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The Great Divergence(s)

Giuseppe Berlingieri (ESSEC Business School and OECD)
Patrick Blanchenay (University of Toronto)
Chiara Criscuolo (OECD)

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The Great Divergence(s)*

Giuseppe Berlingieri^{1,2,4}, Patrick Blanchenay³ and Chiara Criscuolo^{1,4}

¹OECD

²ESSEC Business School

³University of Toronto

⁴Centre for Economic Performance (LSE)

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 populations of firms in 13 countries. First, we document an increase in wage and productivity dispersions, for both manufacturing and market services (excluding the financial sector), 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 is linked to increasing differences between high and low productivity firms. Third, we find that both globalisation and digitalisation imply higher wage divergence, but strengthen the link between productivity and wage dispersion. Finally, the paper analyses the impact of minimum wage, employment protection legislation, trade union density, product market regulation, and coordination in wage setting on wage dispersion and its link to productivity dispersion.

Keywords: Dispersion, Productivity, Wages.

JEL codes: D2, J3

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“Why are similar workers paid differently? Why do some jobs pay more than others? I have argued that wage dispersion of this kind reflects differences in employer productivity. . . Of course, the assertion that wage dispersion is the consequence of productivity dispersion begs another question. What is the explanation for productivity dispersion?”

— Mortensen (2003, p. 129)

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 instance between high- and low-skilled workers (Autor et al., 2003), and between those employed in large versus small businesses (Song et al., 2018). At the same time divergence is becoming evident also amongst businesses: between high and low productivity firms (OECD, 2015; Andrews et al., 2016); between those with high and low returns to capital (Furman and Orszag, 2015); and between large and small firms (Mueller et al., 2015).¹

Recent evidence suggests that these trends might be intertwined. Several studies in different countries have found that a significant share of the increase in overall earnings inequality is accounted for by an increase in wage differences between firms.² And further studies point more specifically at productivity as an important contributor to the “between-firm” component of wage inequality (Davis and Haltiwanger, 1992; Mortensen, 2003; Dunne et al., 2004; Faggio et al., 2010; Christensen and Bagger, 2014).

As suggested by Mortensen (2003, see quote above), if the increase in “between-firm” differences plays such an important role in accounting for the overall increase in wage inequality, then a natural question arises: what drives productivity dispersion? And, more importantly, what affects its impact on wage dispersion? The debate is still open, in particular regarding structural factors such as globalisation and digitalisation driving these trends, and the role that policies and institutional factors play in mitigating or amplifying them.^{3,4} In particular, wage setting policies and institutions such as minimum wage (DiNardo et al., 1996), trade unions (Card et al., 2004; Machin, 2016), wage coordination (Card and De La Rica, 2006; Dell’Arling and Pagani, 2007; Dahl et al., 2013), employment protection legislation and

¹Recent studies point to an increase in within-sector productivity dispersion globally (Andrews et al., 2016) and within countries, e.g. Italy (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., 2017).

²Among other countries, evidence has been found for: 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., 2015), the UK (Faggio et al., 2010), and the US (Dunne et al., 2004; Barth et al., 2014; Song et al., 2018). See Card et al. (2018) for a recent overview.

³Three broad mechanisms have been suggested to explain the divergence in productivity: technological change (see in particular Caselli, 1999), globalisation (Melitz, 2003; Bloom et al., 2016), or changes in the competitive environment and firm organisation (Syverson, 2004).

⁴Separate works have also analysed how globalisation and digitalisation drive wage inequality. On the role of information and communication technologies in driving wage inequality, see for instance Card and DiNardo (2002) and Autor and Acemoglu (2011); on the increase in globalisation and trade competition, especially from low-wage countries Autor et al. (see for instance 2013).

product market regulation, may play an important role in mediating the relationship between productivity dispersion and “between-firm” wage dispersion.

This study furthers the literature on the ‘divergences’ in productivity and in wages by addressing three questions: Is there a link between the observed divergences in wages and productivity? How do structural changes, such as globalisation and digitalisation, affect this link? And to what extent do policies and institutional features affect the link between productivity dispersion and wage inequality?

We contribute to the debate in four ways. First, this paper is the first to provide an answer to these questions in a sectoral level cross-country setting and an almost 20-year time span. It does so by drawing on an unique data source, collected in the OECD MultiProd project, based on the full population of firms, or a representative re-weighted sample, for 16 countries (13 in this study). Thanks to the newly collected data, we show that an important “wage divergence” occurred in wages offered by firms even within the same sector, and that this divergence was driven mainly by an increased dispersion in the lower tail (50-10 percentile ratio) of the wage distribution.

Second, we are the first to look at the evolution of productivity dispersion using representative data for the full population of firms within country and sectors from the mid 1990s. We find that dispersion in productivity, whether measured as real value added per worker (labour productivity) or as multi-factor productivity (MFP), has also significantly increased in the last decade, and that this “productivity divergence” was more pronounced in the lower tail of the productivity distribution.

Third, we show that sectors that experienced more productivity divergence also experienced more wage divergence. In particular the increase in labour productivity dispersion observed over the period explains almost half of the increase in wage dispersion between firm. Our data further allows us to investigate the extent to which wages and productivity are correlated along the whole productivity distribution. This is an important contribution with respect to the existing literature: even though we focus only on the between-firm component of wage inequality, we can offer a much more precise description of the firm side of inequality in a cross-country setting. Previous literature exploiting rich matched employer-employee datasets has either focused on a single country, or has had very limited information on the firm side, at best providing rough measures of productivity such as revenues per employee. The fact that we can analyse the link between wage dispersion and both labour as well as multi-factor productivity dispersions allow us to make progress on the link between worker and firm characteristics.⁵

Lastly, we conduct a new analysis of the role of technological changes, increased globalisation, and changes in the competitive and institutional environment, in explaining the increase in wage dispersion and its relationship with productivity dispersion. Thanks to the rich cross-country sectoral panel, we can identify robust and economically significant conditional correlations within country-sector pairs over time. We find that structural factors, such as globalisation and digitalisation, tend to reinforce the impact of productivity dispersion on wage dispersion; but the direct effect of productivity remains the most significant channel in the increase of wage dispersion. Furthermore we show that the analysed

⁵In a recent study, Alvarez et al. (2018) investigate the role of firms characteristics in explaining the decline in earnings inequality in Brazil, but they can measure labour productivity only.

policies and institutional factors have the intended consequence of reducing wage dispersion but have different effect on the link between wage and productivity dispersion: while stricter employment protection, a more centralised wage bargaining, and higher product market regulation tend to weaken the link between wages and productivity, a higher minimum wage tend to strengthen it.

The rest of the paper is organised as follows: in Section 2, we describe the new data source and the measures that we use in the analysis. Sections 3 and 4 provide evidence on the evolution of, respectively, between-firm wage dispersion and productivity dispersion across 13 countries from the mid-1990s to the recent post-recession period up to 2012. Section 5 investigates the evolution of the wage-productivity link. Section 6 analyses the impact of structural factors and certain policies on wage divergence and its link to increased productivity dispersion. Finally Section 7 concludes.

2. DATA

This section provides an overview of the data, and the main measures of productivity and of dispersion used in the study. The main data source used in the analysis is the OECD “MultiProd” project, a vast distributed microdata project undertaken in the last few years within the Directorate for Science, Technology and Innovation of the OECD. The full details on the methodology, the underlying data sources, and the main characteristics of the final dataset would deflect attention from the analysis. This section therefore gives a broad overview of the data, and more details are available in Berlingieri et al. (2017a), Bajgar et al. (2019), and a second Online Appendix to the paper, which describes in more detail the methodology used in the MultiProd project and the underlying micro-data sources.

2.1 Main data source: the OECD MultiProd project

The data collected in the “MultiProd” project are computed by running a standardised STATA[®] routine on firm-level data based on production surveys and business registers, via a *distributed microdata analysis*.⁶ We collect statistical moments of the distribution of firm characteristics (employment, productivity, wages, age, etc.) by a centrally written routine that is flexible and automated enough to run across different data sources in different countries.

The MultiProd program relies on two main data sources in each country. First, administrative data or production surveys (PS), which contain all the variables needed for the analysis of productivity but may be limited to a sample of firms. Second, a business register (BR), which contains a more limited set of variables (mainly employment, sector of activity, age and ownership) but for the entire population of firms. The program works also in the absence of a business register and this is not needed when administrative data on the full population of firms are available. However, when data come from a PS,

⁶ The approach was pioneered in the early 2000s in a series of cross-country projects on firm demographics and productivity (Bartelsman et al., 2005; Bartelsman et al., 2009). The OECD currently follows the distributed microdata approach in three ongoing projects: MultiProd, DynEmp and MicroBerd. The DynEmp (Dynamics of Employment) project provides harmonised micro-aggregated data to analyse employment dynamics (Criscuolo et al., 2014; Criscuolo et al., 2015) and MicroBerd provides information on R&D activity in firms from official business R&D surveys (Appelt et al., 2018).

its availability substantially improves the representativeness of the results and, thus, their comparability across countries. In particular, given the coverage and the continuity of the administrative information collected for each firm, BR data allow for: i) the calculation of the population breakdowns necessary for obtaining the sampling weights used in the analysis; ii) a much more precise treatment of entry and exit; iii) the calculation of more precise sectoral modes and conversion tables in case of changes in the sectoral classification at the firm level – as the whole life cycle of the business is observed – or of a change in the whole sectoral classification system – as the entire population of businesses is observed.

This study relies on the version 1.0 of the MultiProd database (December 2016), which includes 16 countries (namely, Australia, Austria, Belgium, Canada, Chile, Denmark, Finland, France, Hungary, Italy, Japan, Luxembourg, Netherlands, Norway, New Zealand and Sweden). This study focuses on a final sample of 13 countries that have provided the results at the 2-digit industry level and that have a good coverage of structural characteristics and policy variables (Canada, Chile, and Luxembourg are excluded). For most countries the time period spans from early 2000s to 2012. For Belgium the time horizon is shorter (starting in 2004), whereas for Finland, France, Japan and Norway data are available at least since 1995.

Table 1 details years covered, the underlying data sources, and the sampling thresholds that characterise the data (by default MultiProd restricts the sample to firms with at least one employee). One of the big challenges of conducting cross-country analysis of firm-level data when only production surveys are available is that comparing selected samples of firms might yield a partial and biased picture of the economy. Whenever available, business registers, which typically contain the whole population of firms, are therefore used to compute a population structure by year-sector-size class. This structure is then used to re-weight the data contained in the production surveys in order to construct micro-aggregated data that are as representative as possible of the whole population of firms and hence comparable across countries. For countries included in Eurostat, Table OA-1 in the Online Appendix shows that compared to Eurostat, coverage in MultiProd is high in most of these countries; for countries with a lower coverage (Italy and the Netherlands), the full BR is available and thus the samples can be re-weighted.⁷ The notable exception 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.⁸ In this case the ex-post re-weighting strategy adopted in MultiProd is not effective and the statistics on dispersion will be necessarily downward biased.

⁷Bajgar et al. (2019) investigates to what extent the micro-aggregated data available in MultiProd reflect the patterns observed in aggregate industry data from national accounts. In most countries, the microdata used by MultiProd have a good coverage, representing typically about 80% of total gross output, value added and employment in manufacturing and non-financial services, and the coverage is fairly stable over time. The results also show that MultiProd reproduces aggregate patterns relatively well, with median correlations over time, across industries and across countries between 0.75 and 1.

⁸Future waves of MultiProd will access data from the Census of Manufactures, which contains the universe of plants in years ending with 0, 3, 5, and 8. Challenges will remain, since the data are available for manufacturing only and are at the establishment, not the firm level.

Table 1: Data coverage

Country	Years	Data Source	Sampling Threshold
Australia	2002-2012	Expanded Analytical Business Longitudinal Database (EABLD)	1 employee
Austria	2008-2012	Leistungs- und Strukturstatistik (Structural Business Statistics)	1 employee
Belgium	2003-2011	Central Balance Sheet Office and National Social Security Office	1 employee
Denmark	2000-2012	Accounts Statistics for Non-Agricultural Private Sector, General Enterprise Statistics	1 employee
Finland	1995-2012	Structural business statistics data (surveys, corporate tax records, and Statistics Finland's Business Register)	1 employee
France	1995-2012	FICUS/FARE and LIFI	1 employee
Hungary	1998-2012	Corporate Income Tax data (CIT) of National Tax and Custom Administration	Since 2004, firms reporting at least HUF 50 million HUF turnover in two consecutive years are included.
Italy	2001-2012	ASIA (Business Register), Indagine sulle grandi imprese (SCI), Database Commercio Estero (COE), Balance sheet data for capital companies	1 employee
Japan	1994-2011	Basic Survey of Japanese Business Structure and Activities	50 employees and paid-up capital or invested funds of at least JPY 30 million
Netherlands	2000-2012	Productiestatistieken (PS) and Algemeen Bedrijvenregister (BR)	1 employee before 2004 and in benchmark years, 10 employees in other years
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 employee
Norway	1995-2012	Accounts statistics (incorporated firms) and Establishment population register	1 employee
Sweden	2002-2012	SBS administrative data (tax data)	1 employee

2.2 Data sources for structural and policy variables

The data from MultiProd are complemented with data from external sources for analysing structural factors (Section 6.1), as well as policy and institutional characteristics (Section 6.3). The structural factors include globalisation and digitalisation. Globalisation is captured with data on imports and exports of goods from the OECD STAN Bilateral Trade Database by Industry and End-use category (BTDIxE). Digitalisation is captured with the share of ICT in gross non-residential fixed assets at current prices, taken from the OECD Annual National Accounts, ISIC Revision 4.⁹ This measure is complemented with data on skills, and in particular hours worked by high-skilled persons engaged (share in total hours); these are internal ISIC Revision 4 estimates based on the ISIC 3 original data from the World Input Output Tables (WIOD), Socio Economic Accounts, July 2014 (See Timmer et al., 2015).¹⁰ All variables for the structural factors vary at the country, sector and year level.

