.904	0.889	0.884	0.913	0.910	0.843
Observations	10,268	10,268	10,268	5452	5452	5452	4789	4789	4789

Notes: This table presents point estimates from regressing wage dispersion (WD_{cit}) on productivity dispersion (PD_{cit}), market concentration ($CN4_{cit}$) and their interaction ($PD_{cit} * CN4_{cit}$), i.e. β, γ and δ parameters in equation (8), respectively. The dispersion measures considered capture the entire (90/10), upper (90/50) and bottom (50/10) parts of the respective distributions. $CN4_{cit}$ captures the market shares of the 4 largest firms in each country–industry–year (*cit*) group. All regressions include country–industry (*ci*), country–year (*ct*) and industry–year (*it*) fixed effects, and are weighted by the logarithm of total value-added at the country–industry–year (*cit*) level. Standard errors are clustered at the country–industry (*ci*) level and reported in parentheses below point estimates. Columns (1)–(3), (4)–(6) and (7)–(9) use data for all sectors (NACE 10–82) and countries, all sectors in countries with high collective bargaining power (AT, BE, FI, FR, IT, SE), and all sectors in countries with low collective bargaining power (DE, DK, ES, IE, LU, NL, PT, UK), respectively, based on the number of workers covered by a collective agreement from OECD (2021a).

*, **, *** indicate $p < 0.05$, $p < 0.01$, $p < 0.001$, respectively.

6 | ROBUSTNESS

We conduct seven exercises to test the robustness of our findings. The first robustness test considers measures of superstar firms. Second, we construct measures of wage and productivity dispersion by looking more closely at the tails of the distributions. Third, we compute a measure of total factor productivity instead of labour productivity. Fourth, we focus on a balanced sample of country–industry combinations present in all years to account for the effect of entry and exit of country–industry combinations. Fifth, we use a sample excluding country–industry groups with irregular changes in the number of firms reported between years to account for issues related to the time-varying coverage of our sample. Sixth, we implement the suggestions in Bajgar *et al.* (2020) to further improve the representativeness of Orbis Global. Finally, we control for additional unobserved heterogeneity by including a richer set of fixed effects. Main results hold under all robustness checks. For conciseness, we relegate a presentation of all tables and figures to Online Appendices B and C.

6.1 | Alternative measures of superstar firms

We start with two sets of alternative market concentration measures to test the robustness of our main results. First, we repeat the analysis in Table 3, but now consider a more broadly defined concentration index by using $CN10$ and $CN20$ as proxies for superstar firms. On the other hand, in order to examine top firms more closely, we restrict the concentration index to the top two firms, $CN2$. Results from this exercise, presented in Online Appendix Tables C.2, C.3 and C.4, support our main findings. We thus conclude that irrespective of the measure used, market concentration appears to have a mediating role on the link between productivity and wage dispersion.

Continuing, we employ an alternative measure of market concentration, the Herfindahl–Hirschman Index (HHI). This index sums the squared market share of all firms within a country–industry–year combination. High values indicate a high degree of market concentration—that is, there might be an oligopoly or monopoly position—whereas low values indicate less market concentration—that is, closer to perfect competition.[34] As above, we repeat the analysis from Table 3 now using HHI, and present results in Online Appendix Table C.5. This exercise supports the main conclusions found when using the CN measures to proxy market concentration.[35]

Finally, although market concentration and markups are often closely related empirically, they do not necessarily represent the same concepts (Berry *et al.* 2019; Syverson 2019). Thus, we repeat our baseline analysis, but now replace market concentration ($CN4_{cit}$) with a measure of aggregate markups (M_{cit}). Following De Loecker and Warzynski (2012) and De Loecker *et al.* (2018, 2020), M_{cit} is the weighted average of firm-level markups (M_{jcit}) in each country–industry–year combination, where M_{jcit} is computed based on the inverse of the firm's variable input (material) revenue share—that is, assuming a Cobb–Douglas production function—and aggregated using input weights.[36] Results, presented in Online Appendix Table C.6, suggest that our baseline findings for 'highly concentrated sectors' hold for 'high markup sectors'.

