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KU LEUVEN

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Abstract

This paper examines links between evolutions in productivity dispersion, wage dispersion, and superstar firms. Using a rich sample of firms in 14 EU countries from 2000-2016, we confirm increases in all three variables—albeit with a moderating effect for wage and productivity dispersion in recent years. We document a positive correlation between productivity and wage dispersion, pointing to an incomplete pass-through of productivity gains to wages. Our analysis yields novel evidence that the rise of superstar firms is associated with a mediating effect on this correlation. This underscores theoretical work which posits that highly productive firms enjoy increased profit margins from access to globalisation while being shielded from local wage competition through increased labour market power. Most of the effects driving our main results are observed in the lower part of the productivity and wage distributions, consistent with a series of underlying structural changes in the economy.

Keywords: Wage dispersion, Productivity dispersion, Superstar firms, Market concentration
JEL classification: D33, E25, F62, F66, J31

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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, i.e. 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 globalisation 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 are compelling explanations, 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 which dominate product market shares (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); set higher mark-ups (Autor et al. 2020); and have a lower firm-specific labour share despite paying above-average wages (Gouin-Bonenfant 2018). 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 Lexington County, South Carolina. Despite creating approximately 4,000 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

[1]Recent research has documented increases in productivity dispersion and wage dispersion in a large set of countries. Studies which explore changes in productivity dispersion include Andrews et al. (2015) and Andrews et al. (2016), among others. For research related to increases in wage dispersion see, for example, Bagger et al. (2013); Card et al. (2013, 2014, 2016, 2018); 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 (for a detailed discussion 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. 2019; Kline et al. 2019).

[5]Two key factors are typically cited as potential explanations: globalisation (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 important explanations examined include: the relative supply of highly-educated workers (Card and Lemieux 2001); union power (Machin 2016); centralisation of wage bargaining (Dahl et al. 2013); and minimum wage (DiNardo et al. 1996).

supports theoretical considerations proposed by Gouin-Bonenfant (2018) about the link between productivity dispersion and the labour share. 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 decline in workers' wages—to levels below their marginal value of revenue. Overall, a rise in market concentration is expected to weaken the link between productivity and wage dispersion, which we empirically examine 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 in the literature is the time period covered, with most previous studies ending in or 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 primarily driven 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 one. 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' labour market power (Berger et al. 2019).

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). We show that high market concentration industries—a proxy for superstar firms—are associated with a weaker link. As such, superstar firms appear to induce a larger disconnect between productivity and wages, and hence a more incomplete pass-through. These results provide positive affirmation of the mechanism referred to above: highly productive firms enjoy increased profit margins from access to globalisation while being shielded from local wage competition through increased labour market power. Upon deeper examination, we show that this result is most prominent at the bottom part of the

[6]Factors which 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); among others.

[7]Structural changes in firms' operating environments which 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); among others.

distribution and for services in particular. The latter point is especially of interest, given rapidly expanding research on the structural differences between services and manufacturing, including each sector's overall dynamism.

Our analysis relies upon 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.

The remainder of this paper is structured as follows. In Section 2 we discuss the construction of the main variables of interest along with the choice of empirical specifications. Section 3 describes the dataset used in the empirical analysis. Section 4 presents results and Section 5 provides robustness checks. Finally, Section 6 concludes.

2 Empirical methodology

This section discusses the construction of our main variables and empirical strategy used in the paper. We first discuss how we measure productivity and wages at the firm level as well as the construction of measures which 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 introduce the empirical specification which links productivity dispersion to wage dispersion. Finally, we elaborate on the construction of proxies which reflect the evolution of superstar firms. With these at hand, 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. Various indices and estimation methods of productivity exist, each one with its own strengths and weaknesses (see Van Biesebroeck 2015, for a review). The most widely used measure in the literature is labour productivity (henceforth P), defined as:

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

where VA_{jcit} is value added and L_{jcit} employment (in full time equivalents) for firm j in country c, industry i, and year t. The use of this measure has two main advantages. First, it is straightforward to compute and interpret. Second, information on value added and employment—necessary to calculate the measure—are well reported in the financial statements of firms and thus available in most firm-level datasets and business registries. The main drawback of this measure is that it attributes all changes in labour productivity to a single factor of production, labour, while neglecting contributions from other factors of production, such as capital.

Alternatively, we could rely on measures of total factor productivity where multiple inputs of production are considered, e.g. labour, capital, energy, materials, etc. Despite major advances in the identification of such measures, their estimation hinges upon additional firm-level information, such as: physical capital stock, intermediate inputs, etc. However, not all firms are legally required to report such information in their financial statements and we thus miss meaningful parts of firm-level variation. Nevertheless, Berlingieri et al. (2017) find similar patterns in the evolution of productivity dispersion under both labour and total factor productivity indices. Therefore, for the rest of our analysis we rely upon the measure of labour productivity (P) and provide robustness of the baseline results using total factor productivity measures.

For wages we rely on the average firm wage (W) which is calculated as follows:

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

where TLC_{jcit} captures the total labour cost for firm j in country c and industry i at time t. This measure is advantageous in that it is widely used in the literature and well reported in firms' financial statements across sectors and countries. A shortcoming is that, by construction, we assume that all employees earn the same wage within the firm. Therefore, we cannot capture any potential wage dispersion among employees/occupations within the firm, since firms are not requested to file such granular information in standard financial statements.[8] However, recent studies using employer-employee data in both developed and emerging economies provide evidence that the between-firm wage differentials account for the majority of the overall evolution in wage dispersion (Dunne et al. 2004; Barth et al. 2016; Helpman et al. 2017; Song et al. 2019).

Overall, using average firm wages still allows us to capture a sizeable part of the wage dispersion both at the cross-section and over time. As such, results in this paper focus on a specific channel of the income distribution, namely between-firm wage differentials which

[8] More detailed data is needed for the analysis of within-firm inequality and is typically not available for a large set of countries.

remain meaningful in understanding the evolution of overall wage dispersion (see Berlingieri et al. 2017, for an in depth discussion on this matter using similar data structures).

2.2 The evolution of productivity and wage dispersion

To measure productivity dispersion we compare the productivity of firms at the top relative to the bottom of the distribution, an approach which is standard in the literature. Specifically, 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 $PD_{cit}^{90/10} = \ln\left(PD_{cit}^{90}/PD_{cit}^{10}\right)$. This ratio tells us how many times more productive the firm at the 90th percentile of the productivity distribution is relative to the firm at the 10th percentile. Higher (lower) values correspond to larger (smaller) productivity dispersion within the country-industry-year group. At the extreme, a ratio value of one (zero in logs) indicates that the firms at the 90th and the 10th percentile of the distribution have exactly the same productivity.

To capture the evolution of productivity dispersion, we estimate the following specification:

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

where D_t is a vector of year dummies, FE_{ci} is a set of country-industry fixed effects, and ε_{cit} is an identically and independently distributed error term. Country-industry fixed effects eliminate all cross-sectional variation and thus account for any compositional differences in dispersion between country-industries. As such, the remaining variation refers to intertemporal changes within each country-industry which is captured by β_t. 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.[9] We weight the regression by the natural logarithm of value added at the country-industry-year level such that relatively larger sectors have a relatively larger impact on the evolution of productivity dispersion.

Similarly, we define wage dispersion as the natural logarithm of the ratio of the 90th to the 10th percentile of the firm wage distribution within each country-industry-year group cit, denoted by $WD_{cit}^{90/10} = \ln\left(WD_{cit}^{90}/WD_{cit}^{10}\right)$. In line with equation (3), we capture the evolution of wage dispersion by estimating the following specification:

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

where now the dependent variable is wage dispersion and β_t captures the estimated changes of wage dispersion in each year t relative to the reference year. All other controls remain the same as in (3) and the regression is weighted by the natural logarithm of total value added at the country-industry-year level.

[9]The global constant is subsumed in the fixed effects FE_{ci}.

To uncover potential underlying heterogeneity, we repeat the analysis by focusing on different sub-sections of the entire distribution. This includes replacing the productivity and wage dispersion measures $\left(PD_{cit}^{90/10} \text{ and } WD_{cit}^{90/10}\right)$ with those capturing the upper or lower parts of the distributions, and repeating the analysis from above. The upper $\left(PD_{cit}^{90/50} \text{ and } WD_{cit}^{90/50}\right)$ and lower $\left(PD_{cit}^{50/10} \text{ and } WD_{cit}^{50/10}\right)$ parts refer to the ratios of the 90$^{\text{th}}$ to the 50$^{\text{th}}$ and the 50$^{\text{th}}$ to the 10$^{\text{th}}$ percentile of the relevant firm-level distributions, respectively.

2.3 The link between productivity and wage dispersion

To empirically examine the link between productivity and wage dispersion we follow Berlingieri et al. (2017) and use the following specification:

$$WD_{cit}^{90/10} = \beta PD_{cit}^{90/10} + FE_{ci,ct,it} + \varepsilon_{cit} \tag{5}$$

where PD_{cit} and WD_{cit} refer to the measures of productivity and wage dispersion, respectively, at the country-industry-year level. All other components are defined as before, 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, e.g. business cycle variation across countries and industrial technological progress. The regression is weighted by the natural logarithm of total value added at the country-industry-year level.

The parameter of interest β identifies the conditional correlation between productivity dispersion and wage dispersion. In a perfectly competitive labour and product market, we expect a complete pass-through, i.e. β is equal to one. However, the pass-through becomes incomplete in the presence of market inefficiencies or frictions (Van Biesebroeck 2015). Hence, the testing hypothesis of interest is whether β is equal to one under the null or less that one under the alternative. In line with the above, a value statistically less than one is expected, which would suggest incomplete pass-through of productivity to wages.

2.4 Superstar firms

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 $CN4_{cit}$ which reflects the market share of the four largest firms in cit. However, we also test the robustness of our main results against the versions $CN10_{cit}$ and $CN20_{cit}$, corresponding to the market share of the ten and twenty largest firms, respectively. Note that market shares are denoted in terms of value added in line with what is used for the measures of productivity (dispersion).

To examine the overall evolution of superstar firms in the economy, we construct an aggregate measure of market concentration at the yearly level. To do so, we regress 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.

2.5 The mediating role of superstar firms

Finally, we explore whether superstar firms, proxied by market concentration $CN4_{cit}$, affect wage dispersion. To do so, we augment specification (5) such that:

$$WD^{90/10}_{cit} = \beta PD^{90/10}_{cit} + \gamma CN4_{cit} + \delta \left(PD^{90/10}_{cit} * CN4_{cit} \right) + FE_{ci,ct,it} + \varepsilon_{cit} \tag{6}$$

where γ captures the direct effect and δ—estimated through the interaction term—captures the indirect effect of superstar firms on wage dispersion. In particular, the direct effect estimates whether superstar firms increase ($\gamma > 0$) or decrease ($\gamma < 0$) wage dispersion, ceteris paribus. On the other hand, the indirect effect 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.[10]

3 Data

We source data from Orbis Global which is a product of Bureau van Dijk Electronic Publishing (2020a) (BvDEP). Orbis Global collects firms' financial statements from various national sources (e.g. statistical offices) and standardizes them for cross-country comparability.[11] We use the balance sheet information of firms which file unconsolidated accounts[12] from 2000 to 2016 in the following 14 European countries: Austria; Belgium; Denmark; France; Finland; Germany; Ireland; Italy; Luxembourg; Netherlands; Portugal; Spain; Sweden; and the United Kingdom. Specifically, for each identifier to which the firm belongs we retain firm-year observations which report strictly positive values of: value added; number of employees; and total cost of employees.