The policy and institutional analysis will investigate the role of: i) minimum wage; ii) employment protection legislation (EPL); iii) trade union density; iv) coordination in wage setting and; v) product market regulation (PMR). The minimum wage is measured in two ways: the real hourly minimum wage in 2014 US dollars at purchasing power parities, and the minimum wage relative to average wages of full-time workers. The EPL indicator captures the strictness of employment protection, for both individual and collective dismissals of regular workers.¹¹ Both the minimum wage and the EPL indicator come from OECD Stats, further information on the detailed national sources is available at <http://stats.oecd.org>. Trade union density is the ratio of wage and salary earners that are trade union members, divided by the total number of wage and salary earners; the data on trade union members are from the the ICTWSS database (Institutional Characteristics of Trade Unions, Wage Setting, State Intervention and Social Pacts, release 3.0), while the number of workers are from the OECD Labour Force Statistics.¹² Coordination in wage setting identifies the extent to which institutional features of wage setting arrangements are likely to generate more or less coordination (on a scale from 1 to 5, where 1 corresponds to 'Fragmented wage bargaining, confined largely to individual firms or plants' and 5 to 'Maximum or minimum wage rates/increases based on centralised bargaining') and comes from the ICTWSS database, release 5.0, November 2015. The indicator of PMR is the economy-wide OECD product market regulation index (Koske et al., 2015), with values interpolated across years. All policy and institutional variables vary at the country and year level.

2.3 Measures of productivity

The analysis relies on three measures of productivity. The first, labour productivity, is the most widely used in the literature and aims at capturing the amount of output produced by a firm for a given amount

⁹Further information and details are available at <http://stats.oecd.org>.

¹⁰For details of digitalisation measures constructed at the OECD, see Calvino et al. (2018).

¹¹The indicator used is the EPRC Version 2.

¹²See https://www.oecd.org/els/emp/UnionDensity_Sourcesandmethods.pdf.

of labour input. It is computed at the firm level as the (real) value-added per worker:

$$LP_VA_{it} = \frac{VA_{it}}{L_{it}} \quad (1)$$

where VA_{it} is the value-added of firm i at time t , and L_{it} is its employment.¹³ The advantage of this measure is that it is widely available, and fairly immune to measurement error. Moreover, it can be easily aggregated into sector-level or country-level labour productivity using employment weights.

One of the main drawbacks of labour productivity is that it does not quantify the impact of other inputs, such as capital, while for some policy questions it might be important to disentangle whether labour productivity gains are actually driven by an increase in physical capital. In order to do this, the MultiProd data contain two measures of multi-factor productivity (henceforth MFP), which is a productivity measure that accounts not only for labour but also for capital productivity.¹⁴

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 Appendix A.

2.4 Measures of dispersion

In order to capture heterogeneity in the data, we calculate several measures of productivity and wage dispersion within macro-sectors and 2-digit industries.¹⁵ This study focuses on three measures of dispersion: 90-10, 90-50, and 50-10 ratios.

- The 90-10 wage (resp. productivity) ratio is defined as the ratio between the 90th and the 10th percentile of the wage (productivity) distribution. It is used widely in both the inequality and the productivity literature to assess the spread of the distribution of wages and productivity. The measures are quite intuitive since 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’.

¹³For 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; only when HC is not available, we rely on full time equivalents (FTE).

¹⁴For the MFP calculations a measure of capital stock is needed. If information on investment is available, the capital input is measured through the Perpetual Inventory Method (PIM); otherwise, the deflated book value of capital is used.

¹⁵More precisely the data of MultiProd are collected at the A38 level, which is slightly more aggregated than 2-digit (for the exact definition, see Berlingieri et al., 2017a). Still, we use the two terms interchangeably throughout the paper. Outcomes are also available at a more aggregated A7 or macro-sector level.

- The 90-50 wage (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.
- 50-10 wage (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.

3. DIVERGENCE IN WAGES

3.1 Overall vs between-firm inequality

The database of the MultiProd project is constructed using data sources at the level of the firm. This implies that the measure of wages contained in the dataset, firm's total labor costs divided by the number of employees, corresponds to the average wage at the firm level and that the dispersion of wages within the firm is not observed. Therefore whenever we discuss wage dispersion we analyse the dispersion of wages between firms, and not the overall dispersion of workers' wages. This is because at present the MultiProd network does not have access to matched employer-employee data sources that would be needed to carry out the analysis both at the worker and at the firm level. This means that we cannot control for worker level characteristics (such as age, experience, tenure, gender and education), nor calculate overall or within-firm wage dispersion.¹⁶

When analysing the evolution of overall wage inequality in the last decades, this is a clear shortcoming, but not as severe as it might appear. There is in fact mounting evidence that the observed increase in overall wage inequality over time is driven by increasing between-firm wage differentials, as opposed to within-firm differences due to worker specific characteristics. For instance amongst OECD economies, evidence for the US (Dunne et al., 2004; Song et al., 2018) shows that over two thirds of the increased wage inequality observed in the last three decades is accounted for by increased variance across businesses. In Germany, the increase in wage variance across workers and across businesses seem to contribute equally to the increase in overall wage inequality (Card et al., 2013), with evidence for Sweden (Håkanson et al., 2015) and Italy (Card et al., 2014) following a similar pattern.¹⁷ Similar evidence has also been found for emerging economies: Helpman et al. (2017) find that in Brazil the between-firm component accounts for 86% of the increase in wage inequality within sectors and occupations over the 1986-1995 period, while worker observables only account for 2% of the total and the residual within-firm component is even negative.

¹⁶An on-going OECD project is aimed at performing a distributed micro-data exercise using matched employer-employee data. However the country coverage will be considerably more limited due to the higher level of project complexity and the limited number of countries for which this type of data is available.

¹⁷Note that thanks to the availability and accessibility of matched employer-employee several studies have focused on Germany (e.g. Card et al., 2013; Goldschmidt and Schmieder, 2015; Baumgarten et al., 2016) and Sweden (e.g. Skans et al., 2009; Akerman et al., 2013; Håkanson et al., 2015)

In light of the widespread evidence that a significant part of the increase in earnings inequality observed in the last decades is driven by an increase in the wage differentials between firms, the present analysis on between-firm inequality can offer useful insights also for trends in overall wage inequality.^{18,19}

3.2 Divergence in between-firm wage dispersion

We now examine the evolution of between-firm wage dispersion and provide evidence for why it makes sense to speak of a “Great Divergence”.

3.2.1 The evolution of between-firm wage dispersion

To analyse the increase in wage dispersion more accurately we focus on its evolution within countries and disaggregated sectors, to make sure that wage dispersion at the macro-sector level is not driven by a compositional effect of more disaggregated sectors. More precisely, we use an econometric approach that removes country by 2-digit sector fixed effects, as shown in the following regression:

$$(\log W_{90} - \log W_{10})_{cjt} = \beta_t \mathbf{y}_t + z_{cj} + \varepsilon_{cjt} \quad (2)$$

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.²⁰ Year dummy estimates β_t capture the average dispersion in a given year controlling for specific country-sector fixed effects z_{cj} . The latter control for the specific levels of dispersion in each country and sector, so that the estimates of the year dummies coefficients β_t capture a more accurate evolution of wage dispersion within each 2-digit sector in each country.

Figure 1 shows that within-country sector wage dispersion has been increasing over time, indicating that by 2012, the within country-sector 90-10 wage ratio is 12.7% higher than in 2001.²¹ 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

¹⁸A caveat of the within-sector between-firm analysis carried out in the rest of the study is that the occupation structure is not observed in the micro-data. This contrasts with studies where the object of interest is the residual wage inequality between workers with the same characteristics (e.g. sector, occupation, education etc.) employed in different firms. To overcome this issue we will control for the level of skills at the sectoral level over time, which can partially capture the changing occupation structure at the sectoral level. In any case it is reassuring that Helpman et al. (2017) find that the sectoral component is more important than the occupation component (it accounts for a larger share of the overall change in wage inequality: 27% versus 8% of the occupation component).

¹⁹In Online Appendix OA-B 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.

²⁰Since the data in MultiProd are micro-aggregated moments (and means in particular) from firm-level data, in all regressions we weight each observation cjt by the number of firms reporting a non-missing information for the relevant variable in a given country-sector-year (using analytical weights in STATA[®]).

²¹The 12.7% figure is calculated as $100 \times [\exp(\hat{\beta}_{2012}) - 1]$ where $\hat{\beta}_{2012} = 0.120$ is the estimate of the 2012 year dummy in equation 2. The detailed results of the regression are presented in Table B.1 in Appendix B.

Figure 1: The “Great Divergence” of wages
Wage dispersion over time within sectors and countries



Note: The solid line plots the estimated year dummies β_t of a regression of log-wage dispersion (90th and 10th percentiles difference) on year dummies, controlling for country-sector pairs, as specified in Equation (2). 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, NLD, 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; data for the Netherlands are available only in 2002, 2006, and 2010.

the OECD Earnings Distribution database. Figure 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 a 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 is in the same ballpark figure as the increase in overall earnings inequality.²²

3.2.2 Evolution of dispersion at the top and at the bottom of the wage dispersion

There has also been variation in the nature of the within-country wage divergence over time. An interesting question is whether the divergence is driven by an increasingly strong push outward at the top of the distribution, i.e. firms at the top increasingly paying more than the median firm, or whether firms at the bottom of the wage distribution are paying increasingly less relative to the median firm. To answer this question, we perform an exercise similar to the econometric approach of Equation (2) but separately for the 90-50 and the 50-10 log-wage differences. That is, we econometrically estimate the yearly average

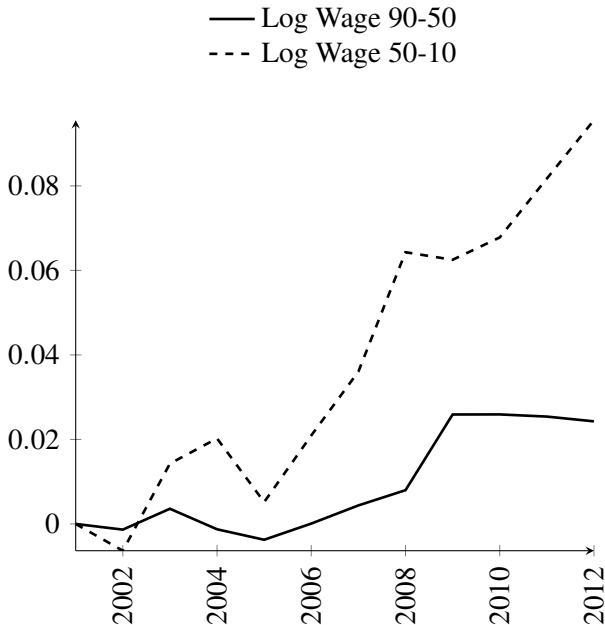
²²Note that in the rest of the paper we will use – for brevity sake – “wage dispersion” to indicate “between-firm wage dispersion” as the latter is the only type of dispersion we can calculate given the information available in MultiProd.

wage 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.

Over the decade considered, results shown in Figure 2 suggest that, within each country-sector pair, the divergence has been more severe at the bottom of the wage distribution. Appendix B.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%. The increase in the overall dispersion between top and bottom deciles is therefore mostly explained by the increased divergence between the median and bottom decile, rather than between the top decile and median.

