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The great divergence(s)[☆,☆☆]

Giuseppe Berlingieri[a,b,*], Patrick Blanchenay[c], Chiara Criscuolo[b,d]

[a] *ESSEC Business School and THEMA, France*
[b] *Centre for Economic Performance (LSE), United Kingdom*
[c] *Norwegian Church Aid, Norway*
[d] *OECD, France*

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ABSTRACT

This paper provides new evidence on the increasing dispersion in wages and productivity using a unique micro-aggregated firm-level data source, representative for the full population of firms in 12 countries. First, we document an increase in wage and productivity dispersions, for both manufacturing and market services, and show that the increase is mainly driven by the bottom of the wage and productivity distributions. Second, we show that between-firm wage dispersion increased more in sectors that experienced an increase in productivity dispersion; the estimated elasticity is larger at the bottom than at the top of the wage/productivity distributions, consistent with a framework in which more productive firms charge higher mark-ups and/or larger wage mark-downs. Third, we find that both globalisation and digitalisation strengthen the link between productivity and wage dispersion. Our results suggest that policies designed to mitigate wage inequality must take into consideration gaps between firms of the same sectors, and how both globalisation and digitalisation affect these gaps.

1. Introduction

In the last decades, economies have experienced increasing inequality in income between the rich and the poor (OECD, 2016; Piketty, 2014) and in earnings between workers, for example between high- and low-skilled workers (Autor et al., 2003) and between those employed in large versus small businesses (Song et al., 2019). A growing literature shows that a large fraction of the increase in wage inequality is explained by increasing differences in wages *between* firms (e.g., Barth et al., 2016) and that productivity differences are an important driver of the "between-firm" component of wage inequality.[1] At the same time, the productivity gap between high and low productivity firms is increasing (OECD, 2015; Andrews et al., 2016), which suggests that the evolution of the productivity distribution and of the wage distribution might be linked.

This paper furthers the literature on the between-firm 'divergence' in productivity, and 'divergence' in wages, by empirically answering two questions. First, are the divergences in wages and in productivity related? That is: Is it the case that sectors where the productivity dispersion grew faster are also sectors in which the wage dispersion grew faster? Second, if this is the case, is the link between productivity dispersion and wage dispersion homogeneous, or is it affected by structural factors such as digitalisation and globalisation?

We answer these questions by drawing on a unique data source from the OECD MultiProd project, which offers multiple advances over existing cross-country empirical sources. It provides harmonised moments from the distributions of firm average wages and of firm productivity at the 2-digit sector level across 12 OECD countries, with an almost 20-year time span. It provides measures of wage dispersion and productivity dispersion (90–10 percentile gap) based on the entire

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☆☆ The opinions expressed and arguments employed herein are solely those of the authors and do not necessarily reflect the official views of the OECD or of its member countries, nor of Norwegian Church Aid.

* Corresponding author at: ESSEC Business School and THEMA, France.
E-mail address: giuseppe.berlingieri@essec.edu (G. Berlingieri).

[1] See for instance Davis and Haltiwanger (1992), Mortensen (2003), Dunne et al. (2004), Faggio et al. (2010), Bagger et al. (2014).

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population of firms, or a representative re-weighted sample, covering both manufacturing and non-financial services. Finally, it allow us to measure productivity both as real value added per worker (labour productivity) and as multi-factor productivity (MFP). We describe the new data source and our measures of dispersions in Section 2.

Our cross-country data document a secular within-sector divergence in wages and productivity (Section 3). Despite some heterogeneity across countries, we find that wage dispersion increased on average by 12.6% between firms of the same country-sector over the 2001–2012 period. This finding confirms, across 12 countries and within 2-digit sectors, a vast literature showing an increase in wage inequality, and specifically in *between-firm* wage inequality.[2] Furthermore, our data allow us to show that the increase in between-firm wage inequality is due to a greater increase in the gap between the bottom decile and the median of the distribution rather than between the median and the top decile. We estimate that the increase in dispersion in the lower half (50–10 percentile ratio) of the distribution of firm-specific average wages accounts for more than 80% of the increase in within-sector wage dispersion.

In addition, this paper is the first to document, based on the quasi population of firms across 12 countries, an increase in productivity dispersion within 2-digit sectors, for both labour productivity and multi-factor productivity. Over the 2001–2012 period, the within-sector MFP dispersion increased by an average 13.9%, showing a widespread and growing gap between the best and worst performers within sectors. We further show that the productivity divergence occurred mostly at the bottom of the (sectoral) productivity distribution: increasing dispersion in the lower half of the productivity distribution accounts for 75% of that within-sector divergence.

We hypothesise that these two phenomenon are linked. To guide our analysis, we set out a simple conceptual framework linking firms' productivity and wages (Section 4). In a perfectly competitive environment, we would expect a one-to-one passthrough of productivity to wages. But with imperfect markets either for output or labour (e.g. Manning, 2006), the passthrough is imperfect. As a result, we expect the correlation between productivity *dispersion* and wage *dispersion* to be positive but less than one. We demonstrate empirically that sectors that experienced more productivity divergence also experienced more wage divergence (Section 5.1); our estimates for the elasticity of wage dispersion with respect to changes in the productivity dispersion range from 0.22 to 0.50. We also find that these elasticities are larger at the bottom of the wage/productivity distributions than at the top, which is consistent with our framework in which more productive firms charge higher mark-ups and/or apply larger wage mark-downs.[3]

We connect the link between wage divergence and productivity divergence with two structural factors: globalisation on one hand, and digitalisation and intangible capital on the other. In our framework, trade affects product mark-ups and wage mark-downs, which in turn increase the passthrough of productivity to wages. Additionally, ICT and intangible capital produce spillovers that are stronger for more productive firms thanks to their higher absorptive capacity, which again results in a higher measured productivity-wage passthrough. On that basis, we expect the relationship between the divergence in wages and the divergence in productivity to be stronger in sectors that are more open to trade, and more intensive in ICT and/or intangible capital. We confirm these predictions empirically using multiple measures of openness to trade, both in goods and services, and ICT/intangible capital. First, the correlation between productivity dispersion and wage dispersion is indeed higher in sectors more open to trade (Section 5.2). This is true both for manufacturing and service sectors, but stronger for trade in goods (and partially for manufacturing), suggesting a potentially stronger pro-competitive effect. Second, we show that in sectors with higher intensity of ICT use or intangible capital, the correlation between wage dispersion and productivity dispersion is higher (Section 5.3), confirming the role of digitalisation in the joint divergence of productivity and wages. Our findings are consistent across several measures of ICT use and intangible capital, which we construct as time and country invariant in order to capture structural characteristics regarding the scope for the use of digital technologies in each sector.

We rely on a novel firm-level dataset that improves on existing studies with its extended scope: it is based on the near universe of firms across 12 countries, both for manufacturing and services, and measures both labour productivity and multi-factor productivity. We make three main contributions to the literature. First, this paper documents the increase over time in the *dispersion* of productivity and wages within 2-digit sectors, systematically across multiple countries. It complements an expanding literature identifying these divergences, usually separately and for individual countries at a coarser sectoral level. Increasing productivity dispersion has, for instance, been documented for Italy (Del Gatto et al., 2008; Calligaris et al., 2016), Japan (Ito and Lechevalier, 2009), the UK (Faggio et al., 2010), and the US (Decker et al., 2020). Because of the lack of access to cross-country matched employer–employee data, we can only analyse *between-firm* wage dispersion. However, this paper corroborates an extensive literature showing the importance of, and increase in, between-firm wage inequality.[4] This paper furthers this literature by documenting that the divergence of productivity and the divergence of wages co-occur systematically within sectors, based on the entire distribution of firms across 12 countries.

Our second contribution is to show that the gap between firms grew faster in the bottom half of the distribution than in the top half. The existing literature has typically focused on the increase in dispersion at the top. For productivity, the literature has identified the rise of "super-star firms" (e.g. Andrews et al., 2016; Autor et al., 2020). Similarly, the literature on earnings inequality and wages inequality has typically focused either on what happens at the top of individual-level distribution of earnings (e.g. the share of top 1% earners in Piketty and Saez, 2003; Piketty et al., 2017), or on overall between-firm inequality (e.g. Song et al., 2019). Our analysis instead focuses on firms in the middle 80% of the productivity and wage distributions (what happens between the 10th and the 90th deciles). It is therefore the first, to our knowledge, to identify that the productivity gap grew faster between the bottom (decile) and the median, than between the median and the top (decile) of a sector, a result that we show to be systematic across countries and sectors. This finding speaks to the literature documenting an increase in misallocation at the bottom of the productivity distribution (e.g., Gopinath et al., 2017), decreased business dynamism (e.g., Decker et al., 2016), and the slowdown in the knowledge diffusion process (e.g., Andrews et al., 2016; Akcigit and Ates, 2021, 2023).