6.2 | Wider dispersion measures and outliers

We construct alternative measures of productivity and wage dispersion by looking more closely at the tails of the distribution. Specifically, for each country–industry–year group of firms (cit), we use the ratio of the 95th and 5th percentiles of the firm-level distribution, which tells us how many times more productive the firm at the 95th percentile is relative to that at the 5th percentile of the distribution. With these dispersion measures, we repeat the analysis in Table 3. Results presented in Online Appendix Table C.7 confirm the robustness of our baseline findings.

To ensure that we approximate closely the top and bottom parts of the distributions, we use even wider measures of dispersion based on the ratio of the 97.5th and 2.5th percentiles of the firm-level distribution. Results in Online Appendix Table C.8 confirm the baseline findings, albeit with smaller point estimates and larger standard errors for the top part of the distribution (column (2)). However, as discussed in the third subsection of Section 2, the positive monotonic relationship between the productivity and wage ranking appears to break closer to the tails of the distribution, where we observe larger variation due to outliers, that is, approximately below the 5th and above the 95th percentile of the distribution (see Online Appendix Figure B.1).

For example, in 2016, the top 100 firms in terms of productivity represented a total of 530 employees, or an average of 5.3 employees per firm. This indicates that the outliers at the tail of the distribution represent mainly firms with a huge productivity ratio (driven by a small denominator), rather than superstar firms. Moreover, the average wage in these top 100 firms is €15.5 million per employee compared to €43,188 per employee for the non-top 100 firms.

Furthermore, even if the monotonic relationship between productivity and wages holds for firms at the tails of the distribution, this does not guarantee that those firms are necessarily superstars. For example, in a certain year, one Austrian firm in the 'Manufacture of food products' industry (NACE Rev.2 code 10) is number one in terms of average wage/productivity per employee, but ranks only 245th in terms of market share. This is likely due to the fact that it has only three employees and a relatively high reported wage costs/value-added ratio.

In the same spirit, we investigate more closely the link between the firm size and productivity distribution. Specifically, we look at the relationship between firm size, proxied by the log of the average number of employees in each percentile, and firm productivity, proxied by the log of the average labour productivity in each percentile (see Online Appendix Figure B.2). We observe that between the 5th and 95th percentiles, there is a positive monotonic relationship between firm size and productivity. However, outside these bounds—that is, towards the bottom 5 and top 5 percentiles of the distributions—this monotonic relationship breaks down due to non-linearities. In particular, the largest firms in terms of employees display the highest productivities around the 95th and, for example, not the 99th productivity percentile. Likewise, less productive firms tend to be smaller. This result does not hold for the least productive firms at the bottom of the productivity distribution that can end up with sizes comparable to firms in the middle of the productivity distribution.

Such data irregularities underscore why, both in the literature and in our main analysis, the focus is on firms between the 10th and 90th percentiles, while moving closer to the tails may expose the analysis to outliers. To that end, we also provide a robustness check whereby we repeat the baseline analysis, but first trim the top and bottom 0.1 percentiles of the firm-level productivity and wage distributions to account for outliers. Results presented in Online Appendix Table C.9 remain robust.

6.3 | Total factor productivity

We now compute the Hicks-neutral total factor productivity term from a gross-output production function with capital, labour and material inputs. To identify the production function, we follow the non-parametric estimation strategy of Gandhi *et al.* (2020).[37] We then construct the measures of productivity dispersion for country–industry–year, and (a) plot their evolution over time (see Online Appendix Figure B.9), and (b) repeat the analysis in Table 3 (see Online Appendix Table C.10). In both cases, the main results remain robust to this alternative measure of firm performance that accounts for the contributions from factors of production other than labour.