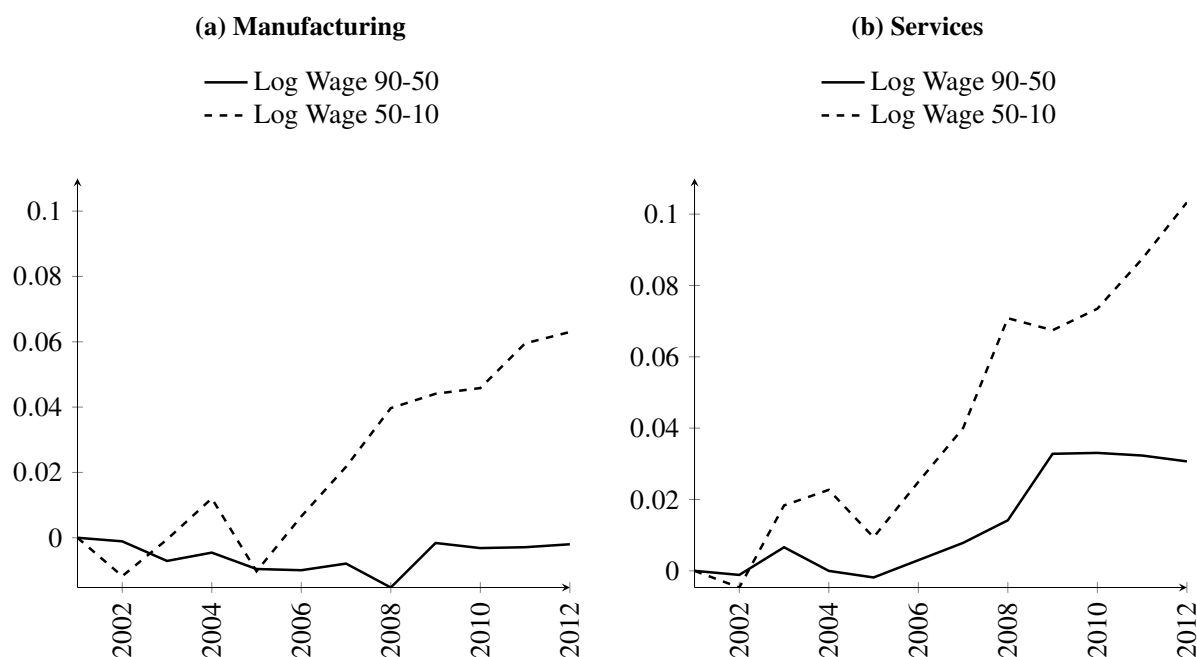
The divergence at the top has remained relatively stable in manufacturing over the whole period and in non-financial market services until 2006, when it grew significantly until 2009 (Figure 3). Interestingly, the diverging patterns at the top and bottom of the wage distribution seem to have become increasingly different after the Great Recession, suggesting that workers in the lowest-paying firms might have disproportionately suffered in the aftermath of the crisis relative to workers in the median firm. At the same time dispersion at the top of the distribution has declined after 2009, again suggesting that the workers in the top tail of the distribution (in this case the highest paying firms) have lost their pay-advantage relative to workers in the median firm after the crisis. These two countervailing forces – compression at the top and increased dispersion at the bottom – are masked when looking at the 90-10 ratio, whose trend does not seem to be particularly affected by the Great Recession (Figure 1).

Figure 2: Wage dispersion at the top versus bottom of the distribution



Note: The figure plots the year dummy estimates of a regression of log-wage dispersion 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, NLD, NOR, NZL, SWE.

Figure 3: Wage dispersion at the top versus bottom of the distribution



Note: The figure plots the year dummy estimates of a regression of log-wage dispersion 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, separately for manufacturing and services. 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, NLD, NOR, NZL, SWE.

The divergence at the bottom is in apparent contrast to much of the literature on wage inequality, or on firm-performance, which typically finds that the divergence is driven by the top of earning distribution (Piketty, 2014), or the top-performing firms (Autor et al., 2017). However, our data focusses on the middle 80 percent of the between-firm wage distribution. This does not preclude that some divergence is also occurring at the top end of the between-firm wage distribution, which will not be captured by a 90-10 percentile difference. Furthermore, our data focusses on firm-level wage average, and therefore does not capture the increasing divergence in individual earnings by top earners. Finally, our results are in line with Dreger et al. (2015), who find similar evidence between 2006-2011 for EU-28 countries using EU-SILC data.

3.2.3 Cross-sectional wage dispersion

The literature has shown that the between-firm wage dispersion is particularly important to explain the overall change in wage inequality over time, and this is why our analysis focusses on the evolution of wage dispersion over time. Still, also our data display a substantial level of wage inequality even on the cross section, and the previous graphs clearly mask this fact since the dispersion in wages is indexed at zero at the beginning of the period.

Table 2 reports for 2001 the average 90-10 log wage differences across 2-digit sectors, separately for each country and for manufacturing and services. The magnitude of the spread between the top and

bottom decile of the wage distribution gives us an insight into the inequality of wages, and the results show that the wage dispersion between firms within countries and sectors is clearly substantial. For instance, in manufacturing in 2001, wages in the highest paying firms, i.e. those at the 90th percentile of the wage distribution, were on average 3.4 times those at the bottom decile (an average log wage differential of 1.23). The spread is even more pronounced in non-financial market services, where the ratio is 5.8 for the average country (an average log wage differential of 1.76).

Table 2: 90-10 log wage difference in 2001

	90-10 log wage difference	
	Manuf.	Services
Denmark	1.07	1.53
Finland	1.08	1.98
France	1.05	1.41
Hungary	1.68	2.39
Italy	1.10	1.29
Japan	0.84	1.04
Netherlands	1.64	2.70
New Zealand	1.45	1.82
Norway	1.20	1.72

Note: In each country-sector, for 2001, the 90-10 log wage difference is computed using firm-level data. For each country, and separately for manufacturing and services, the 90-10 difference is then averaged across 2-digit sectors, weighted by employment. Countries with data starting after 2001 or for which the 90-10 log wage difference cannot be computed at the 2-digit sector level are not included.

In Online Appendix OA-C, we decompose the variance of wages into within- and between-sector variance; we show that most of the variance in wages between wages occurs within, rather than between, well-defined sectors. Moreover, we show that the share of within-sector variance has increased over time.

4. DIVERGENCE IN PRODUCTIVITY

In the previous section we have shown that over the last decade there has been a steady increase in wage dispersion, which can be attributed mostly to differences in pay across firms operating within the same sectors. Taking as a starting point the quote of Mortensen's work on wage inequality reported at the beginning of the report:

Why are similar workers paid differently? Why do some jobs pay more than others? [...] wage dispersion of this kind reflects differences in employer productivity. [...] Of course, the assertion that wage dispersion is the consequence of productivity dispersion begs another question. What is the explanation for productivity dispersion?

We now look at whether the observed pattern in wage divergence is paralleled by a divergence in productivity within country-sectors during our sample period.

4.1 Productivity dispersion and its evolution over time

Table 3: 90-10 log productivity differences in 2001

	Log-LP 90-10 diff.		Log-MFP 90-10 diff.	
	Manuf.	Services	Manuf.	Services
Denmark	1.31	1.90	1.19	1.73
Finland	1.19	1.34	1.14	1.22
France	1.30	1.64	1.33	1.62
Hungary	2.45	3.09	2.38	2.83
Italy	1.71	1.93	1.65	1.77
Japan	1.13	1.25	1.02	1.21
Netherlands	1.86	2.69	2.34	2.89
New Zealand	1.93	2.15	1.94	2.00
Norway	1.52	1.96	1.67	1.94

Note: In each country-sector, for 2001, the 90-10 log productivity difference is computed using firm-level data. For each country, and separately for manufacturing and services, the 90-10 difference is then averaged across 2-digit sectors, using employment and log value-added as weights for labour productivity and MFP respectively. Countries with data starting after 2001, or for which the 90-10 log productivity difference cannot be computed at the 2-digit sector level are not included.

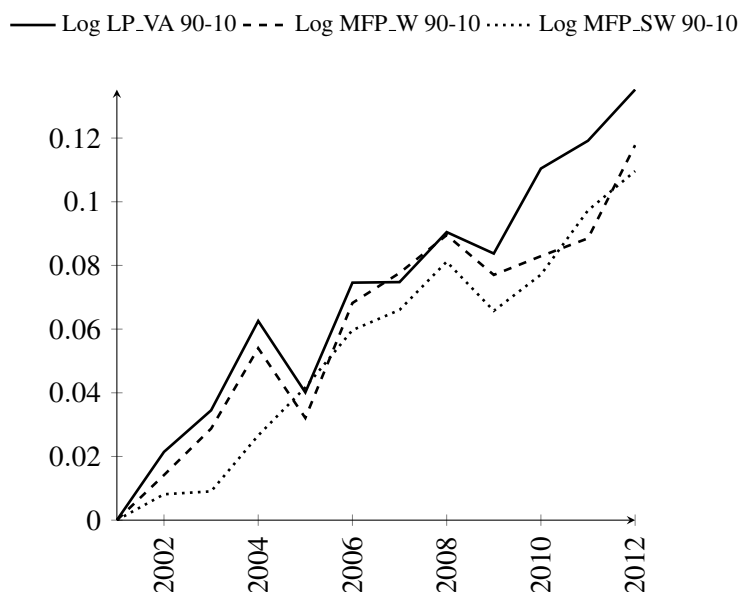
The large dispersion in productivity even within narrowly defined industries is an established fact in the literature (e.g. Syverson, 2004). Table 3 revisits this fact for several countries and provides a simple descriptive account of the dispersion in productivity, measured as the difference between the 90th and 10th percentiles of the log productivity distribution. As expected, there is a rather significant dispersion in both manufacturing and services between the top and the bottom performing firms in terms of labour productivity (LP) and multi-factor productivity (MFP).²³ In 2001, on average across countries, firms in the top decile of the distribution can produce almost five times as much value added per worker as firms in the bottom decile in the same country's manufacturing sector, and more than seven times as much in services. When looking at (log) MFP, firms at the top of the distribution produce, with the same amount of measured inputs, more than five times the output of firms at the bottom of the distribution in manufacturing, and almost seven times in the service sector.²⁴

The previous simple cross-country averages are silent on the changes that have taken place over time. However, as in the case of wages, the dispersion has actually increased substantially over time, a fact that has not received sufficient attention in the literature so far. So we now look at whether the observed increase in wage divergence is paralleled by a divergence in productivity within countries and sectors over the same period. Productivity divergence will have taken place within a country's sector if productivity for the group of most productive firms increased faster than it did for the least productive

²³Note that, in the case of labour productivity, the percentiles of the level and the log of LP are different due to the presence of negative value added firms. As standard in the literature, we analyse Log-LP and leave the investigation of the role of negative value added firms to future research. In a preliminary analysis we find that the share of this type of firms has increased during the crisis, and that for certain countries negative value added firms are a sizeable share of the total. By removing these firms from the sample, the current analysis could therefore underestimate the extent of the increase in productivity dispersion over the period.

²⁴These figures are obtained by taking the exponential of the unweighted average across countries of the 90-10 log-productivity differences reported in the table; respectively 1.59 and 1.99 for LP, and 1.63 and 1.91 for MFP. These figures are in line with the estimates for the manufacturing sector reported, for example, in Syverson (2011).

**Figure 4: The “Great Divergence” in productivity:
90-10 difference in log Productivity**



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. 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, NLD, NOR, NZL, SWE.

firms. To illustrate the trends in the relative productivity performance of top performers vs. laggards, Figures B.2 and B.3 in the Appendix plot the difference between the 90th and 10th percentiles of log-productivity over time by country. Here we analyse productivity divergence more rigorously to ensure that the observed increase in productivity dispersion is not driven by changes in the underlying sample of countries and/or sectors. As with the divergence of wages in Section 3, we estimate the following regression:

$$(\log P_{90} - \log P_{10})_{cjt} = \beta_t y_t + z_{cj} + \varepsilon_{cjt} \quad (3)$$

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 β_t capture the average within country-sector dispersion in a given year, and as such can be used to depict the evolution of productivity dispersion within countries-sectors over time.

Figure 4 shows that for both labour and multi-factor productivity, within-sector dispersion has increased over time on average across all countries.²⁵ 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. We can therefore speak of the “Great Divergences” of both wages and productivity, and the very similar patterns they display over time call for an investigation of the potential concomitant forces that drive both phenomena (Section 5).

²⁵The exact regression results are given in Table B.2 in the Appendix.

4.2 Evolution of productivity dispersion at the top and at the bottom of the distribution

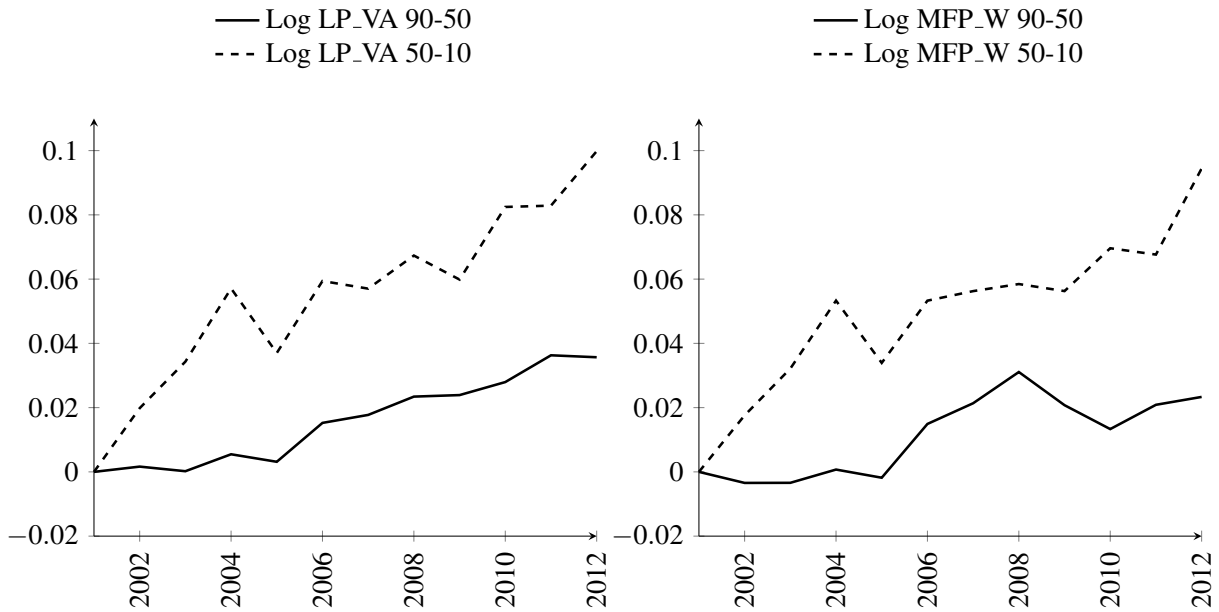
An interesting question is whether productivity divergence is driven by an acceleration of frontier firms or by a slowing down of productivity at the bottom relative to the median firm. To answer this question, we estimate the yearly average productivity dispersion within countries and sectors, separately for the top 90-50 and bottom 50-10 differences of the log-productivity distribution.