Our third contribution is to show that the link between productivity divergence and wage divergence is systematically deepened by openness to trade, and by ICT and intangible capital use. This complements the literature showing productivity divergence as a result of globalisation (e.g., Melitz, 2003; Bloom et al., 2016; Bonfiglioli et al., 2018), technological change (see in particular Caselli, 1999), or changes in the competitive environment and firm organisation (e.g., Syverson, 2004)

[2] See Card et al. (2018) and OECD (2021) for recent overviews.

[3] Among others, Edmond et al. (2015) show that higher productivity firms capture higher market shares and charge higher mark-ups. See also Wong (2021) and Yeh et al. (2022) for recent empirical evidence on more productive firms marking down their wages more intensively.

[4] Evidence for between-firm wage inequality has for instance been documented in Brazil (Helpman et al., 2017), Denmark (Bagger et al., 2013), Germany (Baumgarten, 2013; Card et al., 2013; Goldschmidt and Schmieder, 2017), Italy (Card et al., 2014), Sweden (e.g. Håkanson et al., 2021), the UK (Faggio et al., 2010), the US (Dunne et al., 2004; Barth et al., 2016; Song et al., 2019).

on the one hand. On the other, it relates to the large body of the literature on wage inequality, which suggests that the increasing wage gap could be driven by technological change (Card and DiNardo, 2002; Acemoglu and Autor, 2011), as well as globalisation (Helpman et al., 2010) and import competition, especially from low-wage countries (e.g. Autor et al., 2013). We link these two strands of literature by showing that within sectors more open to trade, and sectors with higher ICT use and intangible capital use, the link between productivity divergence and wage divergence is stronger. Taken together, our findings suggest that policies designed to mitigate wage inequality must take into consideration gaps between firms of the same sectors, and how globalisation and digitalisation affect these gaps.

2. Data

2.1. Wages and productivity

The main data source used in the analysis is the OECD "MultiProd" project, a vast distributed microdata project that collects statistical moments of the distribution of firm characteristics (employment, productivity, wages, age, etc.) from representative data across multiple countries. The data are computed by running a standardised program that micro-aggregates confidential firm-level administrative data in each of the participating country. This methodology ensures a high degree of harmonisation and comparability across countries and, at the same time, lowers the burden on national statistical agencies and overcomes the confidentiality constraints of directly using national micro-level administrative databases.[5]

This study relies on the version 1.0 of the MultiProd database (December 2016) and focuses on a subset of the output contained in the data: 2-digit sectoral level measures of productivity dispersion (both labour productivity and multi-factor productivity) and wage dispersion (see Section 2.2). The final sample used in the analysis consists of 12 countries that have provided the results at the 2-digit sector level and for which trade and ICT data offers good coverage. We restrict our analysis to manufacturing and non-financial market services. For most countries the time period spans from early 2000s to 2012. Table 1 details years covered, the underlying data sources, and the sampling thresholds.

Representativeness and comparability are common concerns with cross-country analysis from selected firm-level data. The MultiProd program alleviate these concerns by relying either on data on the full population of firms or by re-weighting data from surveys. The primary source of data for the MultiProd database is indeed administrative data covering the universe or near-universe of businesses with positive employment. For one country in the sample (Italy) administrative data on the full population of firms do not exist, so the program relies on a production survey combined with a business register (BR). The former contains all the variables needed for the analysis of productivity but is limited to a sample of firms; the latter contains a more limited set of variables (mainly employment, sector of activity, age and ownership) but for the entire population of firms. The program uses the BR to compute a population structure by year-sector-size classes (at the 4-digit sectoral level and for eight size bins) that is then used to construct variable-specific weights to re-weight the data contained in the production survey. This methodology ensures that the constructed micro-aggregated data that are as representative as possible of the whole population of firms, and hence comparable across countries.[6] One notable exception among the covered countries is Japan, for which the only data source available for both manufacturing and services on a long time period is the Basic Survey of Japanese Business Structure and Activities, which contains the near universe of firms above 50 employees. In this case the ex-post re-weighting strategy adopted in MultiProd is not effective and the statistics on dispersion will be downward biased in light of the large empirical literature on the presence of firm size-wage and size-productivity premia (e.g., Moore, 1911; Troske, 1999; Bloom et al., 2018, among others).[7,8]

More details on the representativeness of the MultiProd dataset are available in Online Appendix A. The full details on the methodology, the underlying data sources, and the main characteristics of the final dataset are available in Berlingieri et al. (2017) and Bajgar et al. (2019).

2.2. Measures of productivity and wages

The analysis relies on three measures of firm-level productivity, which we label LP_VA, MFP_W, and MFP_SW. The first, labour productivity (LP_VA), is computed as the (real) value-added per worker:

$$\text{LP\_VA}_{it} = \frac{VA_{it}}{L_{it}} \tag{1}$$

where VA_{it} is the value-added of firm i at time t, and L_{it} is its employment.[9] The advantage of this measure is that it is widely available, and fairly immune to measurement error.

Since labour productivity does not quantify the impact of other inputs such as capital, the MultiProd data contain two measures of multi-factor productivity (henceforth MFP). The main measure of MFP in the data, that we label MFP_W, is estimated econometrically at the firm-level using Wooldridge (2009) instrumental variable approach and value added as a measure of output. For robustness, we also include a non-parametric measure of MFP that does not rely on production function estimation. We compute a productivity measure similar to a Solow residual, which we label MFP_SW. While this measure is less data intensive, it relies on important assumptions, departures from which would bias this measure of productivity. Nonetheless, most results obtained when using our estimated MFP_W also carry through using MFP_SW. All the details on the definition and estimation of our measures of multi-factor productivity are contained in Online Appendix B.

For wages, we compute a firm-specific average wage, as the total labour cost TLC for firm i at time t, divided by its employment L_{it}:

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

Since wages are computed as an average at the firm-level, this measure can only account for between-firm wage differentials. Nonetheless, studies in a number of countries have shown that a large portion of the increase in earnings inequality is driven by a divergence in between-firm wages (see Card et al., 2018, for a recent overview). We also show in Online Appendix C that our between-firm measure of wage

[5] This distributed microdata approach was pioneered in the early 2000s in a series of cross-country projects on firm demographics and productivity (Bartelsman et al., 2005, 2009). The OECD currently follows the distributed microdata approach in multiple ongoing projects: MultiProd, DynEmp and MicroBerd (Criscuolo et al., 2014, 2015; Appelt et al., 2018).

[6] The BR also allows for: (i) a more precise treatment of entry and exit; (ii) the calculation of more precise sectoral modes and conversion tables in case of changes in the sectoral classification over time.

[7] Berlingieri et al. (2018) show that the firm size-wage and size-productivity premia are attenuated in the service sector, but still strong for firms below 50 employees.

[8] All the results contained in this paper hold when excluding Japan from the sample.

[9] For the sake of maximising cross-country comparability we rely on headcount (HC) for measuring labour input since it is the one most commonly available in the countries considered. For two countries (Finland and Sweden), HC measures are not available and we rely on full time equivalents (FTE). In Figure F.7 in Online Appendix F we show that Finland and Sweden are the two countries in which the relationship between wage and productivity dispersion is the strongest, so we are confident that the main results of the paper are robust to trends in part-time work.

Table 1
Data coverage.

Country	Years	Data source	Sampling threshold
Australia	2002–2012	Expanded Analytical Business Longitudinal Database (EABLD)	1 employment unit
Austria	2008–2012	"Leistungs- und Strukturstatistik" (Structural Business Statistics, based on corporate tax return data, business register etc.)	1 employment unit
Belgium	2003–2011	Central Balance Sheet Office and National Social Security Office	1 employment unit
Denmark	2000–2012	Accounts Statistics, General Enterprise Statistics (VAT statistics, employment statistics, Business Register etc.)	1 employment unit
Finland	1995–2012	Structural business statistics data (surveys, corporate tax records, and Statistics Finland's Business Register)	1 employment unit
France	1995–2012	FICUS/FARE and LIFI	1 employment unit
Hungary	1998–2012	Corporate Income Tax data (CIT) of National Tax and Custom Administration	Double-entry bookkeeping companies. Since 2004, mandatory for companies with turnover higher than HUF 50 million.
Italy	2001–2012	ASIA (Business Register), Indagine sulle grandi imprese (SCI), Database Commercio Estero (COE), Balance sheet data for limited companies	1 employment unit
Japan	1994–2011	Basic Survey of Japanese Business Structure and Activities	50 employment units and paid-up capital or invested funds of at least JPY 30 million
New Zealand	2000–2011	Longitudinal Business Frame (LBF), Linked employer–employee Data (LEED), Tax-filed company accounts (IR10), and Annual Enterprise Survey (AES)	Mandatory tax filing threshold of NZD 40 000 (rising to NZD 60 000 at end of period), or 1 employment unit
Norway	1995–2012	Accounts statistics (incorporated firms) and business register	1 employment unit
Sweden	2002–2012	SBS administrative data (tax data)	1 employment unit

dispersion is highly correlated with OECD measures of overall wage inequality.