[10] In Section 5 we check for the robustness of this baseline specification under alternative market concentration measures and a richer set of fixed effects.

[11] Orbis Global provides correspondence tables to explain the standardization process for each country (Bureau van Dijk Electronic Publishing 2020b).

[12] 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, they allow 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 which 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.

To implement the country-industry-level analysis, we classify firms' principal production activity in 2-digit industries based on their NACE Rev.2 industry codes.[13] Orbis covers all non-farm business sectors, i.e. those which correspond to NACE 2-digit codes 10-82 (Bajgar et al. 2020).[14] For the sectoral analysis, we focus on manufacturing sectors (10-33) and business services sectors (49-82).

Cross-country comparability is a large advantage of this dataset (Kalemli-Ozcan et al. 2015; Merlevede et al. 2015). This comes at the expense of reduced representativeness and coverage for smaller-sized firms for which there are simplified reporting obligations for their financial statements (European Commission 2020). However, while the sample does not cover a large number of reported firms in the economy, it captures the bulk of economic activity in terms of employment (see Appendix Table A.3).[15]

Table 1: Summary statistics

				Percentile			
	Mean	St.Dev.	Min	25th	50th	75th	Max
$PD_{cit}^{90/10}$	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
$WD_{cit}^{90/10}$	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
$CN4_{cit}$	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*) pairs. 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.

Overall, the firm-level dataset includes an unbalanced panel of 3,601,418 firms between 2000 to 2016. This represents on average 67% of total private employment across the 14 EU

[13]NACE is the industry standard classification system used in the European Union. (Eurostat 2020b) provides a detailed description of the NACE Rev.2 2-digit industries included in our sample.

[14]This includes 11 sectors of the economy: manufacturing (10-33); electricity, gas and water supply; sewerage, waste management and remediation activities (35-39); construction (41-43); wholesale and retail (45-46); transportation and storage (49-53); accommodation and food service activities (55-56); information and communication (58-63); financial and insurance activities (64-66); real estate activities (68); professional, scientific and technical activities (69-75); and administrative and support service activities (77-82).

[15]In 2015, 92.8% of enterprises in the EU 28's non-financial business economy were micro, i.e. employed less than ten persons, but accounted for 29.1% of total employment and 20.3% of total value added (Eurostat 2020c).

countries considered. The data Appendix Section A, provides a detailed discussion over the steps followed to construct the firm-level sample and its representativeness across countries, industries, and over time.

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 the upper panel of the table we see that, on average across all countries, industries, and years in the sample, a firm in the 90^{th} percentile of the productivity distribution is approximately $e^{1.74} = 5.7$ times more productive than the 10^{th} percentile firm.We observe that dispersion is larger for the top part of the productivity 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.

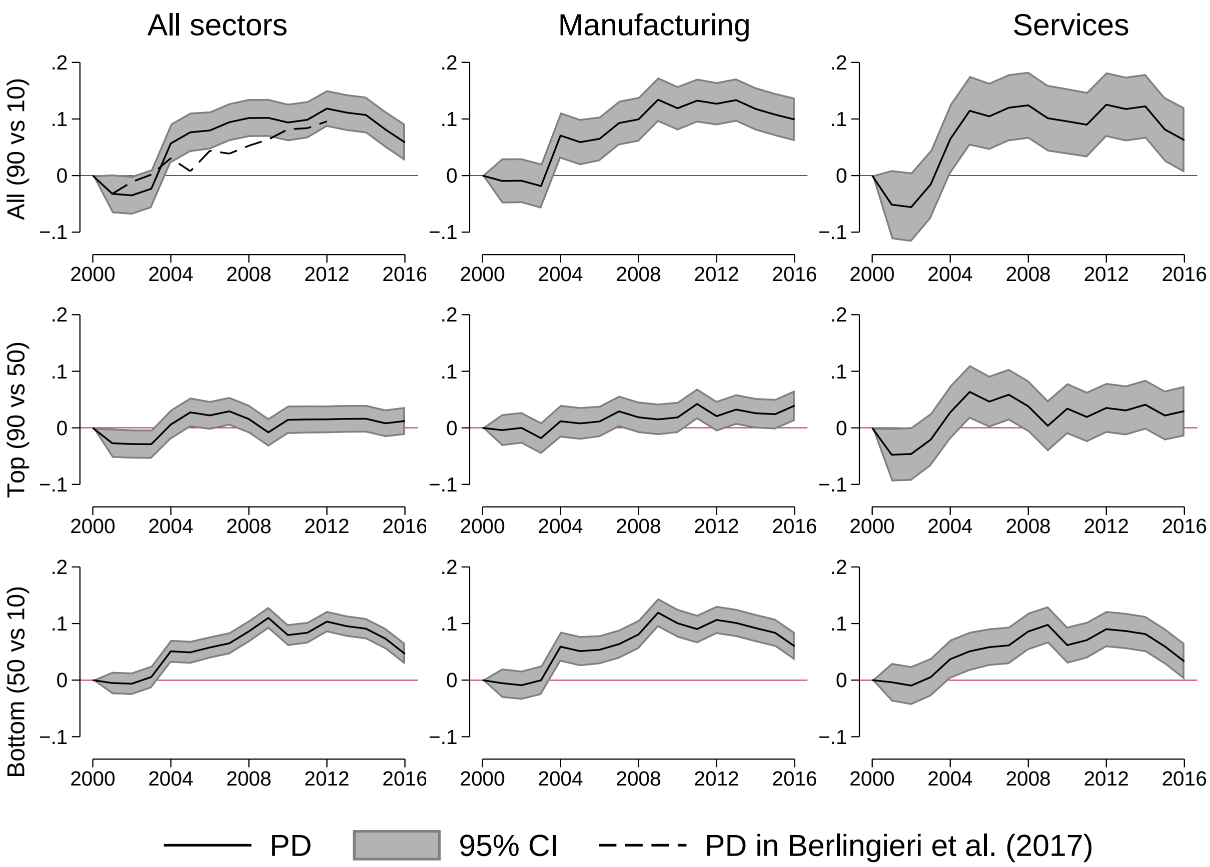
Next, in the middle panel of the table we observe that the wage dispersion is smaller compared to the productivity dispersion on average. The average wage in the top firm is 3.3 times larger than the average wage in the bottom firm $\left(WD_{cit}^{90/10}\right)$. Interestingly, in contrast to productivity 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 the lower panel of the table 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 pair 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 25^{th} percentile, market concentration is 0.19. At the 75^{th} percentile it is 0.51. This suggests that the degree of competition varies across industries which appear to be monopolies/oligopolies versus those which 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

In this section we describe 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 and for the manufacturing and services sector. 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.

Figure 1: Evolution of productivity dispersion (*PD*)



Source: Authors' estimations using Orbis Global database.

Notes: The solid line connects the estimated coefficients from regressing productivity dispersion (PD_{cit}) on a set of year dummies, 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. Left, middle and right column panels use data for all sectors (NACE 10-82), manufacturing (NACE 10-33), and services (NACE 49-82), respectively. The dashed line in the top-left panel corresponds to PD_{cit} found in Berlingieri et al. (2017).

4.1 The rise of productivity and wage dispersion

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 in Figure 1 shows that the average country-industry productivity dispersion $\left(PD_{cit}^{90/10}\right)$ has statistically significantly increased between 2004 and 2012. Specifically, frontier firms at the top part of the productivity distribution are, on average, increasing the productivity gap with laggard firms at the bottom part. 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 2013-2016 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 further examine 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) (dashed line). Their dataset is representative for the population of firms in 14 OECD countries[16]—some of which are included in our sample—and available for the period 2001-2012. For the overlapping years, the evolution of productivity dispersion moves roughly in parallel. This provides further assurance that our selected sample generates similar aggregate trends to those presented in the literature to date.

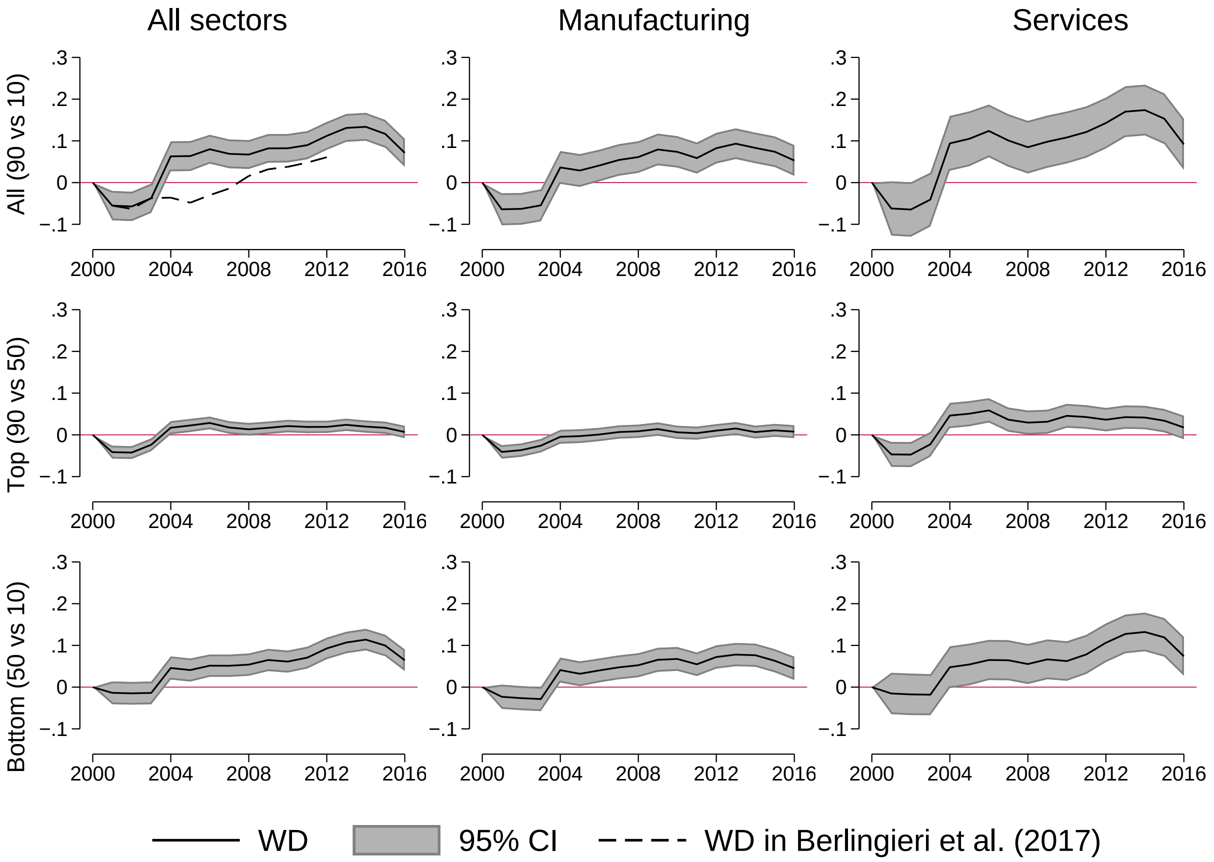
Next, we explore whether this increase happens at the top or bottom of the productivity distribution. In line with the analysis from above, we thus estimate the yearly coefficients β_t for the upper $\left(PD_{cit}^{90/50}\right)$ and lower $\left(PD_{cit}^{50/10}\right)$ parts of the productivity distribution. Results are plotted in the second and third row of the first column in Figure 1, respectively. We find that the widening of productivity dispersion occurs at the bottom part of the distribution rather than the top. In particular, the evolution of productivity dispersion at the top hovers around zero, but remains statistically insignificant in nearly all years (see the middle-left panel). In contrast, large and statistically significant increases in productivity dispersion at the bottom take place between 2004-2012 (see the bottom-left panel). Despite a moderating effect in more recent years, we still find a significant and positive increase for the period 2013-2016. 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 which support mounting evidence of increased misallocation of resources towards the least productive firms. Such mechanisms include: a decline in business dynamism which results in a limited degree of churning in the economy (Decker et al. 2016); falling real interest rates which cause misallocation of capital inflows towards relatively unproductive firms (Gopinath et al. 2017); the presence of zombie firms which hoard productive inputs and prevent their optimal allocation (Andrews and Petroulakis 2019); and stalling technological diffusion and adoption which prevents laggard firms from catching up (Andrews et al. 2016).