The estimates, shown in Figure 5, suggest that the divergence has happened both at the top and at the bottom of the distribution. The dispersion at the top starts growing after 2005, slightly flattens out during the crisis years but increases again as of 2010. The gap between the median firm and firms in the bottom decile of the distribution has been steadily increasing since 2000 and, especially when focusing on trends in MFP dispersion, the crisis has widened the gap even further. Looking at the same pattern separately for manufacturing and services (Figure 6 for MPP and Figure B.5 in the Appendix for LP), we see that the service sector behaves roughly as the aggregate figure given its large weight in the economy, but the manufacturing sector displays interesting differences. The dispersion at the top even decreases before 2005, and this pattern contributes significantly to the flat dispersion found in the aggregate economy; after 2005 the dispersion peaks up but to a lesser extent compared to services. The dispersion at the bottom still displays a higher growth over the period, but it is more volatile, especially for MFP.

One of the main takeaways from Figure 5 is 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; the divergence at the top has started picking up around the mid-2000s and between 2005 and the crisis shows an increasing trend similar to that of the bottom of the distribution leading to growing divergence overall. When thinking of what is driving the divergence at the bottom, there can be two forces at work: an increasing gap between the median and the worst performing firms might reflect a faster growth at the median relative to the bottom firms, but it could also reflect a worsening of the selection effect at the bottom of the distribution, with unproductive firms managing to remain in the market despite their low productivity. This would mean that the process of productivity enhancing resource reallocation has worsened since the early 2000s. Until the mid 2000s, median firms were gaining a productivity advantage relative to bottom performing firms and they were keeping up with the top performing firms. However, since the mid-2000s they have started losing ground vis-à-vis their national frontier firms, which have steadily become relatively more productive.

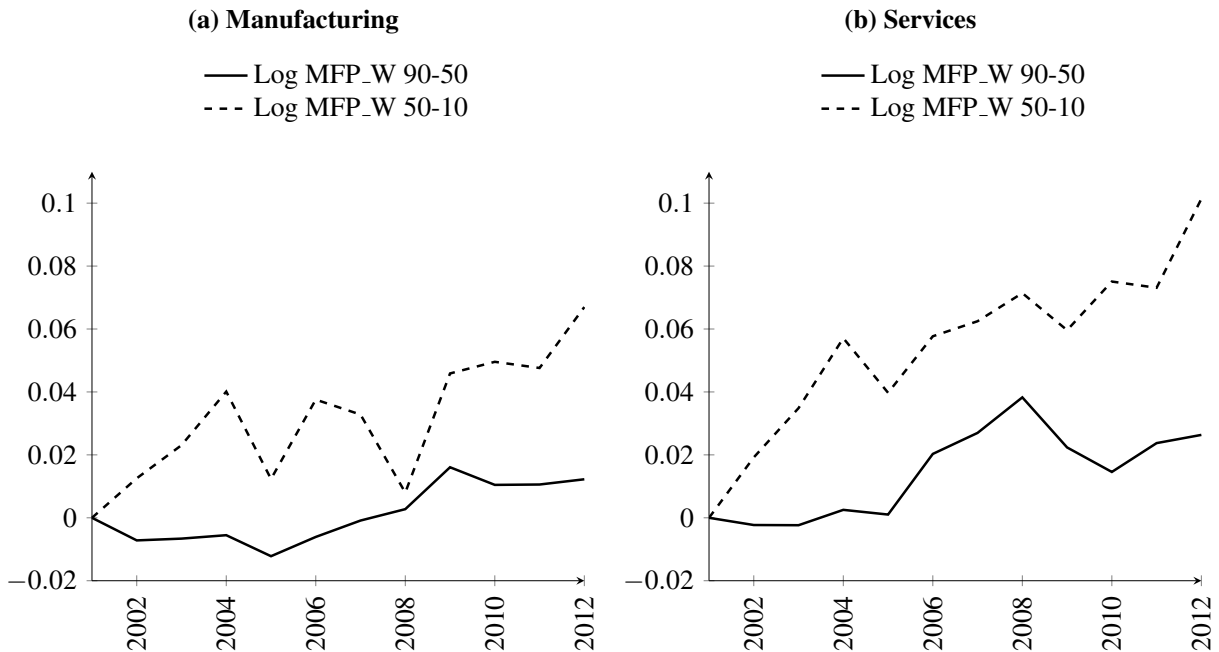
In Online Appendix OA-D, we decompose the variance of productivity into within- and between-sector variance; we show that, like for wages, most of the variance in productivity between wages occurs within, rather than between, well-defined sectors. Moreover, we show that the share of within-sector variance has increased over time.

Figure 5: Productivity dispersion at the top versus bottom of the productivity distribution



Note: The figure plots the year dummy estimates of a regression of log-LP_VA and log-MFP_W dispersion, respectively, at the top (90th and 50th percentiles ratio, solid line) and at the bottom (50th and 10th percentiles ratio, dashed line) 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, NLD, NOR, NZL, SWE.

Figure 6: Log MFP_W dispersion at the top versus bottom of the productivity distribution, for manufacturing and services



Note: The figure plots the year dummy estimates of a regression of log-MFP_W dispersion at the top (90th and 50th percentiles difference, solid line) and at the bottom (50th and 10th percentiles difference, dashed line) on year dummies, controlling for country-sector pairs, separately for manufacturing and services. 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, NLD, NOR, NZL, SWE.

5. THE LINK BETWEEN WAGE INEQUALITY AND PRODUCTIVITY DISPERSION

The analysis of wages and productivity has enabled us to show two results: 1. heterogeneity in wages and productivity is significant, even between firms operating within the same sector; and 2. this heterogeneity has increased over time, a phenomenon we call the ‘Great Divergence(s)’. In a well-functioning economy, wages should reflect the marginal productivity of workers, and as such should reflect firms’ productivity. It is therefore legitimate to investigate whether the Great Divergence in wages and the Great Divergence in productivity are merely two sides of the same coin.

5.1 The correlation between wages and productivity levels

Before diving into the analysis of the forces that might affect the dispersion of wages and productivity, it is instructive to provide a more precise picture of their relationship in levels.

First, Table 4 shows that productivity and wages are positively correlated at the firm level. Interestingly, the firm-level correlations are very similar across the manufacturing and the service sectors and whether the measure of productivity considered is labour or multi-factor productivity, with correlation coefficients ranging between 0.17 and 0.73 across countries. The table therefore confirms that firms with higher productivity levels tend to be also the ones that pay higher wages.²⁶

Table 4: Firm-level correlation Wage-Productivity in 2001

	corr(W,LP)		corr(W,MFP)	
	Manuf.	Services	Manuf.	Services
Denmark	0.64	0.66	0.56	0.53
Finland	0.23	0.29	0.29	0.30
France	0.56	0.50	0.58	0.61
Hungary	0.48	0.30	0.60	0.49
Italy	0.42	0.36	0.51	0.48
Japan	0.72	0.73	0.63	0.61
Netherlands	0.46	0.53	0.51	0.56
New Zealand	0.20	0.17	0.47	0.44
Norway	0.49	0.50	0.61	0.58

Note: The firm-level correlation between wage and productivity levels is computed within each country-sector for 2001, using firm-level data; then, for each country, and separately for manufacturing and services, it is averaged across 2-digit sectors weighted by employment. Countries with data starting after 2001 or for which the correlation cannot be computed at the 2-digit sector level are not included.

²⁶Section OA-E in the Online Appendix reports a more detailed analysis of the evolution of the correlation between wage and productivity levels within country sectors over time. Interestingly, the results show that while the correlation between wages and labour productivity has increased over time, the correlation between wages and MFP has steadily weakened until the crisis and has significantly increased only in recent years.

Second, we investigate how the link between wage and productivity levels changes across the distribution of productivity. The MultiProd data allow us to explore the relative strength of the correlation between wages and productivity at different quantiles of the productivity distribution, for both labour productivity and MFP. We regress firm-level correlation between wages and productivity on dummies for each productivity quantile; the quantile in the middle of the productivity distribution (fourth and fifth deciles) is the reference quantile. Results in Table 5 show that wages and productivity are less correlated for firms at the top and at the bottom of the productivity distribution than they are for firms in the middle of the productivity distribution. The estimated coefficients for the bottom and the top decile of the productivity distribution are in fact negative relative to the baseline category (median quantile).

Table 5: Wage-productivity correlation by quantiles of productivity

	(1) corr(W,LP)	(2) corr(W,MFP)
Productivity quantiles		
Prod Perc 0-10	-0.106*** (0.024)	-0.090*** (0.026)
Prod Perc 10-40	0.108*** (0.017)	0.085*** (0.019)
Prod Perc 60-90	0.108*** (0.013)	0.103*** (0.017)
Prod Perc 90-100	-0.078*** (0.021)	-0.031 (0.025)
Observations	12626	11838
Adj. R-Square	0.648	0.663
Country-sector FE	YES	YES
Year FE	YES	YES
Nb Countries	10	10

Data is at the country-sector-year-productivity quantile level, weighted by the number of firms in each cell.

The dependent variable is the firm-level correlation between wage and productivity within each cell.

Clustered standard errors at the country-sector level in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Countries: AUS AUT BEL DNK FIN HUN ITA JPN NLD NOR.

Weaker correlation between productivity and wages occurs when firms pay too high or too low wages relative to their productivity level. There are several mechanisms that could explain this weaker correlation; these mechanisms could differ at the top and at the bottom of the distribution. At the bottom of the distribution, the weaker correlation might be driven by policies (e.g. minimum wage) that induce less productive firms to pay wages too high compared to their productivity. Alternatively, less productive firms might pay wages that are too low compared to their productivity, because workers in these firms might be willing to accept excessively low wages (e.g. if they have no experience, are immigrants etc.). At the top, the productivity-wage correlation might be weaker because competition for talents pushes firms to pay excessively high wages relative to the productivity of workers (especially for managers); this would be in line with recent models of CEO pay (Gabaix and Landier, 2008). Alternatively, as suggested

by the recent literature on decoupling between wages and productivity (e.g. Autor et al., 2017), firms at the top of the productivity distribution might pay wages that do not fully reflect their productivity advantage, because productivity gains of these top performing firms are not translated into wage gains for their workers. All these mechanisms explain why wages might be less correlated with productivity for firms at the top and at the bottom of the productivity distribution.

5.2 The link between growing wage inequality and increase in productivity dispersion

We now turn to investigate the main question of this study, namely whether wage dispersion is correlated with productivity dispersion. To examine this claim, we estimate the following regressions:

$$WD_{cjt} = \beta \cdot PD_{cjt} + \mathbf{y}_t + \mathbf{z}_{cj} + \varepsilon_{cjt} \quad (4)$$

where WD_{cjt} denotes wage dispersion, PD_{cjt} denotes productivity dispersion, \mathbf{z}_{cj} and \mathbf{y}_t indicate respectively country-sector and year fixed effects.²⁷ As for the regressions of wage and productivity dispersions, we weight each observation cjt by the number of firms reporting non-missing information for the relevant variable in a given country-sector-year.²⁸

Table 6: Regressing wage dispersion on productivity dispersion (country-sector fixed effects)

	(1)	(2)	(3)
	log Wage (90-10)	log Wage (90-10)	log Wage (90-10)
log LP (90-10)	0.422*** (0.072)		
log MFP_W (90-10)		0.143** (0.062)	
log MFP_SW (90-10)			0.074* (0.041)
N	3563	3456	3536
Adj. R-Square	0.968	0.965	0.965
Year FE	YES	YES	YES
Country-sector FE	YES	YES	YES
Nb Sectors	22	22	22
Nb Countries	13	13	13

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, NLD, NOR, NZL, SWE.

²⁷More precisely: $WD_{cjt} \equiv \left(\log \frac{W_{90}}{W_{10}} \right)_{cjt}$, the 90-10 percentile ratio of log wages. Similarly, for a given measure of a productivity P , we denote $PD_{cjt} \equiv \left(\log \frac{P_{90}}{P_{10}} \right)_{cjt}$ the 90-10 percentile ratio of log productivity.