This study focuses on three measures of dispersion for wages, and for productivity: the 90–10, 90–50, and 50–10 ratios. Each of this measure are computed at the country-sector-year level.

- The 90–10 wage ratio (resp. productivity ratio) is defined as the ratio between the 90th and the 10th percentile of the wage (productivity) distribution. A ratio of X can be interpreted as: 'firms at the top of the wage (productivity) distribution, proxied by firms at the 90th percentile, paying (or producing, given the same amount of inputs) X times as much as firms at the bottom of the distribution, proxied by firms at the 10th percentile in the same country-sector-year'.
- The 90–50 wage ratio (resp. productivity ratio) is defined as the ratio of the 90th percentile to the 50th percentile, i.e. the median, of the wage (productivity) distribution. It captures dispersion in the upper tail of the distribution within a country-sector-year.
- 50–10 wage ratio (resp. productivity ratio) is defined as the ratio of the 50th percentile to the 10th percentile of the wage (productivity) distribution. It captures dispersion in the bottom tail of the distribution within a country-sector-year.

We use the word dispersion to describe the static 90–10 gap in wages or productivity at given point in time within a country-sector. We use the word divergence to describe the increase of that gap over time.

2.3. Measures of globalisation and digitalisation

The data from MultiProd are complemented with data from other sources on globalisation and digitalisation. Globalisation is captured with data on imports and exports of goods in manufacturing from the OECD STAN Bilateral Trade Database by Industry and End-use category (BTDIxE), and data on imports and exports of goods *and services* for all sectors from the Trade in Value Added database (TiVA, 2021 edition). These data sources are available at the country, year, and 2-digit sectoral level.

Measuring digitalisation is challenging for two main reasons: (i) it is a multi-faceted phenomenon, and (ii) there are significant limitations to the availability of data in a cross-country cross-sectoral framework and over time. In order to circumvent these issues, and following Calvino et al. (2018), we use five measures of digital intensity capturing different facets of digitalisation, and two measures of knowledge (skill) intensity. All of them, described below, vary at the 2-digit sectoral level, but we construct them as country- and time-invariant. These measures aim at capturing sector-specific structural characteristics in terms of their exposure to digital technology on the one hand, and their need for a highly-skilled or highly-specialised labour force on the other hand.

The five measures of digitalisation are obtained as the following shares: 1. ICT stock in gross non-residential fixed assets; 2. ICT equipment investment in Gross Fixed Capital Formation; 3. Software and database investment in Gross Fixed Capital Formation; 4. ICT hardware expenditures in total Gross Output; 5. ICT services expenditures in total Gross Output;

The measures of ICT in fixed assets, ICT equipment (computer hardware and telecommunication) in GFCF, and software and databases in GFCF take into account both tangible (measures 1 and 2), and intangible ICT capital (measure 3). These measures are obtained from the OECD Annual National Accounts database, ISIC Revision 4. We also use two additional measures based on the use of ICT as intermediate inputs. Given the definition of accounting rules that recommend the capitalisation of expenditures only in case of a useful life of more than one year, the first three measures of ICT stock or investment do not fully reflect the use of digital technologies in the production process. In particular, the previous measures exclude goods or services that are used for a shorter duration (such as software purchased with one year licenses, IT consulting, data processing). Therefore, we also use the purchase of ICT intermediate goods (measure 4) and services (measure 5) normalised by real output, based on the OECD Inter-Country Input-Output (ICIO) database.[10]

Finally, we use two measures of skill and knowledge intensity of sectors. The first measure is based on sector-level skill intensity computed as the share of hours worked by high-skill persons engaged.[11] The second measure captures the knowledge intensity within the service sector.

[10] Further information and details on OECD sources are available at http://stats.oecd.org For details of digitalisation measures constructed at the OECD, see Calvino et al. (2018).

[11] The data on skills, available at country-sector-year level, are ISIC Revision 4 estimates based on the ISIC 3 original data from the World Input Output Database (WIOD), Socio Economic Accounts, July 2014 (Timmer et al., 2015).

Following Berlingieri et al. (2020), we construct a country- and time-invariant dummy variable that divides non-financial market services into knowledge-intensive services (KIS) and less knowledge-intensive services (LKIS).[12]

Note that all the measures of digitalisation and skill intensity are cross-country averages of the underlying data for the period 1995–2000 in each sector, i.e., they are measured at the sector-level and are time invariant. Consequently, these measures do not reflect the heterogeneity in the use of digital technologies across countries in the same industries, nor changes over time, but are likely to capture structural characteristics regarding the scope for the use of digital technologies in each sector.

3. Stylised facts

3.1. The great divergence in wages, and the great divergence in productivity

In this section we document the increase of between-firm wage dispersion and of productivity dispersion, which have occurred within sectors over time. We call this phenomenon the "Great Divergences". For wages, we do so by estimating the following regression:

$$\left(\log W_{90} - \log W_{10}\right)_{cjt} = \boldsymbol{\beta}_t \boldsymbol{y}_t + \boldsymbol{z}_{cj} + \varepsilon_{cjt} \tag{3}$$

where W_{90} and W_{10} are respectively the 90th and 10th wage percentiles, and where c denotes countries, j 2-digit sectors and t years. Observations are at the country-sector-year levels, and are weighted by the number of firms in that country-sector-year. Year dummy estimates $\boldsymbol{\beta}_t$ capture the average dispersion in a given year controlling for any time-invariant country-sector specific unobservable factor through the set of fixed effects $\boldsymbol{z}_{cj}$. The country-sector fixed effects also control for the average levels of dispersion in each country and sector, so that the estimates of the year dummies coefficients $\boldsymbol{\beta}_t$ capture the evolution of wage dispersion within each 2-digit sector in each country.

Fig. 1 shows that within country-sector wage dispersion has been increasing over time, indicating that, by 2012, the 90–10 wage ratio is 12.6% higher than in 2001.[13] It is in that respect that it makes sense to speak of a "Great Divergence" of wages. To get a sense of the magnitude of the results and whether the between-firm wage dispersion captures a meaningful share of overall wage inequality, we run a similar regression using the overall wage inequality in earnings from the OECD Earnings Distribution database. Fig. 1 shows that the evolution of overall wage inequality follows a similar pattern, and in particular that the magnitude of the increase over the analysed period is remarkably similar (13.4% in 2011). Given the different data sources, the level of aggregation, and a somewhat different time coverage, the analysis is only suggestive and it is not possible to draw strong conclusions from this comparison. But the results clearly show that the increase in the between-firm wage dispersion has a similar magnitude to that of the increase in overall earnings inequality.[14]

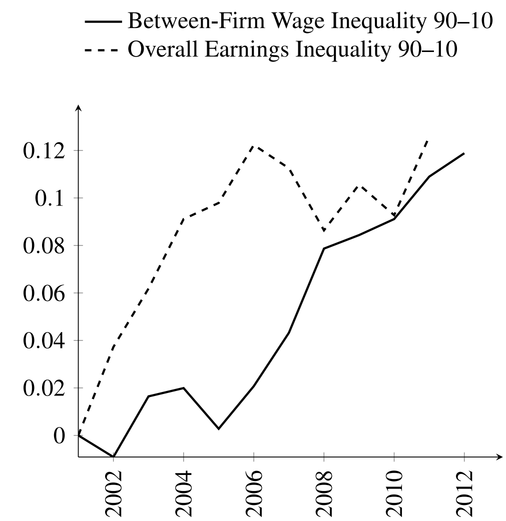

Fig. 1. The "Great Divergence" of wages: Increase in the 90–10 difference in log-wages over time within sectors and countries

Note: The solid line plots the estimated year dummies $\boldsymbol{\beta}_t$ of a regression of log-wage dispersion (90th and 10th percentiles difference) on year dummies, controlling for country-sector pairs, as specified in Eq. (3). The estimates for baseline year 2001 are normalised to 0. Data is at the country-sector-year level, weighted by the number of firms in each cell, from the following countries: AUS, AUT, BEL, DNK, FIN, FRA, HUN, ITA, JPN, NOR, NZL, SWE. As a reference, the dashed line plots the year dummy estimates of a similar regression using the overall inequality in earnings from the OECD Earnings Distribution database within each country. The data on overall inequality are only available at the country level and a few countries have a more limited time coverage. Data for Denmark and Italy are from 2002 but coverage for Italy is limited to even years only.