6.4 | Balanced sample

In this robustness test, we ensure a balanced panel by keeping country–industry combinations that are present throughout our entire sample period. When doing this, the number of observed country–industry–year combinations decreases from 10,280 to 7480. Online Appendix Figures B.10 and B.11 show the evolution of productivity and wage dispersion, and market concentration, respectively, for the balanced sample. To ease comparison, we also present the baseline trends from Figures 1 and 2. We find that productivity and wage dispersion for the balanced and unbalanced samples display practically the same pattern. In level terms, market concentration is slightly lower for the balanced sample, but follows closely the trends in the baseline sample. Using the balanced sample, we next repeat our baseline analysis and present results in Online Appendix Table C.11. We confirm our baseline findings, and thus demonstrate that our results are not driven by varying coverage due to the entry and exit of country–industry combinations.

In both the baseline and balanced sample, we observe a relatively large change in the evolution of productivity dispersion, wage dispersion and market concentration in the year 2002. This change might be driven by the increasing sample coverage of Orbis, especially in the early years of the sample. To ensure the robustness of our results, we repeat the baseline analysis in Table 3, but restrict the sample period to 2002–16. Results presented in Online Appendix Table C.12 are similar to the baseline.

6.5 | Varying sample coverage

Around 2004–5, we observe a kink in the evolution of productivity and wages at the bottom part (10th percentile) of the distributions (see Online Appendix Figures B.3 and B.4, respectively). While this sharp movement is not apparent when we look at the dispersion measures, it might raise concerns about the sensitivity of the baseline results. We conjecture that this data irregularity most likely arises from increased sample coverage along two dimensions. First is the entry and exit of country(–industry) groups in the sample (see Online Appendix Table A.6). However, the robustness exercise with a balanced sample conducted above guards against this possibility. An alternative explanation is the increasing coverage of firms within country–industry cells (see Online Appendix Table A.5). Therefore we repeat the baseline analysis in Table 3, but restrict the sample period to 2006–16. Point estimates presented in Online Appendix Table C.13 are similar to the baseline, albeit with larger standard errors given the smaller sample size.

In line with the previous exercise, the sample now includes country–industry groups that satisfy the following conditions throughout the entire period 2000–16: (1) the number of firms does not double or halve between two consecutive years; and (2) the difference in the number of firms between two consecutive years is smaller than 25. These sample restrictions allow us to exclude country–industry groups where irregular changes in firm coverage over time could arise due to changes in reporting standards. With this sample, we repeat the baseline analysis in Table 3 and present results in Online Appendix Table C.14. We confirm our baseline findings, which support that our results are not driven by the varying coverage of country–industry combinations.

6.6 | Enhancing representativeness

Orbis represents a rich source of cross-country firm-level data, but this comes at the cost of some coverage and representativeness issues. Bajgar *et al.* (2020) document the coverage and representativeness of Orbis, and compare it with industry-level data OECD STAN as well as micro-aggregated data from the OECD MultiProd and DynEmp projects. Firms in Orbis are disproportionately larger, older and more productive, even within a given size class. This explains why reweighting does not improve the representativeness beyond the mechanical effect on the firm size distribution. Bajgar *et al.* (2020) show further that focusing on country–industry combinations that contain at least 5000 firms (which report value-added), imputing value-added,[38] and considering firms with at least ten employees, improves the representativeness considerably. Moreover, despite its somewhat incomplete coverage, Bajgar *et al.* (2020) point out that other commercial datasets still underperform compared to Orbis, thus making it the best option at hand. We restrict our sample by following these three guidelines, and present estimation results in Online Appendix Table C.15. The main findings hold.

6.7 | Fixed effects

As the next robustness check, we extend the set of fixed effects in equation (8) to account for country–industry linear time trends. Adding these to our regression specification controls for various factors such as technical progress or more granular business cycle effects. Online Appendix Table C.16 shows these estimation results. While we lose some statistical significance due to conditioning on a very restrictive set of fixed effects, the estimated magnitudes are in line with the baseline. Overall, this exercise seemingly confirms our main finding that superstar firms weaken the link between productivity and wage dispersion.