²⁸The data in MultiProd are micro-aggregated moments (and means in particular) from firm-level data. For central moments, this weighting strategy implies that our regression estimates would be equivalent to those hypothetically generated using the underlying micro-data samples.

In this regression the coefficient of interest is β . Table 6 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). Unsurprisingly, given the discussion in the previous subsection, the β estimates from the regression reported in Table 6 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.

More precisely, given the inclusion of fixed effects, the coefficients reported in Table 6 indicate a positive link between the evolution of wage dispersion and productivity dispersion within country-sectors. An increase of 10% in the 90-10 percentile ratio of labour productivity is associated with an increase of 4.2% in the 90-10 percentile ratio of wages; this elasticity is positive and statistically different from zero. In Column (2) an increase of 10% in the 90-10 percentile ratio of MFP_W corresponds to a statistically significant increase of 1.43% in 90-10 percentile ratio of wages; at 0.74%, the effect is smaller for the 90-10 percentile ratio of MFP_SW (Column 3) but still significant at the 10% level.

We show in Appendix C that this relationship is not spuriously driven by changes in the workforce composition or business dynamism. An increase in the share of high-skilled workers could affect both the wage distribution, and the productivity distribution. Likewise, business dynamism could affect both wage inequality (Aghion et al., 2009) and productivity dispersion (Decker et al., 2016). Including these as controls does not affect the main estimates of interest (Table C.4).

Table 7: Regressing wage dispersion on productivity dispersion (country-sector fixed effects), separately for top and bottom halves of the distribution

	(1)	(2)	(3)	(4)	(5)	(6)
	log Wage (90-50)	log Wage (90-50)	log Wage (90-50)	log Wage (50-10)	log Wage (50-10)	log Wage (50-10)
log LP (90-50)	0.570*** (0.107)					
log MFP.W (90-50)		0.372*** (0.111)				
log MFP.SW (90-50)			0.020 (0.021)			
log LP (50-10)				0.712*** (0.124)		
log MFP.W (50-10)					0.233*** (0.072)	
log MFP.SW (50-10)						0.148* (0.087)
N	3574	3472	3548	3564	3456	3551
Adj. R-Square	0.931	0.913	0.904	0.952	0.942	0.941
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	13	13	13	13	13	13

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, NLD, NOR, NZL, SWE.

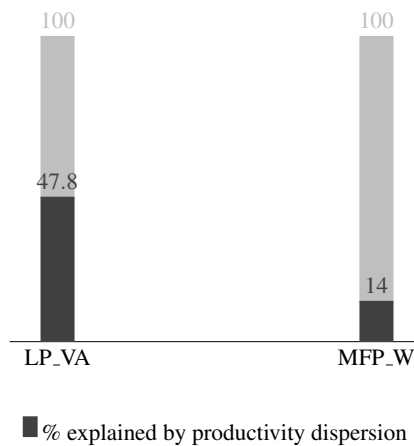
These results suggest that sectors in which the distribution of productivity becomes more polarised over time are also sectors in which wages polarise. Results in the previous two sections have shown that the dispersion has grown faster at the bottom of the distribution, both for wages and produc-

tivity. It is therefore interesting to explore whether the different dynamics at the top and bottom of the wage and productivity distributions also impact the link between the two. In order to do this, we regress wage dispersion at the top (90th-50th percentile ratio) on productivity dispersion at the top (90-50 ratio); and similarly for the the bottom of both distributions (50-10 ratios). Results given in Table 7 suggest that the link between wage and productivity dispersions exists both at the top (columns 1 to 3) and the bottom of the distributions (columns 4 to 6); further, this link is tighter at the bottom for labour productivity and MFP_SW. MFP_W displays a correlation that is roughly the same between the bottom and the top of the distributions.

5.3 Quantifying the effect of productivity dispersion

In this section, we provide a simple quantification of the increase in wage dispersion due to an increase in productivity dispersion. We do so using the estimates from Table 6, which link wage dispersion and productivity dispersion. Within each country-sector, dispersion in labour productivity has increased on average by 14.5% between 2001 and 2012.²⁹ The elasticity estimated in Table 6 suggests that this increase corresponds to $14.5 \times 0.422 = 6.1\%$ increase in wage dispersion. Between 2001 and 2012, between-firm wage dispersion has increased by 12.7%. Therefore the increase in labour dispersion explain 47.8% of the increase in wage dispersion, roughly half. Similar calculations show that the MFP's increase by 12.5% between 2000 and 2001 explains 14% of the increase in wage dispersion (Figure 7). The difference in numbers is mostly due to the smaller correlation between wage dispersion and MFP dispersion.

Figure 7: Share of the increase in wage dispersion explained by productivity dispersion



²⁹The 14.5% figure is calculated as $100 \times [\exp(\hat{\beta}_{2012}) - 1]$ where $\hat{\beta}_{2012} = 0.135$ is the estimate of the 2012 year dummy in equation 3. The detailed results of the regression are presented in Table B.2 in Appendix B.

6. THE ROLE OF STRUCTURAL FACTORS AND POLICIES

In the previous sections we have looked at the divergence in wages and productivity within sectors and countries. In this section, we investigate the role of structural factors as well as policies and institutional features of the economy that might have strengthened or weakened the overall response of wage dispersion to productivity dispersion.

6.1 Divergence and structural factors

We start by exploring the role of increased globalisation and digitalisation of the economy. The analysis is limited by the availability of data on these two phenomena both in terms of country and sectoral coverage, but also in their capacity of capturing these phenomena in their entirety. Tables D.7 and 8 try to capture trends in sectors' globalisation by controlling for changes in imports and exports of goods, and in the sector openness, measured as the sum of imports and exports (in logs). Moreover we seek to investigate the role of digitalisation by including the share of ICT in gross non-residential fixed assets. Finally, to try to capture skill-biased technical change in a different way, we include as regressor the share of hours worked by high skilled workers.³⁰ To account for sectors that might be expanding, all regressions control for the log of Gross Output.³¹

For each of these factors S , we estimate the following regression

$$WD_{cjt} = \beta \cdot \widetilde{PD}_{cjt} + \gamma \cdot \widetilde{S}_{cjt} + \delta (\widetilde{PD} \times \widetilde{S})_{cjt} + \mathbf{y}_t + \mathbf{z}_{cj} + \varepsilon_{cjt} \quad (5)$$

where WD_{cjt} denotes wage dispersion, \widetilde{PD}_{cjt} and \widetilde{S}_{cjt} denote productivity dispersion and the structural factor in deviation from their mean in the sample, and \mathbf{z}_{cj} and \mathbf{y}_t indicate respectively country-sector and year fixed effects.

Results are shown in Table 8 for MFP; the results for labour productivity are available in Table D.7 in the Appendix. As before, all regressions include country-by-sector fixed effects, and year fixed effects; the estimates report the impact of structural factors on changes in the dispersion of wages within country-sectors over time. Unfortunately because of limited availability of some structural factors (for instance, trade data is only available for manufacturing), the sample differs in each regression. As a reference, the first line of the table reports the univariate regression results (Equation 4) for the same sample as the multivariate regression. The coefficients on productivity dispersion are always very close in the two cases because, in the multivariate regressions, 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

³⁰The data sources are described in Section 2.2. Unfortunately the sectoral and country coverage of the various structural factors is not uniform, which is why the number of observations varies across columns of the two tables. Trade in goods is not available for services, hence the first three columns are restricted to manufacturing. The share of ICT is not available for Hungary, Japan, Norway, Sweden, as well as New Zealand, which is omitted in all regressions because gross output is also missing. The share of high skilled workers is not available for Norway and New Zealand, and after 2009.

³¹When imports, exports, and openness are interacted with productivity dispersion, as in columns 1, 2, 3 and 6, an interaction between productivity dispersion and log Gross Output is also included.

at their sample mean. For instance in column (1) in Table 8, the coefficient of MFP dispersion can be interpreted as the effect at the mean of Log Imports; hence in sectors with average imports, a 10% increase in productivity dispersion corresponds to a 3.3% increase in wage dispersion.

Table 8: Divergences and structural factors (MFP)

	(1)	(2)	(3)	(4)	(5)	(6)
<i>Univariate</i>						
Log MFP_W (90-10)	0.307*** (0.049)	0.307*** (0.049)	0.307*** (0.049)	0.133** (0.060)	0.096* (0.057)	0.202*** (0.052)
Log MFP_W (90-10)	0.333*** (0.061)	0.341*** (0.055)	0.346*** (0.059)	0.130** (0.053)	0.101* (0.059)	0.202*** (0.046)
Log Import (goods)	0.079 (0.051)					
Log MFP_W (90-10) × Log Import (goods)	0.138*** (0.035)					
Log Export (goods)		0.174*** (0.050)				
Log MFP_W (90-10) × Log Export (goods)		0.194*** (0.043)				
Log Openness			0.159*** (0.051)			0.078* (0.044)
Log MFP_W (90-10) × Log Openness			0.182*** (0.041)			0.054** (0.025)
Sh. of ICT in fixed assets				1.383** (0.624)		1.856 (1.584)
Log MFP_W (90-10) × Sh. of ICT in fixed assets				0.105 (0.334)		0.116 (1.131)
Sh. high-skilled (in total hours)					-0.488 (0.422)	
Log MFP_W (90-10) × Sh. high-skilled (in total hours)					0.214 (0.305)	
N	1779	1779	1779	1917	2190	1051
Adj. R-Square	0.920	0.925	0.923	0.962	0.969	0.945
Country-sector & year FE	YES	YES	YES	YES	YES	YES
Num. Countries	12	12	12	8	11	8

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 regressions include the logarithm of total gross output in the sector as extra control.

Regressions in columns (1), (2), (3), and (6) 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 NLD NOR SWE.

NZL is missing from the regressions because sectoral data for gross output are not available.

The results indicate that the correlation between wage and productivity dispersion remain strong even after controlling for these structural changes, which also significantly affect wage dispersion.³² More importantly for our analysis, globalisation reinforces the effect of productivity dispersion (estimates for the interaction terms are positive and significant). This results in a stronger increase of wage

³²Note that the main effect of MFP dispersion roughly doubles in columns 1-3, compared to the estimates in Section 5. This is due to the fact that the sample is restricted to manufacturing only, where MFP could be better estimated and the increase in wage dispersion is smaller in the first place.

inequality when the dispersion of productivity increases. In the case of MFP, exports seem to be correlated with wage dispersion both directly ($\hat{\gamma} = 0.065$) and via their positive interaction with productivity ($\hat{\delta} = 0.229$). The positive association between exports and between-firm wage inequality is in line with the existing evidence on the role of trade on wage inequality based on matched employer-employee data of single countries. For example Baumgarten (2013) finds that in Germany, exporting contributes significantly to between-firm wage dispersion, even after controlling for imports and proxies of ICT use. Helpman et al. (2017) find similar evidence on the positive link between trade and wage inequality (at low levels of openness) in Brazil.

When we include both ICT and openness at the same time (column 6 in Table 8), the latter comes out more significant. Interestingly, the effect of MFP dispersion is not strengthened at high levels of ICT (the interaction term is insignificant); this result can be rationalised by the fact that MFP is already controlling for the increase in (ICT) tangible capital.

6.2 Decomposing the increase in wage dispersion

The results of estimating Equation (5) shown in Table 8 can help us quantify the relative importance of productivity dispersion versus structural factors in explaining the increase in wage dispersion. We can do so by performing a simple quantification exercise, similar to that of Section 5.3.

In Table 8, all regressors are in deviation from the mean. The coefficient of each variable can be interpreted as the effect at the mean of the other variable, since the interaction term is then zero. For instance in column (1) of Table 8, the coefficient of Log MFP can be interpreted as the effect of an increase in productivity dispersion on wage dispersion, in a counterfactual country-sector where Log Import is held at its mean value. This allows us to estimate how much of the increase in MFP dispersion translates into increased wage dispersion, holding imports constant. Within each country-sector, dispersion in MFP has increased on average by 12.5% between 2001 and 2012. Holding imports at the mean, this would translate into an increase in wage dispersion of $0.333 \times 12.5\% = 4.2\%$ between 2001 and 2012, explaining 33% of the observed variation in wage dispersion.