In parallel to the wage divergence, the productivity distribution also diverged over the same period. We document this by estimating the following regression:

$$\left(\log P_{90} - \log P_{10}\right)_{cjt} = \boldsymbol{\beta}_t \boldsymbol{y}_t + \boldsymbol{z}_{cj} + \varepsilon_{cjt} \tag{4}$$

where P_{90} and P_{10} are respectively the 90th and 10th productivity percentiles, for a given productivity measure P, and where c denotes countries, j sectors and t years. Year dummy estimates $\boldsymbol{\beta}_t$, which capture the average within country-sector dispersion in a given year, can be used to depict the evolution of productivity dispersion within countries-sectors over time.

Fig. 2 shows that for both labour and multi-factor productivity, within-sector dispersion has increased over time on average across all countries. The pattern is remarkably similar across all productivity measures, including the Solow-type MFP. And the growth in dispersion over the period is of the same magnitude as, if not higher than, the increase in wage dispersion. For instance, by 2012, the within-sector dispersion of multi-factor productivity (MFP_W) was on average 13.9% higher than in 2001; labour productivity was 14.3% higher.[15] We can therefore speak of the "Great Divergences" of both wages and productivity, which occurred over the period. In Online Appendix D.2, we document the heterogeneity of the wage and productivity divergences across countries. With the notable exception of New Zealand, most countries display an increase of both wage and productivity dispersion over time, especially in the service sector.

[12] This index relies on the Eurostat classification of knowledge-intensive services, which is based on the share of tertiary educated persons at the NACE Rev.2 2-digit level. For more details, see https://ec.europa.eu/eurostat/cache/metadata/en/htec_esms.htm.

[13] The 12.6% figure is calculated as $100 \times [\exp(\hat{\beta}_{2012}) - 1]$ where $\hat{\beta}_{2012} = 0.119$ is the estimate of the 2012 year dummy in Eq. (3). The detailed results of the regression are presented in Table D.4 in Online Appendix D.

[14] Note that in the paper we use – for brevity's sake – "wage dispersion" to indicate "between-firm wage dispersion" as the latter is the only type of dispersion we can calculate given the information available in MultiProd. In Online Appendix C we show that the observed between-firm measure of wage inequality drawn from the MultiProd data is meaningfully related to the overall wage inequality in earnings available from the OECD Earnings Distribution Database. Unfortunately the analysis is limited by the fact that data on overall inequality in earnings are available only at the country level and often over a more limited period than in the MultiProd database.

[15] The 13.9% figure is calculated as $100 \times [\exp(\hat{\beta}_{2012}) - 1]$ where $\hat{\beta}_{2012} = 0.130$ is the estimate of the 2012 year dummy in column (2) of Eq. (4). The detailed results of the regression are presented in Table D.5 in Online Appendix D. Figure D.2 plots the difference between the 90th and 10th percentiles of log-productivity over time by country.

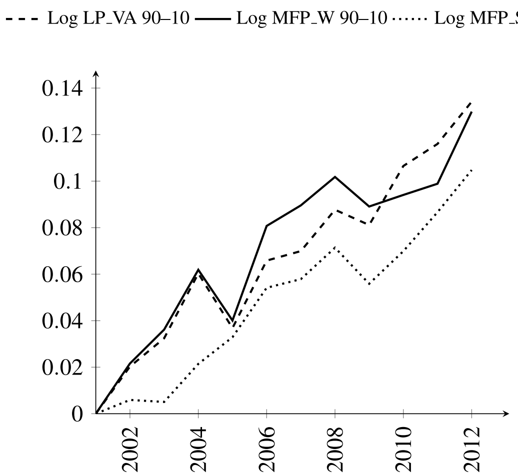

Fig. 2. The "Great Divergence" in productivity: Increase in the 90–10 difference in log-productivity within sectors and countries

Note: The figure plots the year dummy estimates β_t of a regression of log-productivity dispersion (measured as the difference between the 90th and 10th percentiles of log-productivity) on year dummies, controlling for country-sector pairs, as specified in Eq. (4). The estimates for baseline year 2001 are normalised to 0. Data is at the country-sector-year level, weighted by the number of firms in each cell, from the following countries: AUS, AUT, BEL, DNK, FIN, FRA, HUN, ITA, JPN, NOR, NZL, SWE.

3.2. More divergence at the bottom of the distributions

For both wages and productivity, the within-sector divergence comes from the bottom of the distribution. That is, firms at the bottom of the wage distribution are paying increasingly less relative to the median firm; likewise, the gap in productivity between the bottom 10th percentile and the median firm has increased faster than the gap between the median and the top 10th percentile.

To show this, we perform an exercise similar to the econometric approach of Eqs. (3) and (4), this time separately for the 90–50 and the 50–10 log difference in wages, and in productivity. That is, we econometrically estimate the yearly average dispersion within countries and sectors, but separately for the top (90th–50th percentile ratio) and the bottom (50th–10th percentile ratio) of the wage distribution, to ascertain where the divergence was more pronounced.

The results are plotted in Fig. 3(a) for wages, and Fig. 3(b) for productivity where the solid lines are used for the dispersion of MFP and the dashed lines for the dispersion of labour productivity.

Over the decade considered, results shown in Fig. 3(a) suggest that, within each country-sector pair, the divergence in wages is mostly explained by the increased divergence between the median and bottom decile (single line), rather than between the top decile and median (double line). The increase in dispersion in the lower half (50–10 percentile ratio) of the wage distribution accounts for more than 80% of the wage divergence.[16]

Likewise, Fig. 3(b) shows that the within-country sector divergence has been more severe at the bottom of the productivity distribution especially at the beginning of the 2000s and after the crisis (single lines). For labour productivity, the divergence at the bottom accounts for 75% of the increase in within-sector dispersion; for MFP, 80%. We show in Online Appendix D.4 that the divergence "from the bottom" occurs both in manufacturing and in services; the bottom divergence of productivity is particularly pronounced in services.

[16] Online Appendix D.3 shows separately the evolution of the 90th, 50th and 10th deciles of log wages over time: the bottom decile of wages stayed relatively unchanged over the period while the median wage grew by 9.9%, and the top decile by 12.6%.

4. Conceptual framework

In this section, we present a simple framework to understand the link between productivity and wages, and therefore between productivity dispersion and wage dispersion. We first start with a neoclassical production function and perfectly competitive input and output markets, as it is commonly assumed in the large literature on production function estimation (e.g., Olley and Pakes, 1996; Ackerberg et al., 2015). When all these assumptions are satisfied and the labour supply is perfectly inelastic, wages are proportional to productivity, and the elasticity of wage dispersion to productivity dispersion would be equal to one: an increase of 10% in productivity dispersion would create a 10% increase in wage dispersion.

We then show that when relaxing those assumptions (e.g. oligopolistic product market), wages are increasing in, but no longer proportional to, productivity. We can therefore expect the elasticity between wage dispersion and productivity dispersion to be positive, but less than one; we then extend the framework to show how globalisation and digitalisation can affect this elasticity.

For illustration assume that each firm in sector j has a Cobb–Douglas value-added production function with constant returns to scale: $Y_{ij} = A_{ij} L_{ij}^{\alpha_j} K_{ij}^{1-\alpha_j}$, where A_{ij} denote the firm's idiosyncratic multi-factor productivity, and α_j is the sector-specific labour share. If we further assume that input and output markets are perfectly competitive, each firm sells its output at prevailing price ρ_j in sector j, and wages are equal to the marginal revenue of labour. The wage paid by the firm i is given by:

$$W_{ij} = \rho_j \frac{\partial Y_{ij}}{\partial L_{ij}} = \epsilon_{Y,L} \frac{\rho_j Y_{ij}}{L_{ij}} = \alpha_j LP_{ij},$$

where $\epsilon_{Y,L}$ is the labour elasticity of output, and LP_{ij} is firm i's labour productivity. In such a setting, with perfectly competitive input and output markets, and a homogeneous labour elasticity of output across firms within the same sector (α_j), the firm's wage is proportional to labour productivity. When this is the case, the pass-through elasticity of productivity to wages is equal to 1; and by extension the elasticity of wage *dispersion* to productivity *dispersion* would be 1.