7 | CONCLUSION

This paper examines links between evolutions in productivity dispersion, wage dispersion and superstar firms. Using a rich sample of firms in 14 EU countries over the period 2000–2016, we confirm previous findings in the literature of increases in all three variables—albeit with a moderating effect for wage and productivity dispersion in recent years. The positive correlation between productivity and wage dispersion that we document points to an incomplete pass-through of productivity gains to wages.

We present novel empirical evidence that the rise of superstar firms has a mediating effect on this correlation and is observed at both the top and bottom parts of the productivity and wage distributions. At the top, the findings underscore that highly productive firms enjoy increased profit margins from access to globalization while being shielded from local wage competition through increased labour market power. At the bottom, such effects point to underlying structural changes in the labour market from the dominance of superstar firms. Moreover, in support of the mechanisms discussed above, we find stronger mediating effects for tradable (versus non-tradable) sectors, and markets with low (versus high) collective bargaining power.

Our findings suggest that firms in industries with limited product and labour market competition pass on fewer productivity gains to wages compared to more competitive industries. From a policy standpoint, this raises interesting questions related to the optimal degree of regulation of both product and labour markets needed to reduce wage inequality. In its entirety, our analysis lays important groundwork in understanding the role of superstar firms in mediating the transfer of productivity gains to wages. Based on our novel empirical findings, we see rich potential for additional research to identify structurally and test the mechanisms at play.

ACKNOWLEDGMENTS

We thank participants at the KU Leuven and University of Oxford–Oxford Martin School seminars, and the 3rd and 4th conferences on European Studies for their comments and suggestions. Special thanks are extended to Filip Abraham, Giuseppe Berlingieri, Jan De Loecker, Rebecca Freeman, Pete Klenow, Joep Konings, Balazs Murakozy, Werner Roeger and Stijn Vanormelingen. The authors acknowledge support from the European Union Horizon 2020 Research and Innovation action under grant agreement no. 822781, GROWINPRO (Growth Welfare Innovation Productivity) Work Package 3.6 – DE 3.9, and from Methusalem (METH/21/001). This paper circulated previously under the title 'The link between productivity and wage dispersion: the role of superstar firms'.

ENDNOTES

[1] Recent research has documented increases in productivity dispersion and wage dispersion in several countries. Studies that explore changes in productivity dispersion include Syverson (2004), Aghion *et al.* (2009) and Andrews *et al.* (2015, 2016), among others. For research related to increases in wage dispersion, see Autor *et al.* (2008), Bagger *et al.* (2013), Card *et al.* (2013, 2014, 2016, 2018) and Song *et al.* (2019).

[2] This complements mounting empirical evidence documenting that worker compensation is strongly correlated with various measures of firm performance. Note that these findings are in line with both worker sorting in more productive firms and also rent sharing behaviour of firms (see Card *et al.* 2018).

[3] For example, search costs in the labour market prevent the arbitrage of wage differences across jobs or locations. Thus an incomplete pass-through of productivity to wages emerges (Pissarides 2011). See Layard *et al.* (2009) for a review of models with search costs, efficiency wage, union bargaining and rent sharing.

[4] This is in line with evidence on imperfect propagation of productivity shocks to wages (Juhn *et al.* 2018; Berger *et al.* 2022; Kline *et al.* 2019).

[5] Two factors are typically cited as potential explanations: globalization (Helpman 2016) and technological change (Acemoglu and Autor 2011). Both have been shown to have differential effects on wages for various types of labour and skills. This explains increases in the wages of skilled relative to unskilled workers, and thus rising wage dispersion within and between firms. While less eminent, a series of other explanations include the relative supply of highly-educated workers (Card and Lemieux 2001), union power (Machin 2016), centralization of wage bargaining (Dahl *et al.* 2013), and minimum wage (DiNardo *et al.* 1996).

[6] Factors that engender this mechanism include declining business dynamism (Decker *et al.* 2016), falling real interest rates (Gopinath *et al.* 2017), zombie firms (Andrews and Petroulakis 2019) and stalling technological diffusion (Andrews *et al.* 2016).