We now proceed to do a more formal exercise. To better understand the additional impact of globalisation and digitalisation to the increase of wage dispersion, we first construct the counterfactual wage dispersion that would have occurred if the structural factors had not changed over time. More specifically, we construct the counterfactual dispersion \widehat{WD}^{S0} by using the estimates from the previous section, but holding each structural factor constant at its level at the beginning of the period \tilde{S}_{cj0} :

$$\widehat{WD}_{cjt}^{S0} = \hat{\beta} \cdot \tilde{PD}_{cjt} + \hat{\gamma} \cdot \tilde{S}_{cj0} + \hat{\delta}(\tilde{PD}_{cjt} \times \tilde{S}_{cj0}) + \hat{\gamma}_t + \hat{z}_{cj} \quad (6)$$

where \tilde{PD}_{cjt} denotes time-varying productivity dispersion and \tilde{S}_{cj0} the structural factor at its initial level, and the estimates of the elasticities and fixed effects are the ones obtained from Equation (5). Then, we obtain in an analogous way the predicted wage dispersion \widehat{WD} , this time letting both productivity and

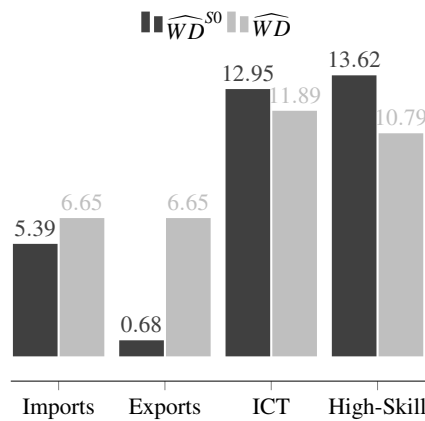
structural factors vary over time:

$$\widehat{WD}_{cjt} = \hat{\beta} \cdot \widetilde{PD}_{cjt} + \hat{\gamma} \cdot \widetilde{S}_{cjt} + \hat{\delta}(\widetilde{PD}_{cjt} \times \widetilde{S}_{cjt}) + \hat{\gamma}_t + \hat{z}_{cj} \quad (7)$$

Contrasting the two predictions for wage dispersion we are able to gauge the contribution of structural factors and their interaction with productivity dispersion to the total increase in wage dispersion. To do so, we regress the predicted values \widehat{WD} and counterfactuals \widehat{WD}^{S0} on year dummies within countries and sectors as in Equation 2. The estimates for the 2012 year dummy capture the predicted increase in wage dispersion between 2001 and 2012 and they are reported in Figure 8.

A large difference between the predicted and the counterfactual increase in wage dispersion indicates that structural factors play an important role in explaining the increase in wage dispersion, either via their direct effect or the interaction with productivity dispersion. With the notable exception of Exports in the case of MFP, in all other cases the direct effect of the increase in productivity dispersion accounts for most of the predicted increase in wage dispersion over the period. For High-Skill and ICT, the counterfactuals that keep the factors fixed at their initial levels actually predict an even higher increase in wage dispersion. In the former case, this is explained by the fact that the share of high-skilled has a negative point estimate. Conversely, in the case of the share of ICT in fixed assets, the predicted change is smaller than the counterfactual because the ICT share has slightly decrease over time within the country and sectors analysed. This fact calls for better measures of digitalisation.

Figure 8: Counterfactual and predicted increase in wage dispersion (MFP)



Note: Change in 90-10 log wage ratio between 2001 and 2012 (2009 for the share of High-Skill). The dark bars represent the counterfactual % increase in 90-10 ratio that would have occurred, holding Openness or Share of ICT constant at their value at the beginning of the period. The gray bars represent the wage dispersion predicted by the model as estimated in Equation (5). The predicted and counterfactual increases in wage dispersion differs across different factors because of sample differences.

6.3 The role of policies

Policies and regulations within countries may also shape the wage and productivity distributions and their evolution over time. The data collected through the MultiProd project matched with information on framework conditions in different countries allow us to shed light on the role of policies.

Some institutions, such as trade unions, and bargaining regimes, might be particularly relevant not only in shaping wage inequality but also the relationship between wage and productivity dispersion.³³ Moreover policies might also counteract some of the effects that structural factors have on wages and productivity. Recent analyses of the impact of globalization on wage inequality in countries such as Sweden (Akerman et al., 2013), Germany (Baumgarten, 2013), and France (Carluccio et al., 2015), all recognise the importance of bargaining regimes in shaping the effect of trade on wages. In fact, cross-country differences might reflect differences in labour market institutions, and the extent to which these institutions might dampen the between-firm wage differences and thus the decoupling between changes in the productivity and the wage distributions (OECD, 2016).

Countries that attempt to shield workers during adverse market conditions may feature lower wage and productivity dispersions. On the one hand, this is of course beneficial to the workers as their jobs and salaries would be better protected and shielded from uncertainty and the economic cycles. On the other hand, if regulations achieve lower dispersion in wages and productivity by inadvertently distorting resource allocation, this might result in lower aggregate productivity. Thus, some policies might be welfare improving in the short-run but may have detrimental consequences in the long run: policies that hinder the reallocation of resources away from poorly performing to highly productive firms can ultimately result in slower aggregate productivity growth.

In a nutshell we would like to understand whether country-specific policies affect wage dispersion and its link with productivity dispersion. To do so, we consider five main policies and institutional features of a country: i) minimum wage (both in terms of hourly real minimum wage and the minimum relative to average wages of full-time workers); ii) employment protection legislation (strictness of employment protection for both individual and collective dismissals); iii) trade union density; iv) coordination in wage setting and; v) product market regulations.^{34,35} We regress wage dispersion on productivity dispersion, each of the specific policies of interest and their interaction with productivity dispersion. What we want to test is the direct effect of policies on wage dispersion as well as whether they strengthen or weaken the link between wage dispersion and productivity dispersion.

Table 9 shows the results of this exercise when the productivity variable considered is MFP.³⁶ The first two columns report estimates for the minimum wage (column 1 using hourly real minimum wage and column 2 using minimum wage relative to average wage in the country sector year); column 3 considers employment protection legislation; estimates of trade union density and of coordination in wage setting can be found, respectively, in columns 4 and 5; finally the effect of product market regulations is shown

³³Gürtzgen, 2009, for instance, find that wages are related to firm-specific quasi-rents in the non-union sector and under firm-specific contracts using linked employer-employee data for Germany. But wages exhibit a significantly lower responsiveness to firm-specific profitability conditions when industry-wide wage contracts are used.

³⁴Note that we might not be able to fully capture the effects of policies that target more directly workers (e.g. minimum wage) rather than the firm (e.g. EPL) in terms of implications for both wages and labour mobility. This is because we only have average wage at the firm level which does not allow us to look at employees' tenure, skill composition within the firm etc . . .

³⁵Figure D.7 in the appendix shows how policies varied in each country over time. The data sources are described in Section 2.2. The change in the number of observations across the columns of the table is explained by the fact that: i) there is no minimum wage in Austria, Denmark, Finland, Italy, Norway, and Sweden; ii) EPL (EPRC Version 2) and PMR are available starting in 1998.

³⁶Table D.8 in the Appendix presents the results in terms of labour productivity.

in column 6. The regressions include a full set of country-sector and year fixed effects to control for any country-sector specific unobservable factor, hence focusing on the within country-sector variation over time. Note that the regressors are standardised for an easier comparison of the coefficients; this also implies that the coefficient of the level of each variable can be interpreted as the effect at the mean of the other variable (e.g., the coefficient of the minimum wage can be interpreted as the effect at the average level of MFP dispersion).

The results show that the link between wage and productivity dispersion is not broken by the considered policies and still displays a robust positive sign. They also confirm that the policies have the intended consequence of reducing wage dispersion and hence overall inequality, with the exception of competition-friendly product market reforms (lower product market regulations). At the same time they tend to significantly affect the link between wage and productivity dispersion.

While intuitively a higher minimum wage tends to reduce wage dispersion, it also tends to strengthen the link between wage and productivity dispersion. This result contrasts with the effect of other policies and suggests that increases in the minimum wage, both in real and relative terms, are associated with a stronger correlation between wage and productivity dispersion, at least in the case of MFP.³⁷ A few explanations could rationalise this result: i) the exit of firms at the bottom of the productivity distribution; ii) an improvement in firms' performance (higher efficiency and/or higher innovation) in an environment characterised by higher labour costs; iii) a reduction in labour inputs (head counts or hours worked), a substitution of labour with capital, and/or a change in the composition of the workforce towards more productive workers, which again would result in productivity improvements over time. In particular, the capital-labour substitution in response to higher labour costs could drive the increase in the link between wage and productivity dispersion. This implies that the reduction in wage dispersion associated with a higher minimum wage might come at the expense of the employment rate and the labour share (Pak and Schwellnus, 2018).

A higher employment protection legislation is associated with a decrease in wage dispersion. Conversely to a higher minimum wage, a stricter employment protection goes hand in hand with a weaker link between wage dispersion and productivity dispersion. The result seems to be particularly affected by provisions on collective dismissals, which could have strong implications for the reallocation of resources from low to high productivity firms and the matching of talent and skills.³⁸ A higher union density is also associated with lower wage dispersion, but, it does not affect the link between productivity and wage dispersion in a significant way. Controlling for time invariant country-sector characteristics, a higher union density therefore seem to have the intended consequence of reducing wage dispersion without affecting the link between productivity and wages. Given that union density has experienced a significant downward sloping trend over the period, the interpretation of this result is that a lower union density has

³⁷In unreported results, we find that the effect is particularly strong for EU countries at the beginning of the period, which seems to suggest that policy changes taking place in France are partially responsible for this finding.

³⁸The indicator used is the EPRC Version 2. The working paper version of this paper (Berlingieri et al., 2017b) included results using the EPRC Version 1 of the indicator, which has a longer time coverage (including years before 1998) but is constructed using fewer sub-indicators. In particular it does not cover additional provisions for collective dismissals. Using this different indicator, the estimate of the interaction term between EPL and productivity dispersion was negative and close in magnitude, but not significantly different from zero.

Table 9: Divergences and Policy (MFP)

	(1)	(2)	(3)	(4)	(5)	(6)
Log MFP_W (90-10)	0.075* (0.043)	0.063 (0.041)	0.427** (0.167)	0.370*** (0.121)	0.285** (0.121)	0.348*** (0.120)
Real Min Wage (hour)	-0.369*** (0.077)					
Log MFP_W (90-10) × Real Min Wage (hour)	0.054* (0.028)					
Relative Min Wage (wrt av)		-0.124*** (0.038)				
Log MFP_W (90-10) × Relative Min Wage (wrt av)		0.059*** (0.020)				
EPL (indiv. and coll.)			-0.077* (0.045)			
Log MFP_W (90-10) × EPL (indiv. and coll.)			-0.224* (0.118)			
Trade union density				-0.361*** (0.062)		
Log MFP_W (90-10) × Trade union density				0.016 (0.085)		
Wage Setting					-0.103*** (0.021)	
Log MFP_W (90-10) × Wage Setting					-0.132*** (0.050)	
PMR (interpolated)						-0.064*** (0.019)
Log MFP_W (90-10) × PMR (interpolated)						-0.063*** (0.017)
N	1804	1804	3183	3456	3456	3183
Adj. R-Square	0.970	0.967	0.968	0.968	0.966	0.971
Country-sector & year FE	YES	YES	YES	YES	YES	YES
Num. Countries	7	7	13	13	13	13

Data is at the country-sector-year level, weighted by the number of firms in each cell. Policy and institutional variables vary at the country-year level.

The dependent variable is Log Wage (90-10); all regressors are standardised.

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 NLD NOR NZL SWE.

been associated with a increase in wage dispersion but not necessarily a tighter link between wage and productivity dispersion.³⁹

The measure of coordination in wage setting is significant and negative both directly and when interacted with productivity. This policy measure captures the extent to which wage setting arrangements are likely to generate more or less coordination, whereby the lowest level indicates that the wage bargaining is fragmented and confined largely to individual firms or plants while the highest level corresponds to centralised bargaining (with or without government involvement). Hence more centralised bargaining helps limiting the extent of wage dispersion, but at the same time weakens the link between wages and productivity, which might be detrimental for long run growth. These cross-country results are in line and reinforce the evidence found at the country level. For instance, Dahl et al. (2013) find, for Denmark, that wages are more dispersed under firm-level bargaining. Antonczyk et al. (2010) show that the decline in collective wage bargaining contributes to the strong rise in wage inequality in Germany, but this was instrumental for the increase of German competitiveness over the last two decades (Dustmann et al., 2014). Our results show that more coordination in wage setting is on average associated with lower wage dispersion also in countries beyond Germany and Denmark; more importantly, they show that there is a cost in terms of a misalignment with productivity.⁴⁰

Finally, while competition-friendly product market reforms (a reduction in product market regulation) may reduce rents appropriated by capital owners, they are also associated with an increase in between-firm wage dispersion (Column 6). This result is in line with previous studies suggesting that such reforms are associated with increases in wage inequality, with workers in firms at the bottom of the distribution more likely to be those who bear the costs of the reform relative to those in the top of the distribution (Braconier and Ruiz-Valenzuela, 2014). At the same time, and perhaps unsurprisingly, competition-friendly product market reforms are associated with a stronger link between wage and productivity dispersion.

7. CONCLUSIONS

The last decades have seen a growing divergence in wages and productivity. Most of the existing evidence has documented these two trends separately, and often using evidence from a single country. Pioneering studies such as Barth et al. (2014) and Song et al. (2018) for the US and Card et al. (2013) for Germany have found significant evidence of the importance of differences in pay across firms to explain the evolution of wage inequality, in line with the theoretical work of Nobel prize winners Diamond, Mortensen and Pissarides. However, with the exception of the study by Faggio et al. (2010) for the UK, we are not aware of any paper linking dispersion in multifactor productivity performance to wage dispersion and their evolution over time.