Next, we look at the sectoral decomposition of these results. We repeat the analysis from above (first column) for firms in the Manufacturing (second column) and Services sector (third column).Panels from the last two columns in Figure 1 indicate that the productivity dispersion increases in roughly the same way in both sectors. In line with the previous findings, this rise seems to occur predominantly at the bottom rather than the top part of the distribution. As such, increases in the evolution of productivity dispersion in the entire economy do not appear to be driven by sectoral heterogeneity.

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

Figure 2: Evolution of wage dispersion (WD)



Source: Authors' estimations using Orbis Global database.
Notes: The solid line connects the estimated coefficients from regressing wage dispersion (WD_{cit}) on a set of year dummies, i.e. parameter set β_t in equation (4). 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. Left, middle and right column panels use data for all sectors (NACE 10-82), manufacturing (NACE 10-33), and services (NACE 49-82), respectively. The dashed line in the top-left panel corresponds to WD_{cit} found in Berlingieri et al. (2017).

Wage dispersion.—To document the evolution of wage dispersion $\left(WD_{cit}^{90/10}\right)$ we follow the same roadmap as before. Specifically, we estimate the set of parameters β_t from equation (4) which capture the average wage dispersion in each year t relative to the baseline year 2000. Results are plotted in Figure 2. The top-left 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 then weakens towards the end of our sample, but remains significantly higher compared to its level in 2000. 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.[17]

[17] Belgium; Croatia; Finland; France; Hungary; Italy; Lithuania; Portugal; Romania; Slovenia; Spain; and

We now examine how the evolution of wage dispersion emerges in different segments of the distribution. In Figure 2, the mid-left and bottom-left 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 2004-2014, 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 only modestly increased 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 which 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.

Next, we look into sectoral differences in Manufacturing and Services. Results from the second and third column reveal similar patterns in both sectors, i.e. an increase in wage dispersion at the bottom dominates the (marginally significant) increase in wage dispersion at the top of the distribution. Quantitatively, the increase in wage dispersion is larger in Services than in Manufacturing.

4.2 The link betwen productivity and wage dispersion

To examine the link between productivity and wage dispersion we estimate equation (5) 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. Columns (4)-(6) and (7)-(9) repeat the analysis in (1)-(3) for the Manufacturing and Services sectors, respectively. Additionally, we test whether each estimated coefficient is significantly different from smaller than one and present the corresponding test p-values at the bottom of the table.[18]

Sweden.

[18]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. For example, in columns (1)-(3), (4)-(6), and (7)-(9) we drop 12, 9 and 9 observations, respectively.

In column (1), 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 one. Wage dispersion is thus positively linked 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).[19]

Table 2: The link between wage and productivity dispersion

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All Sectors			Manufacturing			Services		
	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$
$PD_{cit}^{90/10}$	0.399***			0.373***			0.401***		
	(0.030)			(0.039)			(0.042)		
$PD_{cit}^{90/50}$		0.262***			0.231***			0.288***	
		(0.028)			(0.022)			(0.038)	
$PD_{cit}^{50/10}$			0.574***			0.488***			0.592***
			(0.045)			(0.059)			(0.060)
$H_0{:}\,\beta - 1$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
R^2	0.892	0.881	0.851	0.911	0.869	0.891	0.880	0.875	0.840
Observations	10,268	10,268	10,268	3,757	3,757	3,757	4,727	4,727	4,727

Notes: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. This table presents point estimates from regressing wage dispersion (WD_{cit}) on productivity dispersion (PD_{cit}), i.e. β parameter in equation (5). 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 one. Columns (1)-(3), (4)-(6), and (7)-(9) use data for all sectors (NACE 10-82), manufacturing (NACE 10-33), and services (NACE 49-82), respectively.

Columns (2) and (3) suggest that the link between productivity and wage dispersion is considerably stronger at the bottom of the distribution versus at the top. Intuitively, firms at the bottom transfer a relatively larger share of their productivity gains to wages compared to firms 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 which are relatively lower than the marginal revenue product of labour (Berger et al. 2019).

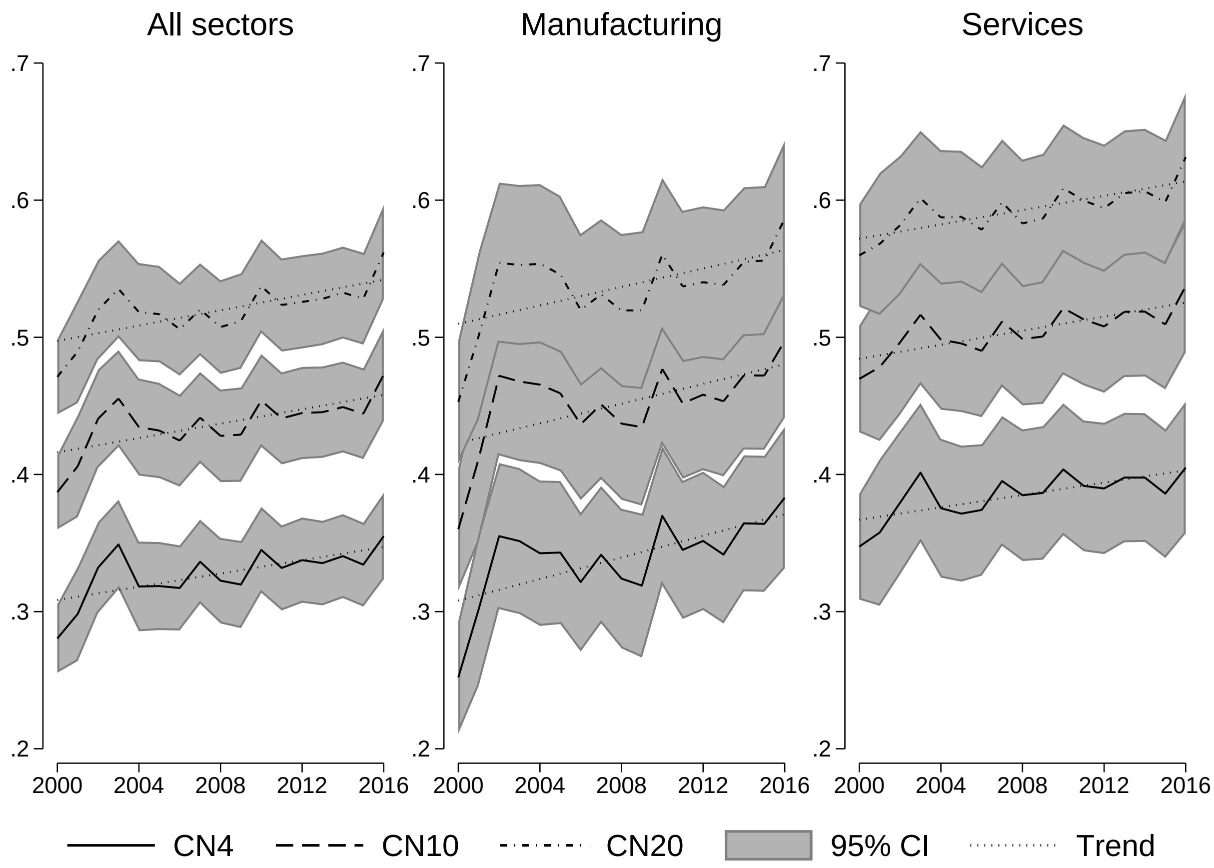
These findings are confirmed at the sectoral level as well: productivity and wage dispersion are positively linked, though the pass-through appears to be incomplete and larger at the bottom part of the distribution. Note that the pass-through is higher in the Services sector (columns 7-9), and especially so at the bottom part of the productivity distribution.

[19] In Appendix Figure B.1 we repeat the analysis in column (1) for each county separately and plot the estimated coefficients. We find that results remain across all 14 EU countries.

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 3 shows their evolution for the total economy (left panel), Manufacturing sector (middle panel) and Services sector (right panel).

Figure 3: Evolution of market concentration (*CN*)



Source: Authors' estimations using Orbis Global database.
Notes: The lines connect the estimated coefficients from regressing the market concentration measures (*CN*4, *CN*10, *CN*20) on a set of year dummies. All regressions are weighted by the logarithm of total value added at the country-industry-year (*cit*) level. The shaded area represents the clustered at the country-industry (*ci*) level 95% confidence interval. Left, middle and right column panels use data for all sectors (NACE 10-82), manufacturing (NACE 10-33), and services (NACE 49-82), respectively.

We find that market concentration is rising in Europe, irrespective of the number of firms considered. For example, *CN*4 increased from 28.0% in 2000 to 35.5% in 2016; the four largest firms' market share grew by 7.5 percentage points on average. The evolution of *CN*10 and *CN*20 exhibits the same pattern, indicating that the four largest firms are driving the overall evolution of the measures. In particular, *CN*10 increased from 38.7% in 2000 to 47.3% in 2016. Since the four largest firms increased their market share by 7.5 percentage points, the remaining 'top six' increased their market share by 1.1 percentage points only. Similarly, *CN*20 rose from 47.1% in 2000 to 56.2% in 2016. Thus, the additional 'top 10' capture only 0.5 percentage point. Overall, we find that a small 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).