[7] Structural changes in firms' operating environments that generate this result include import competition from low-wage countries (Autor *et al.* 2013), increases in firms' monopsony power (Burdett and Mortensen 1998), openness in capital markets (Huber *et al.* 2020) and automation (Acemoglu and Restrepo 2019).

[8] For robustness, we also use total factor productivity where labour, capital and materials are considered. However, the additional data requirements in terms of variables required results in a 22% sample reduction, encompassing dropping all observations for Denmark, Ireland and the UK.

[9] Therefore we cannot capture potential wage dispersion among employees/occupations within the firm, since firms are not requested to file such granular information in standard financial statements.

[10] Specifically, recent studies using employer–employee data provide evidence that between-firm wage differentials account for most of the evolution in wage dispersion (Dunne *et al.* 2004; Barth *et al.* 2016; Helpman *et al.* 2017; Song *et al.* 2019).

[11] This model includes firm heterogeneity in terms of labour productivity and markdowns, as is common in standard labour market friction models such as that of Burdett and Mortensen (1998). Additionally, firms can differ in terms of their labour elasticity of output and markups. See Wong (2021) for a detailed discussion of the underlying assumptions.

[12] See Budd *et al.* (2005) and Abraham *et al.* (2009) on rent sharing models, and Card *et al.* (2014) on wage bargaining models.

[13] Appendix C of Wong (2021) provides detailed derivations under various specific microeconomic foundations.

[14] At the tails of the distribution, i.e. below the 5th and above the 95th percentile, we observe larger variation due to outliers. For example, at the top of the distribution, the average productivity becomes larger for smaller firms where all value-added is assigned to a small number of employees. Similarly, at the bottom of the distribution, the average productivity becomes very small for firms that are close to breaking even. Such data irregularities also underscore why, both in the literature and in our main analysis, the focus is on firms between the 10th and 90th percentiles followed by robustness tests between the 5th and 95th percentiles. The right-hand panel of Online Appendix Figure B.1 also confirms that this monotonic relationship holds when focusing on firms between the 5th and 95th percentiles.

[15] There is a series of alternative empirical models used in the literature on related topics as well as more granular data, e.g. employer–employee. See, for example, Margolis and Salvanes (2001) and Guiso *et al.* (2005) for rich discussions about the econometric challenges involved, including endogeneity, in estimating such models.

[16] Unconsolidated accounts do not incorporate statements of controlled subsidiaries or branches of the firm. Focusing on these accounts comes with three main advantages for our analysis. First, it allows us to capture more granular variation, i.e. we observe information on all individual firms within a corporate group instead of one large consolidated firm. Second, it allows us to closely link firms to the location and sector of economic activity. For example, consolidated accounts could mask the fact that a company consists of various firms that are active in several countries and/or industries, thereby attributing part of the economic activity to the 'wrong' country and/or sector. Finally, it also helps to avoid double counting the statements of firms within the same corporate group.

[17] Orbis covers all non-farm business sectors, corresponding to NACE 2-digit codes 10–82 (Bajgar *et al.* 2020).

[18] For further details on cross-country representativeness, see Online Appendix Table A.3.

[19] As an additional check of the firm-level dataset, we regress the logarithm of average firm wage on the logarithm of labour productivity, weighted by the logarithm of the number of employees. Reassuringly, we find an estimated coefficient 0.61, i.e. more productive firms are associated with paying higher wages, which is in line with existing studies, such as Criscuolo *et al.* (2020), among others.

[20] Online Appendix Figure B.3 plots the evolution of the mean and median productivity relative to the base year. We find that average productivity increased faster than median productivity. This difference increased over time, with a notable spike just before the 2008 financial crisis, and exhibited a relatively stable gap thereafter.

[21] Australia, Austria, Belgium, Chile, Denmark, Finland, France, Hungary, Italy, Japan, the Netherlands, Norway, New Zealand and Sweden.