³⁹To note that in un-reported cross-sectional results a higher trade union density is associated with a significantly lower link between wage and productivity dispersion, see (Berlingieri et al., 2017b).

⁴⁰Using the Eurostat Structure of Earnings Survey, Dreger et al. (2015) show that intermediate levels of collective bargaining seem to produce a more compressed wage structure. Manasse and Manfredi (2014) discuss how the collective bargaining system in Italy might be the cause of the misalignment between productivity and wages.

In this study we exploit a novel data set that contains harmonised micro-aggregated statistics for 16 countries over the last fifteen years on productivity and wage dispersion, based on the OECD Multi-Prod project. Thanks to this unique data source, we have been able to provide, for the first time, detailed cross-country evidence on the evolution of wage and productivity dispersions and the link between the two within 2-digit industries and countries. By linking the database to information on structural factors, such as ICT intensity and openness, as well as policies and institutions that affect the pay settings environment, such as minimum wage and unionisation, we can look at how these policies affect the link between productivity and wage dispersion.

We can summarise the findings of the study in five main takeaways:

1. Between-firm wage dispersion is found to be significantly and positively correlated to the overall wage dispersion and its evolution over time. Most of the between-firm wage variance is driven by differences in pay across firms within sectors rather than by differences in average wages across sectors. There has been a steady increase in wage inequality, measured as the 90-10 wage ratio, driven mainly by an increased dispersion at the bottom of the distribution; the dispersion at the top plays a role only in the service sector after 2005.
2. Similarly, we find that dispersion in productivity, whether measured as real value added per worker (labour productivity) or as multi-factor productivity (MFP), has also significantly increased in the last decades. Most of the increase is driven by within-sector productivity differentials across firms, rather than by cross-sectoral differences. Similar dynamics of increase at the bottom throughout the whole period and at the top only after 2005 are also present in the productivity data, which might point to a link between the co-evolution of wage and productivity dispersion.
3. The evidence suggests that wage dispersion is linked to increasing differences between high and low productivity firms, even controlling for sectors' skill composition. This relationship holds in levels and when looking at short- and long-term changes over time. Moreover, firm-level correlation between wages and productivity is systematically weaker at the top and at the bottom of the productivity distribution.
4. When looking at the role of structural changes, the estimates suggest that both globalisation, proxied by measures of openness, import penetration and export intensity at the sectoral level, and digitalisation, proxied by ICT capital intensity at the sectoral level, are associated with higher wage divergence and tend to strengthen the link between productivity and wage dispersion within sectors and countries over time.
5. Finally, the study provides an analysis of the role of policy on the link between wage inequality and productivity dispersion focusing on minimum wage, employment protection legislation, union density, coordination in wage setting, and product market regulations. The results are to be considered as conditional correlations rather than causal effect of policies, but they point to a significant positive link between higher minimum wages, unionisation, EPL and reduced wage inequality, and, in the case of the minimum wage, to a strengthening of the link between productivity and wages dispersion over time.

Showing a systematic and significant link between these two trends is particularly important in the current policy debate, and analysing how structural factors and policies might affect this link could provide valuable insights for policy makers. First, such an analysis might help provide support to policy measures designed to improve productivity performance of firms at the bottom of the productivity distribution, as an improvement in their performance will not only impact economic growth but also inequalities. Second, one needs to better understand how labour market institutions and policies that are intended to contain wage inequality might at the same time affect firms' productivity and the re-allocation of resources across firms. Indeed our results suggest there might be a trade-off between the goal of containing or lowering wage inequality on the one hand, and ensuring growth-enhancing resource reallocation and the alignment between the evolution of wages and productivity across firms on the other.

A full account of the link between wage inequality and productivity divergence would ideally rely on linked employer-employee data, together with detailed data on firms productivity. Unfortunately, this is a goal that might not be achievable in a cross-country setting in the very short term. But work is already under way at the OECD to extend future waves of the MultiProd project to include these data, at least for the set of countries in which they are available. A wider availability of matched employer-employee data across countries would allow us to provide more detailed answers to these very policy relevant questions.

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APPENDIX

A. ESTIMATION OF MULTI-FACTOR PRODUCTIVITY

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. Firms are assumed to have a Cobb-Douglas production function, but not necessarily constant returns to scale:

$$Y_{it} = A_{it} K_{it}^{\beta_K} L_{it}^{\beta_L} \quad (A.1)$$

where A_{it} , firm i 's MFP at time t , is typically unobserved and has to be estimated. A straightforward estimation of Equation (A.1) using Ordinary Least Squares would likely be biased because MFP is partly known to the firm, and input choices are therefore correlated with productivity.⁴¹

To remedy this, we estimate MFP using the generalized methods of moments approach suggested by Wooldridge (2009). The procedure relies on estimating the endogenous variable inputs with a polynomial of lagged inputs and a polynomial of intermediates. We label the resulting estimates MFP_W , which we use as our main measure of MFP in our analysis. This approach further allows to alleviate the identification concerns pointed out by Akerberg et al. (2015) in earlier instrumental variables methods (Olley and Pakes, 1996; Levinsohn and Petrin, 2003), and yields consistent standard errors without the need for bootstrapping.

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 , by assuming the following production function in gross output:

$$Y_{it} = A_{it} M_{it}^{\beta_M^{SW}} K_{it}^{\beta_K^{SW}} L_{it}^{\beta_L^{SW}} \quad (A.4)$$

where input elasticities β_M^{SW} , β_K^{SW} and β_L^{SW} of firm i are assumed to be the sector-specific median of factor shares across countries and years. With an additional assumption of constant returns to scale, productivity is computed in logs:

$$\log MFP_SW_{it} = \log GO_{it} - \beta_M^{SW} m_{it} - \beta_L^{SW} l_{it} - (1 - \beta_M^{SW} - \beta_L^{SW}) k_{it} \quad (A.5)$$

⁴¹To see this, let's rewrite Equation (A.1) in logs:

$$y_{it} = \beta_K k_{it} + \beta_L l_{it} + (\omega_{it} + \varepsilon_{it}) \quad (A.2)$$

where we split the unobserved $\log A_{it}$ into ω_{it} , the component known to the firm, and ε_{it} , the component that is not. Since ω_{it} is known to the firm at the time of choosing its inputs k_{it} and l_{it} , these will be correlated with ω_{it} and therefore with $\log A_{it}$. A straightforward OLS estimation of Equation (A.2) would yield the following productivity estimate:

$$\widehat{\log A_{it}} = y_{it} - \widehat{\beta}_L^{OLS} l_{it} - \widehat{\beta}_K^{OLS} k_{it} \quad (A.3)$$

This estimate is likely to be biased because k_{it} and l_{it} are correlated with the error term in Equation (A.2).

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.

B. DOCUMENTING THE DISPERSION INCREASE

B.1 Wage and productivity dispersion over time

Results of regressing wage and productivity dispersion on time dummies, as given in Equation (2) and Equation (3), are given in Table B.1 and Table B.2, respectively.

Table B.1: Regressing wage dispersion on year dummies shows an increase of wage dispersion over time, using the specification given in Equation (2).

	(1) log Wage (90-10)	(2) log Wage (90-10)
year=2001	ref.	
year=2002	-0.008	
year=2003	0.018**	
year=2004	0.019*	
year=2005	0.001	
year=2006	0.021**	
year=2007	0.040***	
year=2008	0.072***	
year=2009	0.088***	
year=2010	0.094***	
year=2011	0.107***	
year=2012	0.120***	
year, linear trend		0.012***
Observations	2934	2934
Adj. R-Square	0.967	0.967
Country-sector FE	YES	YES
Nb Sectors	22	22
Nb Countries	13	13

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 NLD NOR NZL SWE

Clustered standard errors at the country-sector level in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

For robustness, we also regress wage productivity dispersion on a time trend, with country-sector fixed effects, according to the following model:

$$\left(\log \frac{P_{90}}{P_{10}} \right)_{cjt} = \alpha + \beta year + z_{cj} + \varepsilon_{cjt} \quad (\text{B.6})$$

The results are given in column 2 of Table B.1 for wage dispersion, and in Table B.3 for productivity dispersion.

Table B.2: Regressing productivity dispersion on year dummies show an increase of productivity dispersion over time, using the specification given in Equation (3).

	(1)	(2)	(3)
	Log LP (90-10)	Log MFP_W (90-10)	LogMFP_SW 90-10 percentiles diff
year=2001	ref.	ref.	ref.
year=2002	0.021***	0.014*	0.008
year=2003	0.034***	0.029***	0.009
year=2004	0.063***	0.054***	0.027***
year=2005	0.040***	0.032***	0.042***
year=2006	0.075***	0.068***	0.060***
year=2007	0.075***	0.078***	0.066***
year=2008	0.090***	0.090***	0.081***
year=2009	0.084***	0.077***	0.066***
year=2010	0.110***	0.083***	0.077***
year=2011	0.119***	0.089***	0.097***
year=2012	0.135***	0.118***	0.110***
Observations	2946	2829	2912
Adj. R-Square	0.976	0.997	0.950
Country-sector FE	YES	YES	YES
Nb Sectors	22	22	22
Nb Countries	13	13	13

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 NLD NOR NZL SWE.

Clustered standard errors at the country-sector level in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.3: Regressing productivity dispersion on a time trend shows an increase of productivity dispersion over time, according to Equation (B.6).

	(1)	(2)	(3)
	LogLP_VA_pd90_10	LogMFP_W_pd90_10	LogMFP_SW_pd90_10
year, linear trend	0.011***	0.009***	0.010***
Observations	2946	2829	2912
Adj. R-Square	0.976	0.997	0.950
Country-sector FE	YES	YES	YES
Nb Sectors	22	22	22
Nb Countries	13	13	13

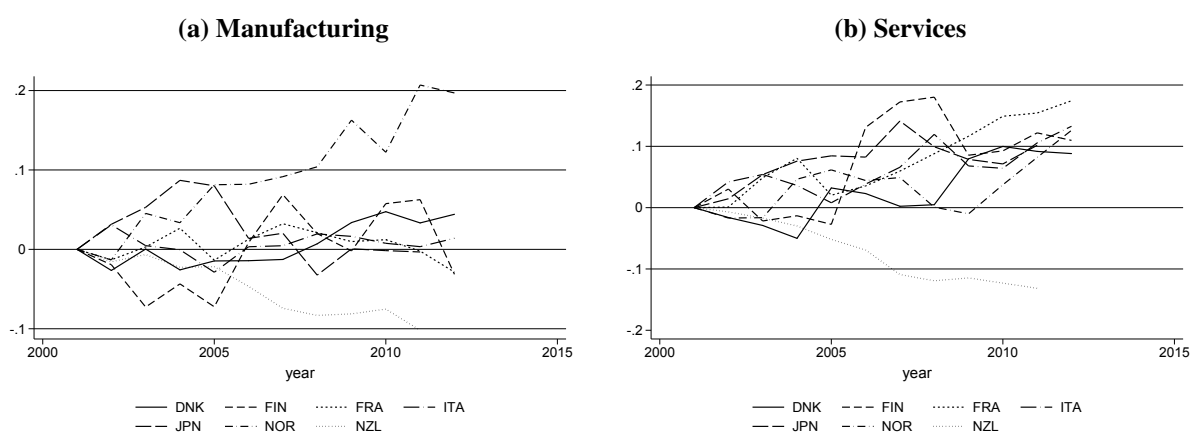
Data is at the country-sector-year level

Clustered standard errors at the country-sector level in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

B.2 Wage and productivity dispersion by country

Our main result concerning the Great Divergence of wages should not hide the fact that there exists important variation across countries in our sample. Figure B.1 plots log changes in the 90-10 wage ratio from 2001, within each country and separately for manufacturing and services. For instance in both manufacturing and services the 90-10 wage ratio increased in most countries, with the exception of New Zealand, where it decreased significantly.⁴²

Figure B.1: Divergence of wages, by country



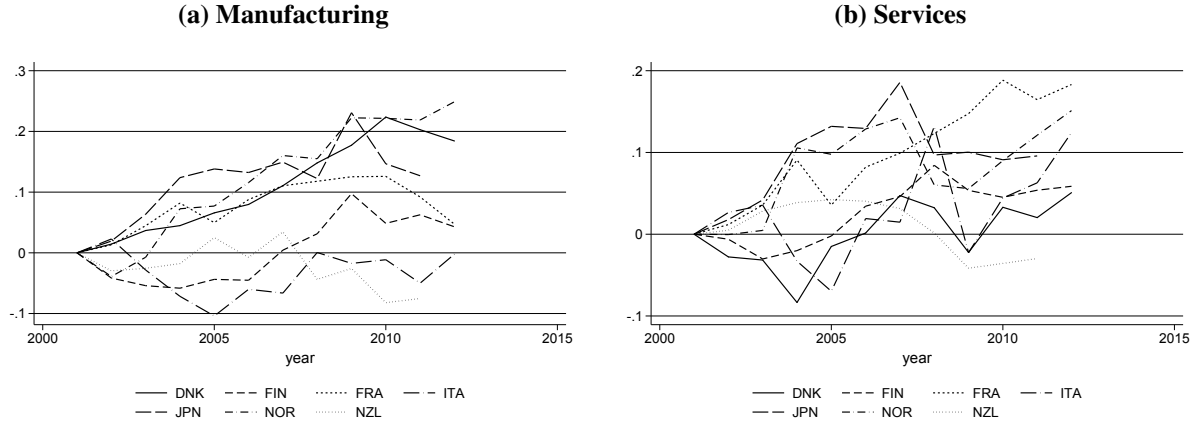
Note: Change in the 90-10 difference of log wages (computed as the difference between the 90th and the 10th percentile of the log of real wages), respectively for manufacturing and services. Data is at the country-sector-year level. For each country, the 90-10 difference is averaged across 2-digit sectors weighted by employment, then normalised at 0 in 2001. Countries with data starting after 2001 or for which data is only available at the macro-sector level are not included in this graphs; Hungary and the Netherlands are also excluded.