Two main findings emerge at the sectoral level. First, comparing the middle and right panel shows that market concentration rises twice as fast in Manufacturing versus Services.[20] Second, market concentration levels in Manufacturing remain below those in Services in 2016, even after the accelerated growth in the most recent years.[21] Market concentration has thus converged to approximately the same magnitude in these two sectors.

4.4 The mediating role of superstar firms

We estimate equation (6) 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. Sectoral results are presented in columns (4)-(9).

Two key findings emerge from column (1). 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 fair-wage models (Egger and Kreickemeier 2012). As superstar firms become more dominant in terms of market share and profitability workers demand fair wages which 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 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.

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, i.e. which 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, while

[20] It increases by 13.1 percentage points ($CN4$), 13.7 percentage points ($CN10$) and 13.4 percentage points ($CN20$) in Manufacturing versus 5.8 percentage points ($CN4$), 6.7 percentage points ($CN10$) and 7.1 percentage points ($CN20$) in Services.

[21] In particular, market concentration equals 38.3% ($CN4$), 49.7% ($CN10$) and 58.7% ($CN20$) in Manufacturing versus 40.5% ($CN4$), 53.7% ($CN10$) and 63.1% ($CN20$) in Services in 2016.

the opposite happens to firms in less concentrated industries (Berger et al. 2019).[22] An alternate 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 which have limited production and profits (Cortes and Tschopp 2020). Therefore, we conclude that between-firm wage inequality increases with concentration of production within industries.

Table 3: Superstar firms and the link between productivity and wage dispersion

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		All Sectors			Manufacturing			Services	
	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$
$PD_{cit}^{90/10}$	0.518***			0.496***			0.560***		
	(0.042)			(0.056)			(0.059)		
$PD_{cit}^{90/50}$		0.312***			0.291***			0.361***	
		(0.042)			(0.054)			(0.059)	
$PD_{cit}^{50/10}$			0.792***			0.529***			0.928***
			(0.079)			(0.066)			(0.118)
$CN4_{cit}$	0.357***	0.061	0.328***	0.386***	0.099	0.117	0.530***	0.106	0.546***
	(0.090)	(0.041)	(0.093)	(0.130)	(0.064)	(0.086)	(0.145)	(0.067)	(0.173)
$PD_{cit}^{90/10} * CN4_{cit}$	-0.196***			-0.212**			-0.258***		
	(0.050)			(0.088)			(0.067)		
$PD_{cit}^{90/50} * CN4_{cit}$		-0.079**			-0.096			-0.114**	
		(0.038)			(0.079)			(0.052)	
$PD_{cit}^{50/10} * CN4_{cit}$			-0.388***			-0.077			-0.596***
			(0.120)			(0.125)			(0.192)
R^2	0.893	0.882	0.853	0.912	0.869	0.891	0.882	0.876	0.844
Observations	10,268	10,268	10,268	3,757	3,757	3,757	4,727	4,727	4,727

Notes: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. 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 (6), 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), manufacturing (NACE 10-33), and services (NACE 49-82), respectively.

When considering different parts of the firm level wage distribution in columns (2) and (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 both at the top and bottom parts of the distribution. However, various different mechanisms

[22] In Appendix Figure B.2 we repeat the analysis in column (1) for each county separately and plot the estimated coefficients. We find that, with the exception of Italy, results remain across all 14 EU countries.

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 which 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 2018). At the bottom part of the distribution, the emergence of superstar firms reduces the overall competitive pressure in the labor 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 2019; Berger et al. 2019).

Turning to results at the sectoral level, columns (4)–(9) also suggest that highly concentrated industries are associated with high wage dispersion. This result appears to hold only for the bottom part of the distribution for the Services sector in column (9). Moreover, columns (4) and (7) show that market concentration weakens the link between productivity and wage dispersion in both Manufacturing and Services sectors—albeit more strongly for Services. When we consider the top and bottom parts of the distribution separately (columns 5 and 8 versus 6 and 9) we find that the mediating effect on the link between productivity and wages is primarily present for Services (column 9). This heterogeneity is likely driven from underlying structural differences in the output and labour markets between Manufacturing and Services sectors, however, further research is needed to fully understand this differential impact.

5 Robustness

We conduct five additional exercises to test the robustness of our findings. The first robustness test considers alternative market concentration measures. Second, we compute a measure of total factor productivity instead of labour productivity. Third, we focus on a balanced sample of country-industry combinations to account for the effect of entry and exit of country-industry combinations. Third, 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.

Alternate market concentration measures.—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 use $CN10$ and $CN20$ as proxy for superstar firms, respectively. Results from this exercise, presented in Appendix Tables C.1 and C.2, support our main findings. We thus conclude that the market share of the four largest firms adequately captures the extent of market concentration.

Continuing, we employ an alternate 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, i.e. there might be an oligopoly or monopoly position, whereas low values indicate less market concentration, i.e. closer to perfect competition.[23] As above, we repeat the analysis from Table 3 now using *HHI*, and present results in Appendix Table C.3. This exercise supports the main conclusions found when using the *CN* measures to proxy market concentration.[24]

Total factor productivity.—We now compute the Hicks-neutral total factor productivity (TFP) 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).[25] We then construct the measures of productivity dispersion at the country-industry-year and: a) plot their evolution over time (see Appendix Figure B.3); and b) repeat the analysis in Table 3 (see Appendix Table C.4). In both cases, the main results remain robust to this alternative measure of firm performance.

Balanced sample.—In this robustness test, we ensure a balanced panel by keeping country-industry combinations which are present throughout our entire sample period. When doing this, the number of observed country-industry-year combinations decreases from 10,280 to 7,480. Appendix Figures B.4, B.5 and B.6 show the evolution of productivity dispersion, wage dispersion and market concentration, respectively, for the balanced sample. To ease comparison we also present the baseline trends from Figures 1, 2 and 3. 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. Using the balanced sample, we next repeat our baseline analysis and present results in Appendix Table C.5. We confirm our baseline findings, and thus demonstrate that our results are not driven by the varying coverage of country-industry combinations.

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 DynEm 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) further show that focusing on country-industries that contain at least 5,000 firms (which report value added), imputing value added,[26] and considering firms with at least ten employees improves the representativeness considerably. Moreover, despite its somewhat incomplete coverage, Bajgar et al. (2020) point

[23]The average and median value for *HHI* are 900 and 452, respectively. The standard deviation equals 1,322. Markets with an *HHI* between 1,500 and 2,500 are considered to be moderately concentrated while markets with a *HHI* above 2,500 are highly concentrated (US Department of Justice 2020).

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

[25]Note that the additional information on production inputs needed for the estimation are not reported by all firms. This results in a reduced sample of 15,268,943 firms in 7,723 country-industry-year groups.

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

out that other commercial datasets still underperform Orbis, thus making it the best option at hand.We restrict our sample by following these three guidelines and present estimation results in Appendix Table C.6. The main findings hold.

Fixed effects.—As a next robustness check, we extend the set of fixed effects in equation (6) 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. Appendix Table C.7 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.

6 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 evidence that the rise of superstar firms has a mediating effect on this correlation, underscoring that highly productive firms enjoy increased profit margins from access to globalisation while being shielded from local wage competition through increased labour market power. Most of the action driving our main results is observed in the lower part of the productivity and wage distributions, consistent with a series of underlying structural changes in the economy. Moreover, we find stronger effects for services (versus manufacturing) sectors, highlighting differences between the nature of the two.

Our findings suggest that firms in industries with limited product 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 structurally identify and test the mechanisms at play.

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Appendices

A Data processing and representativeness

Our empirical analysis relies on unconsolidated firm level accounts between 2000 and 2016 for 14 EU countries: Austria; Belgium; Denmark; Finland; France; Germany; Ireland; Italy; Luxembourg; the Netherlands; Portugal; Spain; Sweden; and the United Kingdom. We include all firms which report employment, costs of employees, value added and their industry code. In what follows, we document our data cleaning procedure and subsequently provide detailed summary statistics on the firm level variables and their representativeness relative to country statistics.

Data cleaning procedure.—We take various steps to ensure a sample of high quality underlying variables. First, we keep only firms which report a strictly positive value for employment, costs of employees and value added. Second, to account for outliers which could suffer from mismeasurement issues (e.g. values in thousands instead of millions), for firms with value added above one million euros, we drop those with value added or cost of employees which is 1,000 times larger or smaller from the previous year. Finally, we drop country-industry-year combinations with less than 20 firms to ensure that our *CN* measures do not capture the full market.

Next, we correct for broken book years that could affect our three variables of interest at the annual level. More specifically, the reported book year should match the corresponding calendar year, i.e. 1 January - 31 December. When this is not the case, we proportionally allocate the reported values of our variables of interest based on the number of months covering the respective calendar year.[27]

Summary statistics and representativeness.—Finally, Appendix Table A.1 shows the number of observations for each time period, which increase from 784,874 in year 2000 to 1,345,071 in 2015. We note that the number of observations in 2016 is slightly lower, 1,178,002. This likely indicates that some firm-year observations have yet to be included in Orbis Global. Appendix Table A.2 shows the number of observations by country. Spain, Italy, France, Portugal, and Sweden are best reported in the data, while Germany, on the other hand, seems to be underrepresented. Key information is lacking for the Netherlands and Luxembourg in certain years, leading to a small sample for these countries. To account for this, we check the robustness of our results using a balanced sample of country-sectors.

[27] For example, assume that a firm produces €100 during a book year which spans 1 April 2004 – 31 March 2005. To align this with the calendar year, we thus assign €75 (9 out of 12 months) to year 2004 and €25 (3 out of 12 months) to year 2005. Now, if in the subsequent book year (1 April 2005 – 31 March 2006) the firm produces €200, we assign €150 to year 2005 and €50 in year 2006. Summing the information within the same year results in a value of €175 for 2005. Note that we only do this if there is information available for a full 12 month period. If not the case, we extrapolate the monthly values within the calendar year. Note that this procedure results in some cases with data in 1999, which we drop.

Table A.1: Number of firm-year observations by year

Year	Observations	Share %
2000	784,874	3.88
2001	864,205	4.28
2002	995,055	4.92
2003	1,023,400	5.06
2004	957,939	4.74
2005	984,121	4.87
2006	1,283,135	6.35
2007	1,271,686	6.29
2008	1,408,581	6.97
2009	1,355,538	6.71
2010	1,225,115	6.06
2011	1,407,991	6.97
2012	1,410,202	6.98
2013	1,396,756	6.91
2014	1,318,824	6.53
2015	1,345,071	6.66
2016	1,178,002	5.83
Total	20,210,495	100.00

Notes: Unbalanced panel of 3,601,418 firms over the period 2000-2016.