However, this set of strong assumptions is unlikely to hold in the data; if either the input or output markets are not perfectly competitive, the pass-through of labour productivity to wages is different from 1. This is indeed what we corroborate empirically in Section 5. For instance if a firm face a downward-sloping demand with elasticity ϵ_{ij}, it charges a mark-up over marginal cost, and the corresponding wage paid to its workers is:

$$W_{ij} = \alpha_j \frac{LP_{ij}}{\mu_{ij}}, \tag{5}$$

where $\mu_{ij} = \frac{\epsilon_{ij}}{\epsilon_{ij}-1}$ is the mark-up of the firm. By taking the ratio between a firm at the 90th and 10th of the distribution of firms within sector j we obtain:

$$\frac{W_{90,j}}{W_{10,j}} = \frac{LP_{90,j}}{LP_{10,j}} \frac{\mu_{10,j}}{\mu_{90,j}}. \tag{6}$$

With an oligopolistic competition market structure (e.g., Atkeson and Burstein, 2008; Edmond et al., 2015, 2023), mark-ups are firm-specific and proportional to the firms' market shares. Higher productivity firms capture higher market shares, charge higher mark-ups, resulting in lower wages (*ceteris paribus*). De Loecker et al. (2020) document a secular increase in aggregate markups, which occurs mostly within industry and is driven by firms in the upper tail of the distribution. Thus, Eq. (6) implies that, in a given sector, the relationship between wage and productivity is increasing, but no longer proportional; instead it depends on each firm's idiosyncratic demand elasticity. Wage *dispersion*, then, is imperfectly correlated with productivity *dispersion*, and the elasticity of wage dispersion to labour productivity dispersion is expected to be less than 1. We test this empirically in the next section;

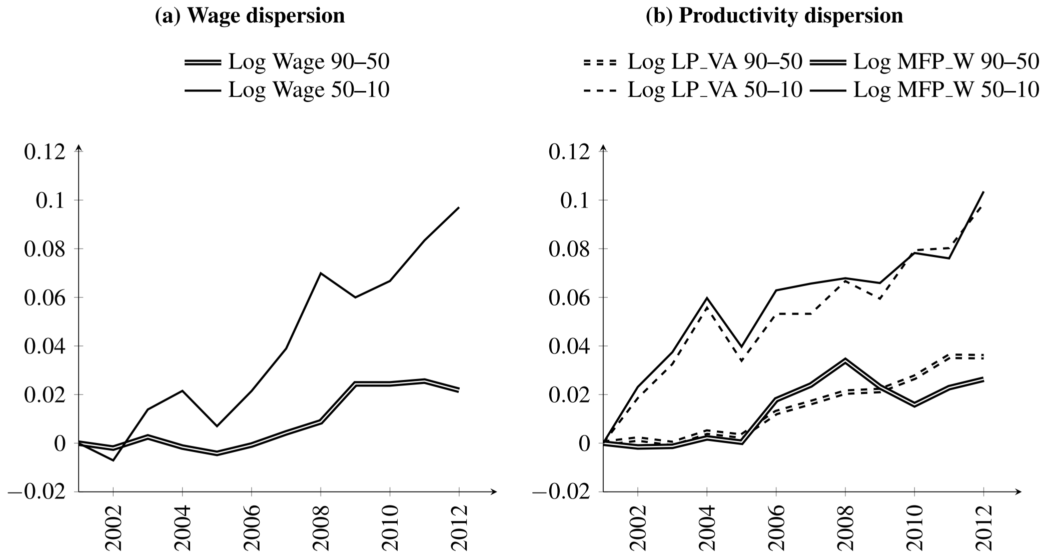

Fig. 3. Divergence at the top vs. bottom of the wage and of the productivity distributions
Note: The figure plots the year dummy estimates of a regression of log-wage dispersion (left panel) or log-productivity dispersion (right panel) at the top (90th and 50th percentiles difference) and at the bottom (50th and 10th percentiles difference) on year dummies, controlling for country-sector pairs. The estimates for baseline year 2001 are normalised to 0. Data is at the country-sector-year level, weighted by the number of firms in each cell, from the following countries: AUS, AUT, BEL, DNK, FIN, FRA, HUN, ITA, JPN, NOR, NZL, SWE.

our estimates for this elasticity, captured by the parameter β in Eq. (8) below, range from 0.22 to 0.50.

Analogously, the presence of imperfect labour markets can also blur the relationship between wage and productivity. A large literature has highlighted the extent of firms monopsony power in labour markets (see Manning, 2011; Card et al., 2018, for a review), which results in wage mark-downs (i.e., the difference between the prevailing wage and the marginal revenue product of labour). Like price mark-ups, wage mark-downs further lower the pass-through of productivity to wages. Furthermore, standard models of imperfectly competitive labour markets (e.g., Burdett and Mortensen, 1998) or more recent oligopsonistic models (e.g., Berger et al., 2022) predict that more productive firms mark-down their wages more intensively because they face a more inelastic labour supply. This fact is supported by recent empirical evidence within 2-digit sectors for France (Wong, 2021) and the US (Yeh et al., 2022, above the 10th percentile of the productivity distribution). In our framework, this implies that the elasticity of wage dispersion to productivity dispersion should be lower at the top of the distribution than at the bottom, and this offers another reason for why the elasticity of wage dispersion to labour productivity dispersion is expected to be less than one.[17]

We have laid out the argument in terms of labour productivity, but the same argument can be made about multi-factor productivity in revenue. For firms with market power, the expression for wages can be rewritten as:

$$W_{ij} = \frac{\alpha_j \rho_j A_{ij}}{\mu_{ij}} \left(\frac{K_{ij}}{L_{ij}}\right)^{1-\alpha_j} = \frac{\alpha_j MFP_{ij}}{\mu_{ij}} \left(\frac{K_{ij}}{L_{ij}}\right)^{1-\alpha_j}, \tag{7}$$

where $MFP_{ij} = \rho_j A_{ij}$ is firm i's MFP in revenue, and μ_{ij} is the firm's mark-up, as before. With imperfectly competitive labour markets, the expression would also include a wage mark-down.

In summary, whether with labour productivity or MFP, we expect the elasticity of wage dispersion to productivity dispersion to be positive but less than one. This is what we investigate in Section 5.1, and find elasticity estimates ranging from 0.22 to 0.50. Although we are not directly interested in the level of pass-through and the specific empirical setting does not allow for direct comparison, our estimates are similar to recent work by Kline et al. (2019) who estimate the pass-through of labour productivity to wages for US patenting firms, and earlier work by Van Reenen (1996) for UK manufacturing firm. We further establish that the pass-through elasticity of productivity to wages is lower at the top of the productivity distribution than at the bottom, in line with the evidence on higher markups and markdowns at the top.

This framework also indicates how globalisation and digitalisation can affect the elasticity of wage dispersion to productivity dispersion. Let us examine these two factors in turn. First, in a class of models of trade and imperfect labour markets (e.g., Helpman et al., 2010) wage dispersion is closely linked to productivity dispersion and opening to trade increases wage dispersion because high-productivity firms start exporting, expand and pay higher wages.[18] As a first order effect, when the economy opens up to trade, an increase in the fraction of exporting firms raises wage dispersion, which increases even further if the underlying productivity distribution becomes more dispersed at the same time.[19] Furthermore, in the presence of pro-competitive effects of trade (e.g., Atkeson and Burstein, 2008; Edmond et al., 2015), firms reduce their mark-ups (proportionally more so at the top), which creates

[17] In presence of imperfect labour markets, Eq. (5) would display an additional term capturing the firm's markdown as follows

$$W_{ij} = \alpha_j \nu_{ij} \frac{LP_{ij}}{\mu_{ij}},$$

where $\nu_{ij} = \frac{\epsilon^L_{ij}}{1+\epsilon^L_{ij}}$ is the firm's markdown and ϵ^L_{ij} is the firm-specific elasticity of labour supply. Multiple sources of labour market imperfections can give rise to a mark-down of wages, including search frictions and information asymmetries.

[18] This results holds as long as not too many firms export, or in the presence of high degree of monopsony power in labour markets as shown in Jha and Rodriguez-Lopez (2021).

[19] Additionally, in Helpman et al. (2010), trade also induces high-productivity exporters to screen more intensively, which strengthens the assortative matching between firms and workers further increasing the link between productivity and wage dispersion.

a higher correlation between wage dispersion and productivity dispersion.[20] Therefore, if the underlying productivity distribution becomes more dispersed and, at the same time, output markets become more competitive, wage dispersion increases even further. For these reasons, we expect a positive interaction between productivity dispersion and trade openness, which is what we test empirically in Section 5.2.

The framework also allows us to understand how digitalisation affects the elasticity of wage dispersion to productivity dispersion. A growing literature documents that larger or more productive firms are more capable at adopting ICT or other forms of intangible capital (e.g., Lashkari et al., 2019; De Ridder, 2024), and that ICT and intangible capital investments trigger wider productivity spillovers (e.g., O'Mahony and Vecchi, 2009; Corrado et al., 2017).