[22] We thank the authors of Berlingieri *et al.* (2017) for sharing the underlying values presented in each of the respective figures in their paper.

[23] Online Appendix Figure B.4 plots the evolution of the mean and median wage relative to the base year. We find that the average wage increased faster than the median wage. This difference increased over time, with a notable reduction around the 2008 financial crisis.

[24] Belgium, Croatia, Finland, France, Hungary, Italy, Lithuania, Portugal, Romania, Slovenia, Spain and Sweden.

[25] When fixed effects are nested within clusters, maintaining groups with one observation, i.e. singletons, can overstate statistical significance and lead to incorrect inference. We use the Stata package '`reghdfe`' by Correia (2015) that iteratively drops singletons from the estimation. In this case, we drop 12 observations in each column.

[26] In Online Appendix Figure B.5, we repeat the analysis in column (1) of Table 2 for each country separately, and plot the estimated coefficients. Results remain across all countries.

[27] This point is supported further by Online Appendix Figures B.7 and B.8, where we see that on average, since 2000, both the productivity and wages of superstar firms have increased at a faster pace than in the rest of firms.

[28] For robustness, we also provide results in Online Appendix Table C.1, where we weigh the regressions with total value-added instead. Results are in line with the baseline estimates.

[29] This is also in line with Mertens (2021), who finds that more concentrated industries compress the wage distribution more so at the top, and thus reduce wage inequality overall for a set of European countries. In turn, this points to a larger disconnect between productivity and wages in concentrated industries.

[30] In Online Appendix Figure B.6, we repeat the analysis in column (1) of Table 3 for each country separately, and plot the estimated coefficients. Apart from Italy (direct effect) and Austria (indirect effect), results remain across all 14 EU countries.

[31] For example, see OECD (2014) for an assessment of the 2012 labour reform on labour outcomes.

[32] We follow the classification suggested by Piton (2021) where tradable sectors cover NACE 2-digit industries 10–33, 49–66 and 69–82, and non-tradable sectors cover NACE 2-digit industries 35–47 and 68.

[33] We rely on the collective bargaining power indicator from OECD (2021a), which is constructed based on the number of workers covered by a collective agreement. With this indicator, we compute the median value across all sample periods for each country, and in turn group countries as high and low. For cases where countries jump across groupings over the years, we choose the group with the most observations in place. Countries with high collective bargaining power are Austria, Belgium, Finland, France, Italy and Sweden. Countries with low collective bargaining power are Denmark, Germany, Ireland, Luxembourg, the Netherlands, Portugal, Spain and the UK.

[34] The average and median values for *HHI* are 900 and 452, respectively. The standard deviation is 1322. Markets with *HHI* between 1500 and 2500 are considered to be moderately concentrated, while markets with *HHI* above 2500 are highly concentrated (US Department of Justice 2020).

[35] For the regressions, we divide *HHI* by 10,000 so that it lies in the interval $[0, 1]$ and the order of magnitude of the estimated coefficient is easier to interpret.

[36] Note that we follow the simplest empirical approach possible since there is an ongoing discussion in the literature about the most informative and consistent ways to estimate and aggregate markups with commonly available datasets, i.e. revenue-based data (see Traina 2018; Bond *et al.* 2021; De Loecker 2021; Doraszelski and Jaumandreu 2021; De Ridder *et al.* 2022; Raval 2023).

[37] Note that the additional information on production inputs needed for the estimation are not reported by all firms. This results in reducing the sample from 20,210,495 to 15,268,943 firm–year observations, and from 10,280 to

7723 country–industry–year groups. This translates to a 22% reduction in the number of firm–year observations, encompassing dropping all observations for Denmark, Ireland and the UK.

[38] This includes proxying value-added as the sum of *ebitda* (earnings before interest, taxes, depreciation and amortization) and costs of employees.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Bormans, Y. and Theodorakopoulos, A. (2023). Productivity dispersion, wage dispersion and superstar firms. *Economica*, 1–28. https://doi.org/10.1111/ecca.12490