Table A.2: Number of firm-year observations by country

Country	Observations	Share %
AT	34,084	0.17
BE	179,590	0.89
DE	468,685	2.32
DK	174,631	0.86
ES	7,567,313	37.44
FI	488,455	2.42
FR	3,071,521	15.20
IE	19,506	0.10
IT	4,548,408	22.51
LU	4,344	0.02
NL	3,326	0.02
PT	1,582,086	7.83
SE	1,614,338	7.99
UK	454,208	2.25
Total	20,210,495	100.00

Notes: Unbalanced panel of 3,601,418 firms over the period 2000-2016.

Moving to our variables of interest, Appendix Table A.3 compares total number of employees for each country in year 2015 based on data from Orbis with official data from Eurostat. Our dataset covers approximately the entire private labour force in Italy, Spain, Ireland, and Portugal. On the other hand, countries like Germany are only partly covered. Next, Appendix Table A.4 shows the number of firms by country-year and Appendix Table A.5 shows the number of sectors at the country-year level. Lastly, Appendix Table A.6 shows the number of sectors which are present in all years at the country-year level, i.e. for the balanced sample.

Table A.3: Representativeness of private sector employment in Orbis Global vs. Eurostat

(1) Country	(2) Total Employment	(3)	(4) Employment	(5) Self-employed	(6) Employment
	Orbis	Eurostat	Share %	Eurostat	Share % excl. (5)
AT	961,630	2,471,300	0.39	261,500	0.44
BE	1,163,283	2,307,400	0.50	468,900	0.63
DE	7,211,553	24,170,700	0.30	2,614,700	0.33
DK	736,287	1,421,800	0.52	143,000	0.58
ES	6,805,309	9,369,200	0.73	2,287,300	0.96
FI	652,583	1,243,900	0.52	183,600	0.62
FR	6,167,852	13,684,600	0.45	1,750,700	0.52
IE	941,396	1,122,700	0.84	176,100	0.99
IT	7,817,975	10,994,000	0.71	3,741,100	1.08
LU	49,481	117,100	0.42	2,700	0.43
PT	1,916,934	2,326,900	0.82	409,900	1.00
SE	1,209,570	2,466,100	0.49	304,100	0.56
UK	6,656,555	15,977,700	0.42	2,974,400	0.51
Mean	3,253,108	6,744,108	0.55	1,178,308	0.67

Notes: Column (2) shows the total number of employees based on our sample from the Orbis Global database. Column (3) shows the total number of employees based on Eurostat (2020a) statistics. Both columns cover NACE Rev.2 2-digit industry categories 10-82. Column (4) is defined as the ratio of column (2) over column (3). Column (5) displays the number of self-employed workers reported in Eurostat which in most countries are not included in the Orbis annual accounts. Column (6) is the ratio of (2) over the difference between (3) and (5).

Table A.4: Number of firm-year observations by country-year groups

	AT	BE	DE	DK	ES	FI	FR	IE	IT	LU	NL	PT	SE	UK	Total
2000	28	11,303	1,416	17,134	256,571	26,570	216,191	0	120,807	0	928	756	95,515	37,655	784,874
2001	36	10,748	1,949	17,746	317,444	29,200	214,183	0	133,245	0	1,255	607	99,807	37,985	864,205
2002	182	7,685	3,932	19,099	386,482	34,304	203,803	0	198,421	0	185	543	103,799	36,620	995,055
2003	237	8,379	5,433	17,557	435,252	36,800	227,134	0	155,191	0	131	165	103,014	34,107	1,023,400
2004	669	8,497	7,394	267	451,154	33,024	233,975	0	91,095	0	167	219	101,807	29,671	957,939
2005	298	8,560	16,053	0	482,047	30,542	228,721	162	96,474	0	239	68	92,172	28,785	984,121
2006	369	9,984	31,389	0	515,057	30,259	191,499	1,631	196,527	0	217	195,640	81,938	28,625	1,283,135
2007	241	10,354	34,012	0	485,829	30,462	180,157	2,336	225,106	29	172	189,737	85,123	28,128	1,271,686
2008	238	10,291	34,874	0	520,476	25,599	167,447	2,221	321,838	130	32	189,178	109,965	26,292	1,408,581
2009	670	10,305	35,614	0	519,493	24,806	176,552	1,988	263,842	380	0	185,840	112,280	23,768	1,355,538
2010	2,630	10,682	37,455	0	494,005	24,738	192,110	1,800	205,000	545	0	140,297	93,880	21,973	1,225,115
2011	4,739	11,051	43,963	2,554	482,023	28,064	177,926	1,604	414,491	589	0	132,153	87,786	21,048	1,407,991
2012	4,910	11,973	65,250	13,955	464,589	29,203	154,401	1,419	432,782	609	0	123,263	87,551	20,297	1,410,202
2013	5,152	12,662	68,825	13,436	456,145	29,431	154,276	1,505	428,377	606	0	118,235	88,118	19,988	1,396,756
2014	5,408	12,862	38,409	13,490	461,301	29,215	145,619	1,742	440,068	608	0	59,263	90,500	20,339	1,318,824
2015	5,320	12,953	32,896	16,272	446,987	26,533	123,417	1,820	442,275	560	0	122,725	92,649	20,664	1,345,071
2016	2,957	11,301	9,821	43,121	392,458	19,705	84,110	1,278	382,869	288	0	123,397	88,434	18,263	1,178,002
Total	34,084	179,590	468,685	174,631	7,567,313	488,455	3,071,521	19,506	4,548,408	4,344	3,326	1,582,086	1,614,338	454,208	20,210,495

Notes: Unbalanced panel of 3,601,418 firms observations over the period 2000-2016.

Table A.5: Number of industries by country-year groups for country-industry-year pairs with more than 20 firm-year observations

	AT	BE	DE	DK	ES	FI	FR	IE	IT	LU	NL	PT	SE	UK	Total
2000	1	51	25	50	64	59	65	0	63	0	16	12	61	62	529
2001	1	51	29	51	64	60	65	0	63	0	19	12	60	63	538
2002	5	48	42	53	65	60	64	0	63	0	4	12	61	63	540
2003	7	50	49	52	65	60	65	0	63	0	2	4	61	62	540
2004	12	52	52	5	65	60	65	0	63	0	3	5	60	62	504
2005	7	50	58	0	65	58	65	5	63	0	6	2	60	62	501
2006	10	52	61	0	65	59	65	26	64	0	5	62	60	63	592
2007	5	52	63	0	65	59	65	32	65	1	4	62	60	62	595
2008	5	52	63	0	65	57	65	32	65	4	1	62	60	63	594
2009	15	52	63	0	65	57	64	32	65	10	0	62	60	63	608
2010	36	53	63	0	65	57	65	29	65	11	0	62	60	63	629
2011	46	52	63	25	64	59	63	28	65	11	0	62	60	63	661
2012	47	52	64	57	64	59	64	26	65	11	0	62	61	61	693
2013	47	53	64	57	64	59	64	25	65	11	0	62	61	61	693
2014	47	53	63	58	64	59	64	28	65	11	0	61	61	62	696
2015	47	53	63	58	64	59	64	27	65	11	0	62	61	62	696
2016	37	53	56	61	64	58	63	22	65	8	0	62	61	61	671
Total	375	879	941	527	1,097	999	1,095	312	1,092	89	60	728	1,028	1,058	10,280

Notes: Unbalanced panel of 10,280 country-industry-year groups over the period 2000-2016.

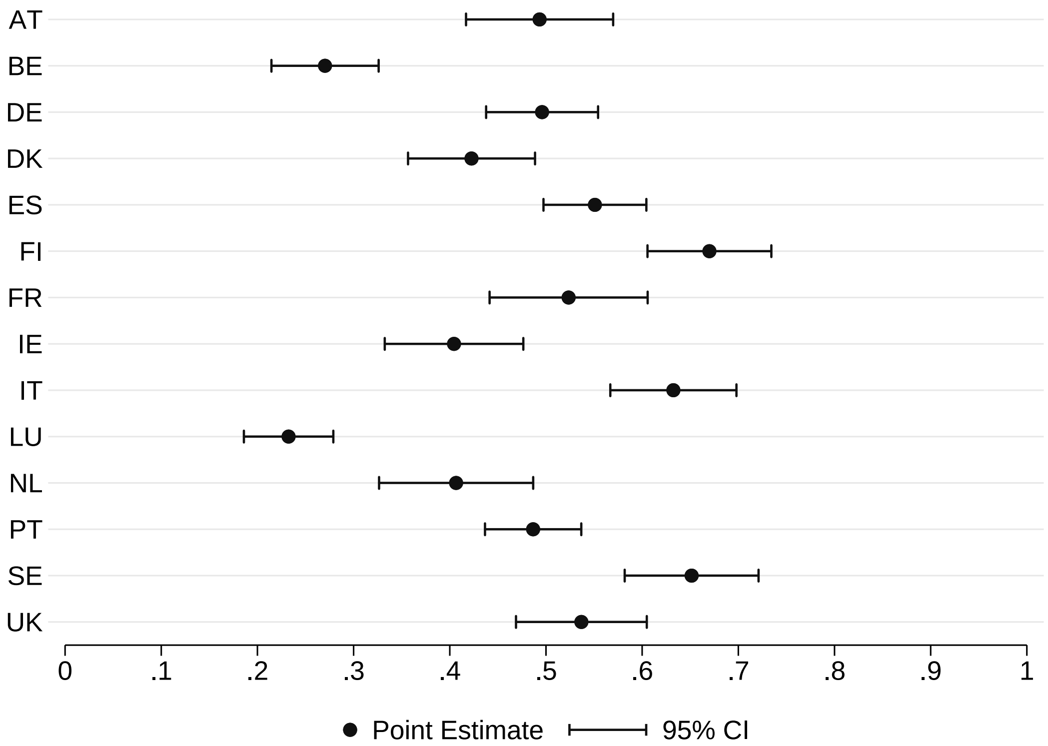
Table A.6: Number of industries by country-year groups for country-industry-year pairs with more than 20 firm-year observations for all years in the sample (balanced sample)

	AT	BE	DE	ES	FI	FR	IT	PT	SE	UK	Total
2000	1	48	24	64	56	63	63	2	60	59	440
2001	1	48	24	64	56	63	63	2	60	59	440
2002	1	48	24	64	56	63	63	2	60	59	440
2003	1	48	24	64	56	63	63	2	60	59	440
2004	1	48	24	64	56	63	63	2	60	59	440
2005	1	48	24	64	56	63	63	2	60	59	440
2006	1	48	24	64	56	63	63	2	60	59	440
2007	1	48	24	64	56	63	63	2	60	59	440
2008	1	48	24	64	56	63	63	2	60	59	440
2009	1	48	24	64	56	63	63	2	60	59	440
2010	1	48	24	64	56	63	63	2	60	59	440
2011	1	48	24	64	56	63	63	2	60	59	440
2012	1	48	24	64	56	63	63	2	60	59	440
2013	1	48	24	64	56	63	63	2	60	59	440
2014	1	48	24	64	56	63	63	2	60	59	440
2015	1	48	24	64	56	63	63	2	60	59	440
2016	1	48	24	64	56	63	63	2	60	59	440
Total	17	816	408	1,088	952	1,071	1,071	34	1,020	1,003	7,480

Notes: Balanced panel of 7,480 country-industry-year groups over the period 2000-2016.