We can capture these channels in our framework by dropping the assumption of a constant labour elasticity of output $\varepsilon_{Y,L}$. For instance we can envisage that the value added of the firm is a function of efficiency units of labour, H_{ij}, which in turn are a CES function of labour inputs L_{ij} and ICT/intangible capital employed by the firm C_{ij}:

$$H_{ij} = \left(\alpha_j^L L_{ij}^{\frac{\sigma_j - 1}{\sigma_j}} + \alpha_j^C C_{ij}^{\frac{\sigma_j - 1}{\sigma_j}} \right)^{\frac{\sigma_j}{\sigma_j - 1}},$$

where σ_j is a constant elasticity of substitution between intangible capital and labour. In this setting the labour elasticity of output becomes

$$\varepsilon_{Y,L} = \frac{\alpha_j \alpha_j^L}{1 + \frac{\alpha_j^C}{\alpha_j^L} \left(\frac{C_{ij}}{L_{ij}} \right)^{\frac{\sigma_j - 1}{\sigma_j}}}.$$

It follows that wage dispersion would also be a function of the difference of the labour elasticity of output between top and bottom of the distribution.[21] In the presence of complementarity between ICT/intangible capital and labour, $\sigma_j < 1$ as in Oberfield and Raval (2021), higher adoption of ICT/intangible capital at the top is an additional force that drives the wage dispersion between top and bottom. This channel is stronger in sectors with higher use of intangible capital, predicting a positive interaction between productivity dispersion and industry-level intangible capital.[22] We test this hypothesis in Section 5.3.

In summary, our framework provides the following predictions. 1. The elasticity of wage dispersion to productivity dispersion is positive but less than one. 2. Openness to trade increases the elasticity of wage dispersion to productivity dispersion. 3. More ICT intensive sectors have a higher elasticity of wage dispersion to productivity dispersion.

5. Empirical investigation

5.1. The link between wage dispersion and productivity dispersion

We now turn to investigate the first prediction of our theoretical framework, namely whether wage dispersion is correlated with productivity dispersion. To examine this claim, we estimate the following regressions:

$$WD_{cjt} = \beta \cdot PD_{cjt} + \mathbf{y}_t + \mathbf{z}_{cj} + \varepsilon_{cjt} \tag{8}$$

where WD_{cjt} denotes log-wage dispersion, PD_{cjt} denotes log-productivity dispersion in country c, sector j and year t. The vectors $\mathbf{y}_t$ and $\mathbf{z}_{cj}$ indicate respectively year and country-sector fixed effects.[23] With this set of fixed effects, the regressions exploit the within-country-sector variations of productivity and wage dispersions over time, that is, the productivity divergence and the wage divergence within country-sector pairs. Since the regression is run on data aggregated at the country-sector-year level, we weight each observation cjt by the number of firms reporting non-missing information for the relevant variable in a given country-sector-year.

In this regression the coefficient of interest is β. Because the regression is run in logs, β is the elasticity of wage dispersion to productivity dispersion. Due to the presence of heterogeneous markups and markdowns across the productivity distribution, we expect $\beta < 1$, in line with the discussion in the previous section. Indeed, when taking logs of Eq. (6) and comparing it with our main estimating equation, it is clear that $\beta \neq 1$ as long as markups are not homogeneous across firms within the same country-sector-year. In light of the evidence that markups have increased more at the top compared to the bottom of the distribution (e.g., De Loecker et al., 2020), we expect an estimate of β lower than one, which is also consistent with the extensive evidence on incomplete pass-through in the rich literature on imperfectly competitive labour markets (e.g., Card et al., 2018). Table 2 reports the estimates of β using different measures of productivity. Column (1) reports the specification where productivity is measured by logged labour productivity; Column (2) reports estimates where the measure of productivity is logged MFP_W; and Column (3) reports estimates of regressions where MFP is a Solow residual (MFP_SW).

The estimates for β from the regression reported in Table 2 are positive and significant. The result suggests that there is a strong correlation between dispersion in wages and dispersion in productivity, for all the productivity measures considered. In other words, sectors that experienced a divergence in productivity also experienced a divergence in wages. An increase of 10% in the 90–10 percentile ratio of labour productivity in given country-sector pair is associated with an increase of 4.9% in the 90–10 percentile ratio of wages; this elasticity is positive and statistically different from zero.[24] In Column (2) an increase of 10% in the 90–10 percentile ratio of MFP_W is associated with an increase by 2.6% of the 90–10 percentile ratio of wages; at 2.1%, the correlation is slightly smaller for the 90–10 percentile ratio of MFP_SW (Column 3) but still significant at the 5% level.

The correlation between productivity dispersion and wage dispersion is positive, but the pass-through of productivity to wages is not homogeneous in a given sector across the distribution. To show this, we look at the correlation between particular percentiles of productivity

[20] Using data for India, MacKenzie (2021) finds that opening to trade induces firms to reduce their wage markdowns as well, but the effect is smaller compared to the effect of trade on firms' markups.

[21] The log difference of the labour elasticity of output between a firm at the 90th and one at the 10th percentile of the productivity distribution can be approximated as

$$\Delta \log \varepsilon_{Y,L} \approx \frac{\alpha_j^C}{\alpha_j^L} \left[\left(\frac{C_{10}}{L_{10}} \right)^{\frac{\sigma_j - 1}{\sigma_j}} - \left(\frac{C_{90}}{L_{90}} \right)^{\frac{\sigma_j - 1}{\sigma_j}} \right].$$

[22] More specifically, we assume that the ICT/intangible capital C_{ij} employed by the firm is a function of industry-level ICT/intangible capital C_j and the firm's absorptive capacity that depends on A_{ij}. Namely, $C_{ij} = f(A_{ij}, C_j)$, with $f_1 > 0$ (more productive firms are better at absorbing industry-level ICT/intangible capital) and $f_2 > 0$ (the firm benefits from industry-level capital, i.e. there are external economies of scale). An alternative mechanism to capital-labour complementarity that would deliver similar results would be productivity spillovers (e.g., O'Mahony and Vecchi, 2009): firms benefit from higher presence of ICT/intangible assets in their industry, and more so firms at the top of the productivity distribution because of their higher absorptive capacity.

[23] More precisely: $WD_{cjt} \equiv \left(\log W_{90} - \log W_{10}\right)_{cjt}$, the 90–10 percentile ratio of log wages. Similarly, for a given measure of a productivity P, we denote $PD_{cjt} \equiv \left(\log P_{90} - \log P_{10}\right)_{cjt}$ the 90–10 percentile ratio of log productivity. The regressions are run using all the available data, that is, an un-balanced panel of country-sector pairs; for time coverage see Table 1. In unreported results, we find that the elasticity of wage dispersion to productivity dispersion is very stable over time, showing that the un-balanced nature of our data does not affect our results.

[24] The 4.9% figure is calculated as $100 \times [1.1^{\hat{\beta}} - 1]$ where $\hat{\beta} = 0.499$.

Table 2
The link between wage dispersion and productivity dispersion.

	(1) log Wage (90-10)	(2) log Wage (90-10)	(3) log Wage (90-10)
log LP (90-10)	0.499***		
	(0.076)		
log MFP_W (90-10)		0.271***	
		(0.086)	
log MFP_SW (90-10)			0.219**
			(0.095)
N	3288	3288	3288
Adj. R-Square	0.972	0.968	0.967
Year FE	YES	YES	YES
Country-sector FE	YES	YES	YES
Nb Sectors	22	22	22
Nb Countries	12	12	12

Clustered standard errors at the country-sector level in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Data is at the country-sector-year level, weighted by the number of firms in each cell.
Countries: AUS, AUT, BEL, DNK, FIN, FRA, HUN, ITA, JPN, NOR, NZL, SWE.

Table 3
Wage-productivity pass-through at the top and bottom of the distribution.

	(1) 90th percentile of LogW	(2) 10th percentile of LogW	(3) 90th percentile of LogW	(4) 10th percentile of LogW	(5) 90th percentile of LogW	(6) 10th percentile of LogW
90th percentile of LogLP_VA	0.266***					
	(0.040)					
10th percentile of LogLP_VA		0.422***				
		(0.055)				
90th percentile of LogMFP_W			0.178***			
			(0.038)			
10th percentile of LogMFP_W				0.271***		
				(0.042)		
90th percentile of LogMFP_SW					0.075	
					(0.051)	
10th percentile of LogMFP_SW						0.451***
						(0.102)
N	3288	3288	3288	3288	3288	3288
Adj. R-Square	0.982	0.985	0.979	0.982	0.977	0.982
Year FE	YES	YES	YES	YES	YES	YES
Country-sector FE	YES	YES	YES	YES	YES	YES
Nb Sectors	22	22	22	22	22	22
Nb Countries	12	12	12	12	12	12

Clustered standard errors at the country-sector level in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Data is at the country-sector-year level, weighted by the number of firms in each cell.
Countries: AUS, AUT, BEL, DNK, FIN, FRA, HUN, ITA, JPN, NOR, NZL, SWE.

and the corresponding percentiles of wage. We estimate the following regressions:

$$W_{cjt}^{X\text{th}} = \beta \cdot P_{cjt}^{X\text{th}} + \boldsymbol{y}_t + \boldsymbol{z}_{cj} + \epsilon_{cjt} \tag{9}$$

where $W^{X\text{th}}$ is the Xth percentile of (log) wages and $P^{X\text{th}}$ is the Xth percentile of (log) productivity in country c, sector j and year t. The vectors $\boldsymbol{y}_t$ and $\boldsymbol{z}_{cj}$ indicate respectively year and country-sector fixed effects. The coefficient of interest, β, is the elasticity of the Xth percentile of wages to the Xth percentile of productivity in a given country-sector. We estimate Eq. (9) for the 90th percentile (top) and for 10th percentile (bottom). The results, given in Table 3, show that the productivity-wage elasticity is higher at the bottom of the distribution. For example, comparing columns (3) and (4) of Table 3, the elasticity of the 90th percentile of wage to the 90th of MFP_W is 0.178, while it is 0.271 for the 10th percentiles. The pattern is similar for the other measures of productivity. This is consistent with Eqs. (5) and (7) in our framework, where more productive firms charge higher mark-ups (or larger wage mark-downs), which induces a lower elasticity of wages to productivity at the top of the distribution than at the bottom.

In Online Appendix F.1, we check the robustness of the correlation between productivity dispersion and wage dispersion by re-estimating Eq. (8) as a pooled regression (Table F.10), and as a long-difference regression (Table F.11); in both cases, the correlation is still positive and statistically significant. In Online Appendix F.2, we re-estimate Eq. (8) country by country to investigate whether our results differ across countries. For MFP, where the full sample elasticity is 0.271, the elasticity estimates range from 0.006 for Australia to 0.721 for Finland (Figure F.7). While the elasticity of wage dispersion to productivity dispersion remains positive and statistically significant in all countries apart from Australia and Austria, the results unveil a certain degree of heterogeneity across countries.

A potential explanation of the correlation of productivity dispersion and wage dispersion is that a change in the skill composition affects both the distribution of productivity and the distribution of wages in a given sector. An increase in assortative matching between productive firms and skilled workers could drive this positive correlation. We tentatively show in Online Appendix F.1 that controlling for the sector's share of high-skill workers does not affect the main estimates of interest (Table F.9). If one believes that the share of high-skill workers is a good measure of skill composition, workers' skill composition does not appear to be a relevant confounding factor in the link between productivity dispersion and wage dispersion. While we acknowledge that this analysis is just a first pass and the literature has produced much more detailed accounts of relative skill supply and observable worker characteristics in individual countries (notably thanks to matched employer–employee data), we are constrained by

Table 4
Trade and the great divergences.

	(1)	(2)	(3)	(4)
Univariate				
Log MFP_W (90-10)	0.308***	0.308***	0.238**	0.264***
	(0.053)	(0.053)	(0.101)	(0.085)
Log MFP_W (90-10)	0.351***	0.290***	0.320***	0.340***
	(0.066)	(0.063)	(0.074)	(0.059)
Log Openness	0.167***			
	(0.051)			
Log MFP_W (90-10) × Log Openness	0.183***			
	(0.044)			
Log Openness (goods&serv) - Man		0.065		
		(0.048)		
Log MFP_W (90-10) × Log Openness (goods&serv) - Man		0.103**		
		(0.040)		
Log Openness (goods&serv) - Serv			0.089**	
			(0.041)	
Log MFP_W (90-10) × Log Openness (goods&serv) - Serv			0.069*	
			(0.037)	
Log Openness (goods&serv)				0.090***
				(0.034)
Log MFP_W (90-10) × Log Openness (goods&serv)				0.075**
				(0.031)
N	1697	1697	1346	3043
Adj. R-Square	0.928	0.923	0.971	0.971
Country-sector & year FE	YES	YES	YES	YES
Num. Countries	11	11	11	11

Data is at the country-sector-year level, weighted by the number of firms in each cell.
The dependent variable is Log Wage (90-10); all regressors are in deviation from the mean.
All regressions include the logarithm of total gross output in the sector as extra control.
Regressions include the interaction of productivity dispersion and total gross output in the sector as extra control.
Clustered standard errors at the country-sector level in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
The largest set of countries include: AUS AUT BEL DNK FIN FRA HUN ITA JPN NOR SWE.
NZL is missing from the regressions because sectoral data for gross output are not available.

the cross-country nature of the analysis and the limited availability of cross-country skill measures at the sectoral level. At the same time, our results dovetail with the large and expanding literature showing the importance of within-sector residual wage inequality as well as the importance of the between firm component in explaining *changes* in overall inequality (e.g., Barth et al., 2016; Helpman et al., 2017, among many others).

These findings do not rule out that unobserved worker characteristics and positive assortative matching between workers and firms can at least in part explain these trends. Even when accounting for unobservable worker characteristics and sorting, Card et al. (2013) find that the firm (establishment) component still plays a sizeable share (25%) of the overall change in wage variance in Germany (with observable characteristics contributing negatively).[25] These results are echoed by the findings of Criscuolo et al. (2020), who show that the sorting of workers across firms based on unobservable characteristics contributes significantly to the *level* but only marginally to *changes* in between-firm wage inequality in a cross-country setting (for Estonia, Italy, Netherlands, Spain, and Sweden). Conversely, Song et al. (2019) find that sorting (on unobservable characteristics) and segregation of similar workers across firms explain the entire increase in between-firm wage inequality in the US. Among the channels that they put forward to explain this phenomenon they discuss 1/ the rise in outsourcing and, 2/ the uneven adoption of technological innovations between firms; these channels would imply a rise in the worker–firm complementarity for some firms and could explain an increase in either sorting or segregation. The latter channel in particular is perfectly consistent with the evidence on ICT we show in Section 5.3. For all these reasons, and since we cannot precisely disentangle the exact source of the increase between-firm wage inequality, we remain agnostic on the exact source, and adopted a flexible framework that can incorporate them all.

5.2. The role of globalisation

Sectors experiencing divergence in productivity also experience a divergence in wages; we explore trade as a potential driver of this relationship, the second prediction of our framework. We explore whether in sectors more open to trade, there is a stronger correlation between productivity divergence and wage divergence.

To do so, we estimate the following equation:

$$WD_{cjt} = \beta \cdot \widetilde{PD}_{cjt} + \gamma \cdot \widetilde{T}_{cjt} + \delta(\widetilde{PD} \times \widetilde{T})_{cjt} + \boldsymbol{X}'_{cjt}\boldsymbol{\kappa} + \boldsymbol{y}_t + \boldsymbol{z}_{cj} + \varepsilon_{cjt} \quad (10)$$

where WD_{cjt} denotes wage dispersion, PD_{cjt} productivity dispersion, T_{cjt} Openness to Trade (Imports + Exports). $\boldsymbol{X}_{cjt}$ denotes a set of controls. All variables are in log and all regressions control for gross output and its interaction with productivity dispersion, so this is equivalent to measure trade as a share of the sector's output. $\widetilde{PD}_{cjt}$ and $\widetilde{T}_{cjt}$ denote the variables in deviation from their mean in the sample; hence the coefficient of each variable can be interpreted as the conditional correlation when the other variables are fixed at their sample mean. All regressions include year, and country-sector fixed effects.

The coefficient of interest is δ, the coefficient on the interaction term between trade and productivity dispersion. According to our conceptual framework, we expect sectors more open to trade to display a stronger correlation between productivity and wage dispersions, which would result in a positive estimate for δ. Indeed models of trade and imperfect labour markets (as in Helpman et al., 2010) predicts that, for a given level of productivity dispersion, opening to trade increases wage dispersion because high-productivity firms start exporting, expand and pay higher wages. This effects is compounded even further if the underlying productivity distribution becomes more dispersed at the same time. Moreover, in the presence of classical pro-competitive effects of trade (e.g., Atkeson and Burstein, 2008; Edmond et al., 2015),

[25] Relatedly, Kline et al. (2019) find that the changing composition of the workforce has little effect on their estimates of rent-sharing and the pass-through from (patent-induced) shocks to labour productivity to wages, which is actually larger for worker who stay in the firm.

firms reduce their mark-ups (and possibly their wage markdowns), strengthening the link between productivity and wage dispersion, as outlined in the conceptual framework of Section 4.

The estimates for Eq. (10) are given in Table 4. Given the change in sample across specifications, the first line of Table 4 includes, as a reference, the univariate regression results (Eq. (8)) for the same sample as the multivariate regression. Column (1) estimates Eq. (10) using openness to trade in goods only, and for manufacturing sectors only. The estimate for δ on the interaction term is positive and statistically significant, indicating that openness to trade increases the elasticity of wage dispersion to productivity dispersion. Given the regressors are expressed in deviations from the mean, the coefficient of MFP dispersion can be interpreted as the effect at the mean of Log Openness; hence in sectors with average openness, a 10% increase in productivity dispersion is associated with a 3.5% increase in wage dispersion.