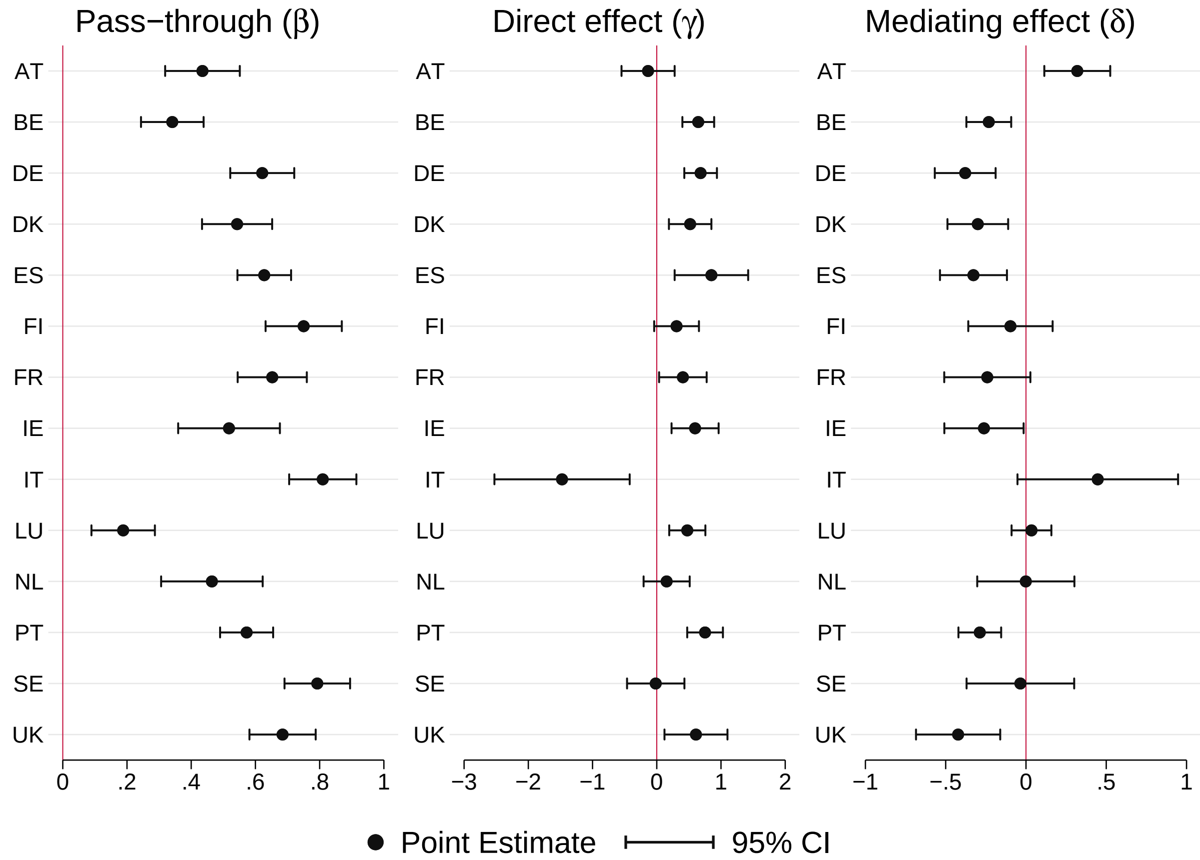
B Additional figures

Figure B.1: The link between wage and productivity dispersion by country



Source: Authors' estimations using Orbis Global database.
Notes: This dot presents point estimates from regressing wage dispersion ($WD_{cit}^{90/10}$) on productivity dispersion ($PD_{cit}^{90/10}$), i.e. β parameter in equation (5), for each country separately. All regressions include industry (i) and year (t) fixed effects, and are weighted by the logarithm of total value added at the industry-year (it) level. The tick-marks around the point estimates represent the clustered at the industry (i) level 95% confidence intervals.

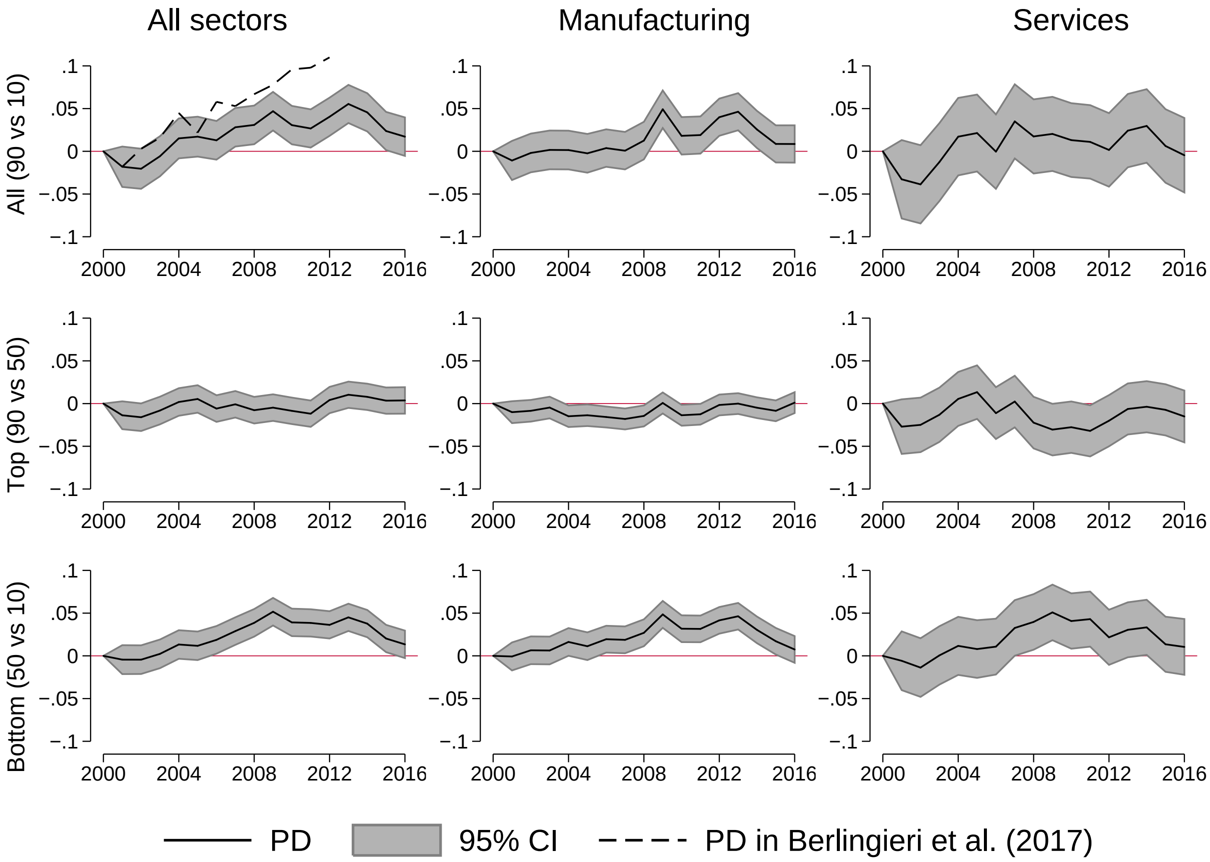
Figure B.2: Superstar firms and the link between productivity and wage dispersion by country



Source: Authors' estimations using Orbis Global database.

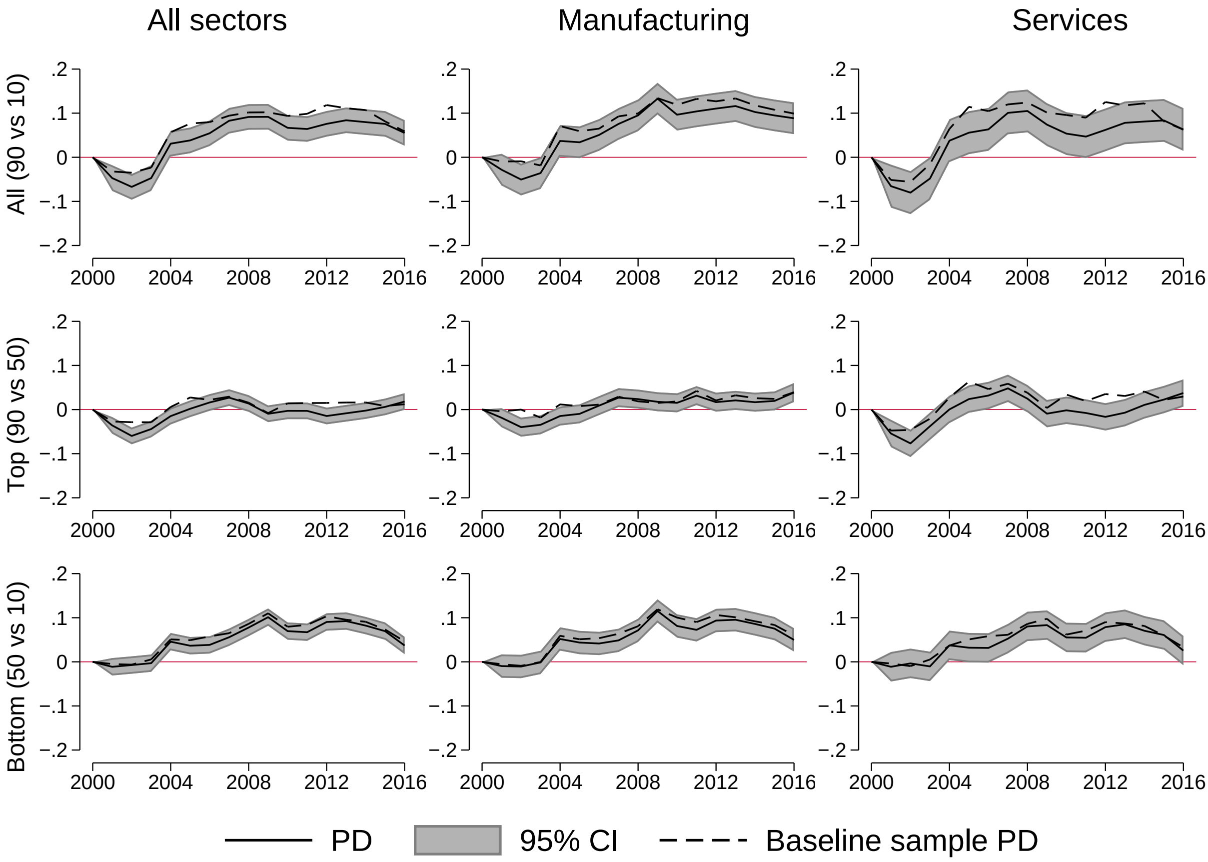
Notes: The dots present point estimates from regressing wage dispersion ($WD_{cit}^{90/10}$) on productivity dispersion ($PD_{cit}^{90/10}$), market concentration ($CN4_{cit}$), and their interaction ($PD_{cit}^{90/10} * CN4_{cit}$), i.e. β, γ, and δ parameters in equation (6), respectively. All regressions include industry (i) and year (t) fixed effects, and are weighted by the logarithm of total value added at the industry-year (it) level. The tick-marks around the point estimates represent the clustered at the industry (i) level 95% confidence intervals.

Figure B.3: Evolution of productivity dispersion (PD) using TFP estimates



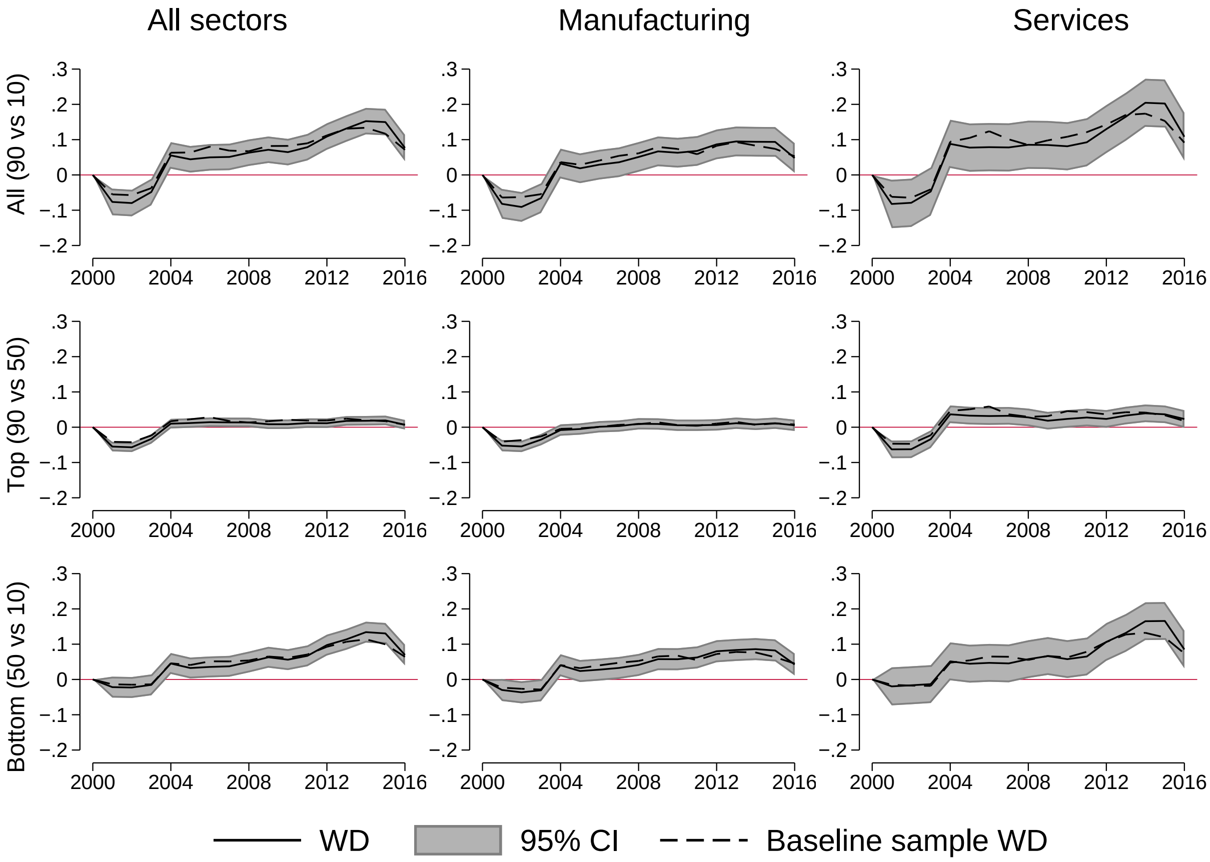
Source: Authors' estimations using Orbis Global database.
Notes: The solid line connects the estimated coefficients from regressing productivity dispersion (PD_{cit}) on a set of year dummies, i.e. parameter set β_t in equation (3). The chosen base year is 2000. All regressions include country-industry (*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. Left, middle and right column panels use data for all sectors (NACE 10-82), manufacturing (NACE 10-33), and services (NACE 49-82), respectively. The PD_{cit} measures are computed using firm-level TFP estimated from a gross-output production function with capital, labour and material inputs following the non-parametric identification strategy of (Gandhi et al. 2020). The dashed line in the top-left panel corresponds to PD_{cit} of TFP found in Berlingieri et al. (2017).

Figure B.4: Evolution of productivity dispersion (*PD*) for balanced sample



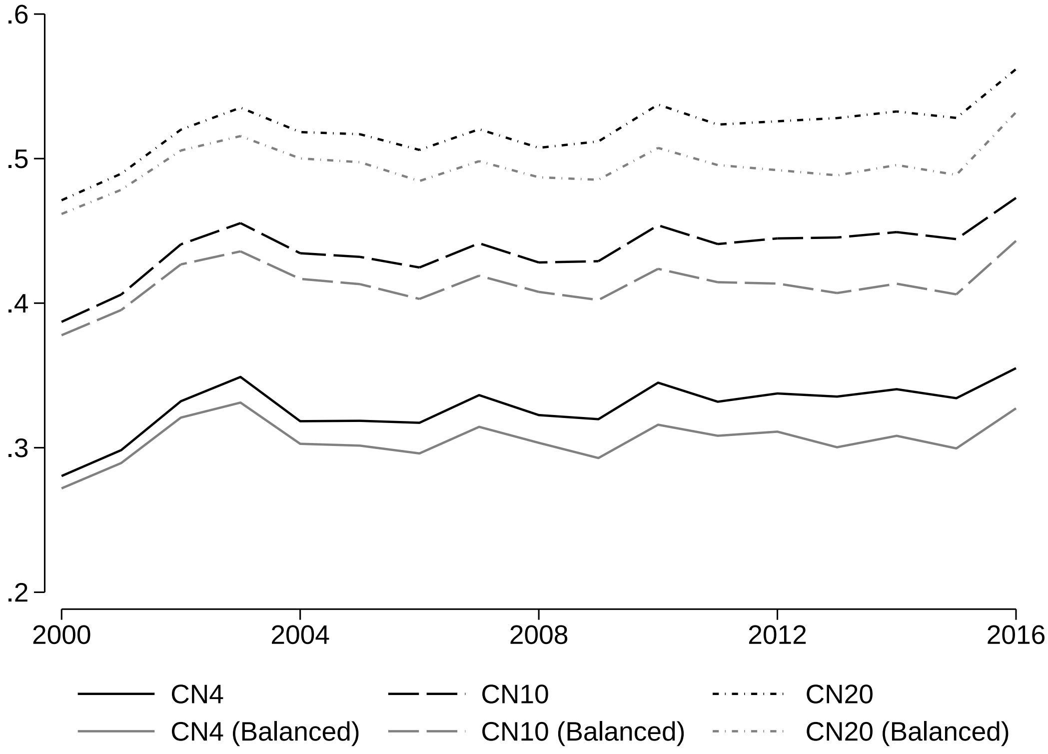
Source: Authors' estimations using Orbis Global database.
Notes: The solid line connects the estimated coefficients from regressing productivity dispersion (PD_{cit}) on a set of year dummies, i.e. parameter set β_t in equation (3). The chosen base year is 2000. All regressions include country-industry (*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. Left, middle and right column panels use data for all sectors (NACE 10-82), manufacturing (NACE 10-33), and services (NACE 49-82), respectively. The dashed line in the top-left panel corresponds to PD_{cit} found in Berlingieri et al. (2017). The sample is balanced and only includes country-industry groups present in all years between 2000-2016.

Figure B.5: Evolution of wage dispersion (WD) for balanced sample



Source: Authors' estimations using Orbis Global database.
Notes: The solid line connects the estimated coefficients from regressing wage dispersion (WD_{cit}) on a set of year dummies, i.e. parameter set β_t in equation (4). 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. Left, middle and right column panels use data for all sectors (NACE 10-82), manufacturing (NACE 10-33), and services (NACE 49-82), respectively. The dashed line in the top-left panel corresponds to WD_{cit} in Berlingieri et al. (2017). The sample is balanced and only includes country-industry groups present in all years between 2000-2016.

Figure B.6: Evolution of market concentration (*CN*) for balanced sample



Source: Authors' estimations using Orbis Global database.
Notes: The lines connect the estimated coefficients from regressing the market concentration measures (*CN*4, *CN*10, *CN*20) on a set of year dummies. All regressions are weighted by the logarithm of total value added at the country-industry-year (*cit*) level. The shaded lines repeat the analysis for the balanced sample, i.e. only includes country-industry groups present in all years between 2000-2016.

C Additional tables

Table C.1: Superstar firms and the link between productivity and wage dispersion with $CN10$ concentration measure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All Sectors			Manufacturing			Services		
	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$
$PD_{cit}^{90/10}$	0.606***			0.574***			0.681***		
	(0.056)			(0.072)			(0.078)		
$PD_{cit}^{90/50}$		0.348***			0.336***			0.416***	
		(0.049)			(0.079)			(0.069)	
$PD_{cit}^{50/10}$			0.907***			0.543***			1.104***
			(0.113)			(0.080)			(0.180)
$CN10_{cit}$	0.452***	0.075*	0.368***	0.474***	0.123	0.129	0.689***	0.135*	0.622***
	(0.120)	(0.044)	(0.106)	(0.141)	(0.077)	(0.097)	(0.192)	(0.070)	(0.203)
$PD_{cit}^{90/10} * CN10_{cit}$	-0.266***			-0.271***			-0.357***		
	(0.074)			(0.099)			(0.104)		
$PD_{cit}^{90/50} * CN10_{cit}$		-0.109**			-0.133			-0.159**	
		(0.047)			(0.097)			(0.064)	
$PD_{cit}^{50/10} * CN10_{cit}$			-0.455***			-0.080			-0.698***
			(0.145)			(0.143)			(0.237)
R^2	0.894	0.882	0.853	0.912	0.869	0.891	0.883	0.876	0.845
Observations	10,268	10,268	10,268	3,757	3,757	3,757	4,727	4,727	4,727

Notes: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. This table presents point estimates from regressing wage dispersion (WD_{cit}) on productivity dispersion (PD_{cit}), market concentration ($CN10_{cit}$), and their interaction ($PD_{cit} * CN10_{cit}$), i.e. β, γ, and δ parameters in equation (6), respectively. The dispersion measures considered capture the entire (90/10), upper (90/50) and bottom (50/10) parts of the respective distributions. $CN10_{cit}$ captures the market shares of the 10 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), manufacturing (NACE 10-33), and services (NACE 49-82), respectively.