Column (2) is still limited to manufacturing sectors, but includes trade in both goods and services. The estimate for δ is lower but positive and statistically significant. Column (3) repeats the same analysis, but for service sectors; the estimate for δ is positive, but smaller and significant at the 10% significance level. Finally, column (4) includes trades in goods and services, and both manufacturing and services sectors. Once again, the estimate is positive and statistically significant.[26]

The results from Table 4 not only shows that openness to trade is associated with higher wage dispersion (consistent with the literature), but also that the elasticity of wage dispersion to productivity dispersion is higher in sectors that are more open to trade. The results show that trade in goods is associated with a tighter link between wage dispersion and productivity dispersion, suggesting that the pro-competitive effects might be stronger for trade in goods compared to trade in services (and in manufacturing compared to service sectors).

5.3. The role of digitalisation

The third result of our investigation is that more ICT-intensive sectors have experienced a stronger correlation between the productivity divergence and the wage divergence.

As ICT use could be affected by a change in the productivity distribution, we construct time (and country) invariant measures of ICT computed at the beginning of our sample, i.e. averaging our measures of sector-specific ICT use across countries for the period 1995–2000. These measures therefore vary at the sector level only, and capture structural characteristics regarding the scope for the use of digital technologies in each sector. Our measures allow us to analyse whether the correlation between productivity and wage divergences is stronger in more ICT-intensive sectors without worrying that the relationship might be confounded.[27]

We do so by estimating the following regression:

$$WD_{cjt} = \beta \cdot \widetilde{PD}_{cjt} + \delta(\widetilde{PD}_{cjt} \times \tilde{I}_j^{95-00}) + \boldsymbol{y}_t + \boldsymbol{z}_{cj} + \varepsilon_{cjt} \qquad (11)$$

where WD_{cjt} denotes wage dispersion, PD_{cjt} productivity dispersion. I_j^{95-00} denotes are measures for the ICT use in sector j, averaged across countries over the period 1995–2000. All regressors are expressed in deviation from the mean. Hence the coefficient of each variable can be interpreted as the effect when the other variables are fixed at their sample mean. A positive estimate for the interaction coefficient δ indicates that more ICT-intensive sectors have experienced a stronger correlation between the productivity divergence and the wage divergence.

The results are given in Table 5. Since availability of some ICT variables induces a change in sample across specifications, the first line of Table 5 includes, as a reference, the univariate regression results (Eq. (8)) for the same sample as the multivariate regression.[28] Comparing the coefficients on MFP dispersion across columns of the univariate regressions (first line) shows that our results are not substantially driven by the change in sample.

In all specifications for ICT intensity, the estimate for the interaction coefficient δ is positive and statistically significant: more ICT-intensive sectors have experienced a stronger correlation between productivity dispersion and wage dispersion. This result is robust to a variety of measuring ICT-intensity. Column (1) of Table 5 shows that sectors where ICT represented a higher share of their Gross Fixed Assets experienced a tighter correlation between productivity and wage divergences. Columns (2) and (3) further shows that this is true for sectors that have a higher share of (tangible and intangible) ICT in Gross Fixed Capital Formation. Likewise, columns (4) and (5) show that sectors with a higher purchase of ICT (as intermediates) also experienced a tighter correlation, particularly sectors that invested purchased ICT goods (column 4). All these results confirm the prediction of our conceptual framework, where more productive firms have a higher capacity to adopt ICT assets leading a positive interaction between productivity dispersion and industry-level ICT/intangible capital.

Conversely, column (6) shows that the correlation between wage and productivity divergences does not seem to be affected by the share of high-skilled workers in the sectors, echoing results shown in Online Appendix F.1 (Table F.9). Finally, column (7) shows that knowledge may play an important role in the divergence between firms in services. Knowledge-intensive sectors are indeed characterised by a stronger correlation between the productivity divergence and the wage divergence.

6. Concluding discussion

This paper documents the link between productivity dispersion and wage dispersion. We use a novel data set that contains harmonised micro-aggregated statistics on the quasi population of firms in 12 countries over a 20 year-span, based on the OECD MultiProd project, which allow us to study the evolution of the wage and productivity distributions, including multi-factor productivity. We are able to provide detailed cross-country evidence on an increase in both within-sector wage dispersion between firms (+12.6%), and within-sector productivity dispersion (+13.9%); we find in particular that a faster increase in the gap at the bottom of the wage and productivity distributions account for more than 75% of these divergences. We show that these trends are intertwined: sectors that experienced more divergence in productivity also experienced a larger wage divergence. Consistent with a model with imperfect labour and/or product markets, we find that the elasticity of the productivity gap to wage gap is less than one but positive. Our estimates for the elasticity of wage dispersion with respect to productivity dispersion range from 0.22 to 0.50, and they are larger at the bottom than at the top of the wage/productivity distributions, in line with our framework in which more productive firms charge higher mark-ups and/or larger wage mark-downs.

By further linking the database to expanded data on ICT intensity and openness, we look at how this elasticity varies across sectors. We find that the elasticity of wage dispersion to productivity dispersion is larger in sectors that are more open to trade, and sectors intensive in ICT and intangible capital. These results suggest that policies designed to mitigate wage inequality must take into consideration gaps between firms of the same sectors, and how globalisation and digitalisation affect these gaps.

[26] Similar results are obtained if we run regressions separately for imports and exports.

[27] In unreported results, we show that our findings are robust to using measures of ICT/intangible intensity for an external benchmark country (the US).

[28] The measure of ICT hardware in GO (Column 4) excludes machinery production sectors for which ICT intermediate goods are likely to be electronic components that do not constitute a complementary investment (see Calvino et al., 2018). In column (7), the analysis is restricted to service sectors.

Table 5
Digitalisation and the great divergences.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Univariate							
Log MFP_W (90-10)	0.271***	0.271***	0.271***	0.269***	0.271***	0.271***	0.248**
	(0.086)	(0.086)	(0.086)	(0.089)	(0.086)	(0.086)	(0.104)
Log MFP_W (90-10)	0.267***	0.247***	0.257***	0.271***	0.265***	0.254***	0.116
	(0.081)	(0.086)	(0.084)	(0.086)	(0.086)	(0.088)	(0.113)
Log MFP_W (90-10) × ICT in Fixed Assets	0.014***						
	(0.005)						
Log MFP_W (90-10) × ICT equipment in GFCF		0.012**					
		(0.005)					
Log MFP_W (90-10) × Software & db in GFCF			0.011***				
			(0.004)				
Log MFP_W (90-10) × ICT hardware in GO				0.149**			
				(0.072)			
Log MFP_W (90-10) × ICT services in GO					0.035**		
					(0.017)		
Log MFP_W (90-10) × Sh. high-skilled						0.009	
						(0.006)	
Log MFP_W (90-10) × Knowledge Intensive Services							0.367***
							(0.120)
N	3290	3290	3290	2679	3290	3290	1453
Adj. R-Square	0.968	0.968	0.968	0.968	0.968	0.968	0.969
Country-sector & year FE	YES	YES	YES	YES	YES	YES	YES
Num. Countries	12	12	12	12	12	12	12

Data is at the country-sector-year level, weighted by the number of firms in each cell.
The dependent variable is Log Wage (90-10); all regressors are in deviation from the mean (apart from the KIS dummy).
Clustered standard errors at the country-sector level in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
The largest set of countries include: AUS AUT BEL DNK FIN FRA HUN ITA JPN NOR NZL SWE.

High within-sector dispersion suggests that productivity policies that aim at reducing economy-wide dispersion through structural adjustments in sectoral composition are unlikely, on their own, to be effective in decreasing the gap between these two groups of firms. These policies ought to be complemented by policies that work towards effective catching up of laggards to the firms that operate at the (national) frontier of the same sector, such as support investment in intangible assets, ICT, and R&D. An important channel through which productivity dispersion translates into wage inequality is the fact that the distribution of ICT and intangible capital is skewed towards the more productive firms. Government support for business expenditures in R&D can, not only foster innovation, but also help firms at the bottom of the productivity distribution catch up (Berlingieri et al., 2020). This in turn can help reduce wage inequality by reducing productivity gaps, and by lowering the elasticity of these productivity gaps to wag inequality. This would especially be the case if government support is focussed on smaller, less productive firms, as is the case for R&D directly funded by the government (Appelt et al., 2022). In a context where between-firm gaps represent a large factor in wage gaps, a well-targeted government support policy can help alleviate wage inequality.

CRediT authorship contribution statement

Giuseppe Berlingieri: Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Patrick Blanchenay:** Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Chiara Criscuolo:** Conceptualization, Methodology, Writing – original draft, Supervision, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The paper is based on confidential administrative firm-level data accessible to approved researchers. The codes to obtain the datasets and replicate the analyses are available upon request.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.respol.2024.104955.

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