Table C.2: Superstar firms and the link between productivity and wage dispersion with $CN20$ concentration measure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		All Sectors			Manufacturing			Services	
	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$
$PD_{cit}^{90/10}$	0.691***			0.643***			0.787***		
	(0.077)			(0.083)			(0.114)		
$PD_{cit}^{90/50}$		0.367***			0.382***			0.432***	
		(0.060)			(0.103)			(0.085)	
$PD_{cit}^{50/10}$			0.996***			0.572***			1.257***
			(0.146)			(0.089)			(0.241)
$CN20_{cit}$	0.532***	0.082	0.383***	0.565***	0.151*	0.169*	0.813***	0.146*	0.681***
	(0.140)	(0.053)	(0.116)	(0.145)	(0.086)	(0.101)	(0.243)	(0.085)	(0.236)
$PD_{cit}^{90/10} * CN20_{cit}$	-0.334***			-0.318***			-0.441***		
	(0.092)			(0.102)			(0.137)		
$PD_{cit}^{90/50} * CN20_{cit}$		-0.118*			-0.170			-0.161*	
		(0.060)			(0.114)			(0.085)	
$PD_{cit}^{50/10} * CN20_{cit}$			-0.506***			-0.107			-0.797***
			(0.168)			(0.144)			(0.282)
R^2	0.894	0.882	0.854	0.913	0.870	0.891	0.883	0.876	0.845
Observations	10,268	10,268	10,268	3,757	3,757	3,757	4,727	4,727	4,727

Notes: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. This table presents point estimates from regressing wage dispersion (WD_{cit}) on productivity dispersion (PD_{cit}), market concentration ($CN20_{cit}$), and their interaction ($PD_{cit} * CN20_{cit}$), i.e. β, γ, and δ parameters in equation (6), respectively. The dispersion measures considered capture the entire (90/10), upper (90/50) and bottom (50/10) parts of the respective distributions. $CN20_{cit}$ captures the market shares of the 20 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), manufacturing (NACE 10-33), and services (NACE 49-82), respectively.

Table C.3: Superstar firms and the link between productivity and wage dispersion with *HHI* concentration measure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All Sectors			Manufacturing			Services		
	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$
$PD_{cit}^{90/10}$	0.424***			0.409***			0.431***		
	(0.033)			(0.041)			(0.045)		
$PD_{cit}^{90/50}$		0.279***			0.254***			0.308***	
		(0.033)			(0.029)			(0.044)	
$PD_{cit}^{50/10}$			0.630***			0.507***			0.670***
			(0.049)			(0.057)			(0.060)
HHI_{cit}	0.285**	0.066	0.322***	0.377**	0.118**	0.141	0.375**	0.090	0.451**
	(0.120)	(0.062)	(0.116)	(0.151)	(0.060)	(0.133)	(0.188)	(0.088)	(0.180)
$PD_{cit}^{90/10} * HHI_{cit}$	-0.132**			-0.198**			-0.149*		
	(0.062)			(0.092)			(0.079)		
$PD_{cit}^{90/50} * HHI_{cit}$		-0.085			-0.111			-0.098	
		(0.057)			(0.069)			(0.072)	
$PD_{cit}^{50/10} * HHI_{cit}$			-0.331**			-0.114			-0.438**
			(0.149)			(0.185)			(0.196)
R^2	0.892	0.881	0.852	0.911	0.869	0.891	0.881	0.875	0.841
Observations	10,268	10,268	10,268	3,757	3,757	3,757	4,727	4,727	4,727

Notes: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. This table presents point estimates from regressing wage dispersion (WD_{cit}) on productivity dispersion (PD_{cit}), market concentration (HHI_{cit}), and their interaction ($PD_{cit} * HHI_{cit}$), i.e. β, γ, and δ parameters in equation (6), respectively. The dispersion measures considered capture the entire (90/10), upper (90/50) and bottom (50/10) parts of the respective distributions. HHI_{cit} is the Herfindahl-Hirschman Index for 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), manufacturing (NACE 10-33), and services (NACE 49-82), respectively.

Table C.4: Superstar firms and the link between productivity (using TFP estimates) and wage dispersion

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All Sectors			Manufacturing			Services		
	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$
$PD_{cit}^{90/10}$	0.329***			0.620***			0.223***		
	(0.052)			(0.071)			(0.078)		
$PD_{cit}^{90/50}$		0.181***			0.484***			0.145**	
		(0.041)			(0.084)			(0.060)	
$PD_{cit}^{50/10}$			0.404***			0.549***			0.241**
			(0.083)			(0.082)			(0.112)
$CN4_{cit}$	0.213***	0.092***	0.169**	0.133	0.122**	0.033	0.030	0.093	0.082
	(0.076)	(0.034)	(0.069)	(0.124)	(0.050)	(0.078)	(0.162)	(0.066)	(0.134)
$PD_{cit}^{90/10} * CN4_{cit}$	-0.143**			-0.059			-0.012		
	(0.064)			(0.173)			(0.096)		
$PD_{cit}^{90/50} * CN4_{cit}$		-0.112**			-0.260**			-0.087	
		(0.052)			(0.120)			(0.074)	
$PD_{cit}^{50/10} * CN4_{cit}$			-0.244**			0.089			-0.089
			(0.116)			(0.234)			(0.170)
R^2	0.884	0.866	0.850	0.928	0.895	0.902	0.864	0.850	0.834
Observations	7,696	7,696	7,696	2,977	2,977	2,977	3,364	3,364	3,364

Notes: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. 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 (6), 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), manufacturing (NACE 10-33), and services (NACE 49-82), respectively. The PD_{cit} measures are computed using firm-level TFP estimated from a gross-output production function with capital, labour and material inputs following the non-parametric identification strategy of (Gandhi et al. 2020).

Table C.5: Superstar firms and the link between productivity and wage dispersion with balanced sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		All Sectors			Manufacturing			Services	
	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$
$PD_{cit}^{90/10}$	0.636***			0.571***			0.654***		
	(0.062)			(0.062)			(0.088)		
$PD_{cit}^{90/50}$		0.296***			0.370***			0.303***	
		(0.049)			(0.074)			(0.066)	
$PD_{cit}^{50/10}$			0.947***			0.647***			1.062***
			(0.117)			(0.067)			(0.174)
$CN4_{cit}$	0.492***	0.020	0.498***	0.484***	0.157**	0.286***	0.469*	-0.089	0.716***
	(0.134)	(0.036)	(0.130)	(0.131)	(0.077)	(0.090)	(0.259)	(0.058)	(0.233)
$PD_{cit}^{90/10} * CN4_{cit}$	-0.298***			-0.275***			-0.267*		
	(0.085)			(0.092)			(0.142)		
$PD_{cit}^{90/50} * CN4_{cit}$		-0.050			-0.202**			0.048	
		(0.037)			(0.099)			(0.054)	
$PD_{cit}^{50/10} * CN4_{cit}$			-0.645***			-0.300**			-0.846***
			(0.179)			(0.135)			(0.280)
R^2	0.917	0.925	0.884	0.941	0.885	0.931	0.909	0.927	0.879
Observations	7,446	7,446	7,446	2,788	2,788	2,788	3,366	3,366	3,366

Notes: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. 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 (6), 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), manufacturing (NACE 10-33), and services (NACE 49-82), respectively. The sample is balanced and only includes country-industry groups present in all years between 2000-2016.

Table C.6: Superstar firms and the link between productivity and wage dispersion with enhanced data representativeness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All Sectors			Manufacturing			Services		
	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$
$PD_{cit}^{90/10}$	0.594***			0.638***			0.601***		
	(0.063)			(0.145)			(0.078)		
$PD_{cit}^{90/50}$		0.294***			0.257***			0.315***	
		(0.087)			(0.051)			(0.113)	
$PD_{cit}^{50/10}$			0.710***			0.660***			0.766***
			(0.059)			(0.142)			(0.071)
$CN4_{cit}$	0.394***	0.054	0.236***	0.200	0.061	0.060	0.500***	0.041	0.351***
	(0.113)	(0.078)	(0.069)	(0.145)	(0.046)	(0.115)	(0.175)	(0.121)	(0.091)
$PD_{cit}^{90/10} * CN4_{cit}$	-0.257***			-0.204*			-0.286***		
	(0.077)			(0.109)			(0.106)		
$PD_{cit}^{90/50} * CN4_{cit}$		-0.103			-0.120*			-0.088	
		(0.096)			(0.066)			(0.138)	
$PD_{cit}^{50/10} * CN4_{cit}$			-0.272***			-0.130			-0.350***
			(0.091)			(0.157)			(0.108)
R^2	0.912	0.880	0.874	0.908	0.905	0.851	0.902	0.865	0.875
Observations	9,987	9,987	9,987	3,695	3,695	3,695	4,654	4,654	4,654

Notes: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. 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 (6), 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), manufacturing (NACE 10-33), and services (NACE 49-82), respectively. The sample used follows the suggestions in Bajgar et al. (2020) to further improve the representativeness of Orbis Global (see Section 5).

Table C.7: Superstar firms and the link between productivity and wage dispersion with additional trends

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		All Sectors			Manufacturing			Services	
	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$
$PD_{cit}^{90/10}$	0.429***			0.362***			0.471***		
	(0.041)			(0.061)			(0.059)		
$PD_{cit}^{90/50}$		0.290***			0.210***			0.344***	
		(0.044)			(0.045)			(0.061)	
$PD_{cit}^{50/10}$			0.648***			0.435***			0.704***
			(0.063)			(0.073)			(0.080)
$CN4_{cit}$	0.255***	0.038	0.251***	0.179	0.020	0.056	0.302**	0.071	0.262*
	(0.089)	(0.048)	(0.089)	(0.154)	(0.058)	(0.109)	(0.134)	(0.074)	(0.140)
$PD_{cit}^{90/10} * CN4_{cit}$	-0.130***			-0.077			-0.163***		
	(0.047)			(0.103)			(0.061)		
$PD_{cit}^{90/50} * CN4_{cit}$		-0.066			0.003			-0.109*	
		(0.049)			(0.070)			(0.065)	
$PD_{cit}^{50/10} * CN4_{cit}$			-0.254**			-0.010			-0.270*
			(0.110)			(0.147)			(0.150)
R^2	0.927	0.913	0.900	0.934	0.905	0.917	0.916	0.906	0.891
Observations	10,268	10,268	10,268	3,757	3,757	3,757	4,727	4,727	4,727

Notes: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. 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 (6), 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, country-industry linear time trends, 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), manufacturing (NACE 10-33), and services (NACE 49-82), respectively. The number of observations differs slightly compared to Table 3 due to dropping more singleton groups from the presence of the additional trends (Correia 2015).

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