To illustrate the trends in the relative productivity performance of top performers vs. laggards by country, Figures B.2 and B.3 plot the difference between the 90th and 10th percentiles of log-productivity (labour productivity and MFP, respectively) over time, normalised at 0 in 2001. In each figure, the left panel represents log-productivity dispersion in manufacturing and the right panel represents log-productivity dispersion in (non-financial) market services, where the patterns at the macro-sector level are obtained by country as averages across 2-digit sectors weighted by employment.

Figures B.2 and B.3 illustrate well the trend in log-productivity dispersion, which is increasing both in manufacturing and in services. For the majority of countries dispersion in 2012 is higher than in 2001: in services this is the case for all countries but New Zealand in terms of labour productivity; in manufacturing for all but Italy and New Zealand – both in terms of labour and multi-factor productivity.

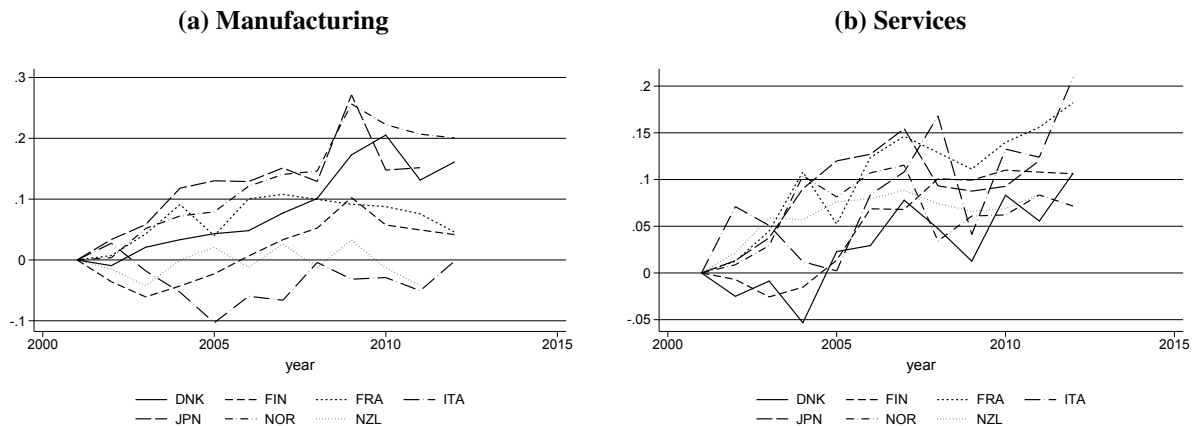
⁴²In un-reported results obtained at the macro-sector level, we find that wage dispersion has decreased in Canada as well (data for Canada are not available at the 2 digit level). This result is reminiscent of the findings in Fortin and Lemieux (2015) who, using data from the 1997 to 2013 Labour Force Survey for Canada, show that overall wage inequality has decreased in a few Canadian provinces due to the extractive resources sector boom.

Figure B.2: Divergence of (log) Labour Productivity over time



Note: Change in 90-10 difference of log-labour productivity for manufacturing (left panel) and services (right panel). Data is at the country-sector-year level. Within each country-year, the 90-10 log-labour productivity difference is averaged across 2-digit sectors weighted by employment; the resulting country-year data is normalised at 0 in 2001. Countries with data starting after 2001 or for which data is only available at the macro-sector level are not included in this graphs; Hungary and the Netherlands are also excluded.

Figure B.3: Divergence of (log) MFP over time

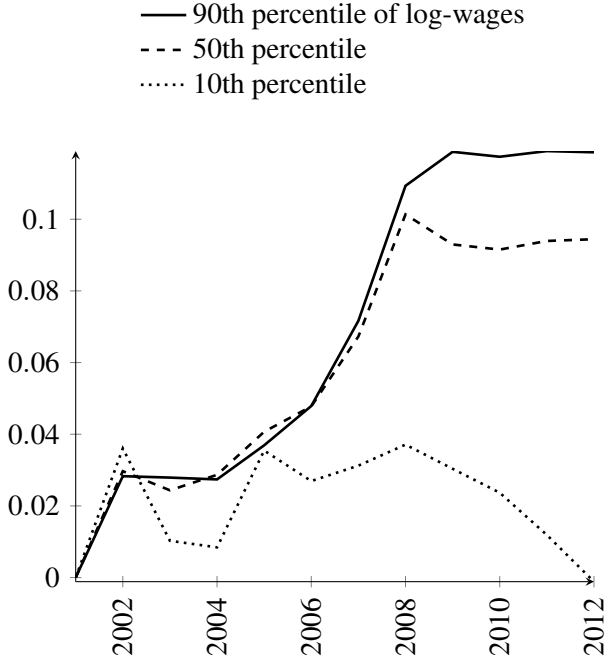


Note: Change in the 90-10 difference of log-MFP (Wooldridge) for manufacturing (left panel) and services (right panel). Data is at the country-sector-year level. Within each country-year, the 90-10 log-MFP difference is averaged across 2-digit sectors weighted by log value-added; the resulting country-year data is normalised at 0 in 2001. Countries with data starting after 2001 or for which data is only available at the macro-sector level are not included in this graphs; Hungary and the Netherlands are also excluded.

B.3 Wage dispersion was more pronounced at the bottom of the distribution

We can further illustrate the claim made in Section 3.2.2 that wage dispersion was more pronounced in the bottom half of the wage distribution. We regress separately the 90th, 50th and 10th percentiles of log-wages (computed for each country-sector-year) on year dummies, controlling for country-sector pairs. The results are plotted in Figure B.4. The median and top decile of wages grew almost at the same speed (within each country-sector), indicating a compression of dispersion at the top. Instead, the bottom decile of wages was almost constant between 2001 and 2012, creating an increasing gap between median and low-paying firms.

Figure B.4: Divergence of wages at the bottom of the between-firm wage distribution

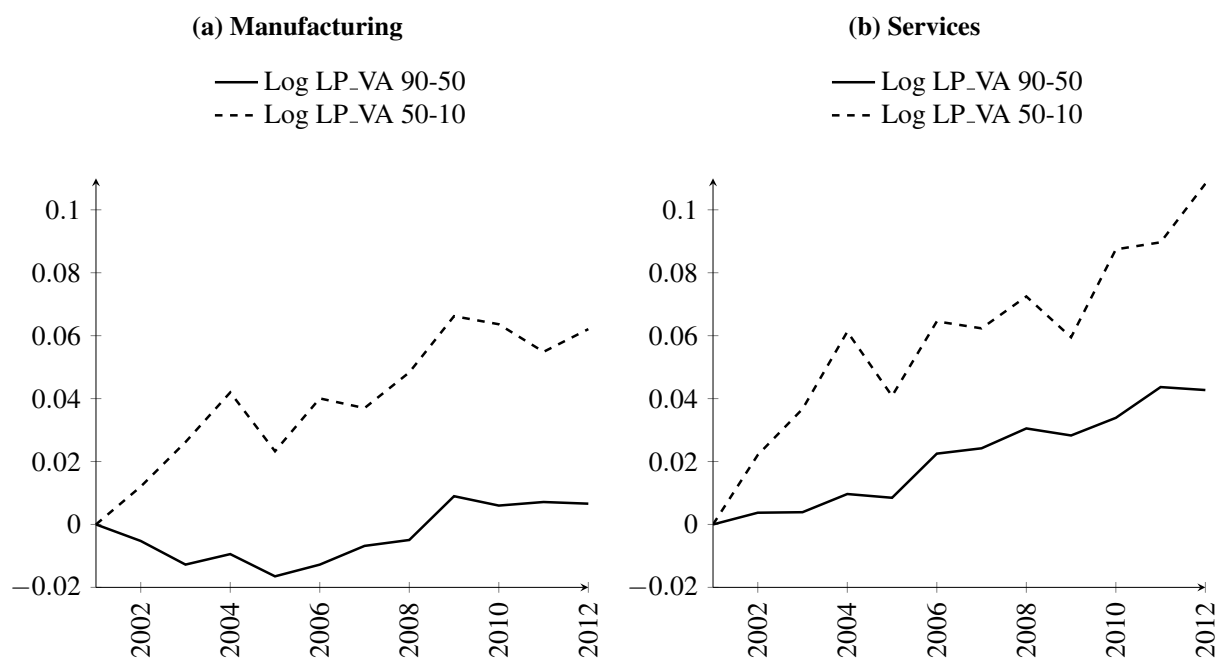


Note: The solid, dashed, and dotted lines plot, respectively, the estimated year dummies β_t of a regression of, respectively the 90th, 50th and 10th percentiles of log-wages (computed for each country-sector-year) on year dummies, controlling for country-sector pairs. The estimates for baseline year 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, NLD, NOR, NZL, SWE .

B.4 Labour productivity dispersion at the top and at the bottom of the distribution by macro sector

Figure B.5 replicates Figure 6 in the main text for the case of labour productivity. LP displays similar trends compared to MFP, just less volatile over time.

Figure B.5: LP dispersion at the top versus bottom of the productivity distribution, for manufacturing and services



Note: The figure plots the year dummy estimates of a regression of log-labour productivity dispersion at the top (90th and 50th percentiles difference, solid line) and at the bottom (50th and 10th percentiles difference, dashed line) on year dummies, controlling for country-sector pairs, separately for manufacturing and services. 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, NLD, NOR, NZL, SWE.

C. THE LINK BETWEEN WAGE AND PRODUCTIVITY DISPERSION: ROBUSTNESS CHECKS

In this section we investigate the robustness of the link between wage and productivity dispersion. First, we check that the relationship is not driven by obvious confounders. The first element that could affect the wage distribution is the quality of the workforce. We control for the share of hours worked by high-skilled workers in each sector, taken from the WIOD database.⁴³ The share of high-skilled workers capture changes in the workforce composition that could drive both changes in the wage distribution, and in the productivity distribution.

We also control for the log of the average firm age, which captures differences in business dynamism across sectors (firms are on average younger in more dynamic sectors). Business dynamism might confound the relationship between productivity dispersion and wage dispersion because it could affect both (see Aghion et al., 2009, for the role of entry in the increase in inequality and Decker et al., 2016, for the link between business dynamism and productivity dispersion).

Unfortunately the sample size is affected by the inclusion of these controls. Data on skill share are not available for Norway and New Zealand, nor after 2009. Including business dynamism (log of average firm age) further reduces the sample because it is not available at the 2-digit sector level for Australia, Finland and New Zealand. Requiring both controls to be available drops the number of observations approximately by half: the controls are not available for certain countries (Australia, Finland, the Netherlands, Norway, and New Zealand), and for certain years (2010 and after).

This makes it difficult to compare results with those of Table 6: estimates of interest could change either because of the added control variables, or because of the change in sample. To remedy this, we run the regressions with and without the controls, on the same sample. More specifically, we run the following regression:

$$WD_{cjt} = \alpha + \beta \cdot PD_{cjt} + \mathbf{X}'_{cjt} \boldsymbol{\gamma} + \mathbf{y}_t + \mathbf{z}_{cj} + \varepsilon_{cjt} \quad (\text{C.7})$$

where \mathbf{X} denotes time-varying controls. The results are given in Table C.4; the coefficients of interest are the coefficients on productivity dispersion (90-10 percentile difference of log labour productivity in columns 1 to 3, 90-10 percentile difference of log MFP_W in columns 4 to 6, and percentile difference in log MFP_SW in columns 7 to 9). For each of the three measures of productivity dispersion PD (LP_VA, MFP_W, and MFP_SW), each regression is run three times: on the full sample (columns 1, 4 and 7 of Table C.4 below, identical to columns 1, 2 and 3 from Table 6); only for observations where the share of high-skill workers is available (columns 2, 5 and 8); and only for observations where both the share of high-skill workers and the average age of firms are available (columns 3, 6 and 9). In each case, we run the regression first without including the controls (“Univariate” panel at the top), and then including the controls (“Multivariate” panel at the bottom).

⁴³The data on skills are not available for Norway and New Zealand; they are ISIC Revision 4 estimates based on the ISIC 3 original data from the World Input Output Tables (WIOD), Socio Economic Accounts, July 2014 (See Timmer et al., 2015).

Table C.4: Regressing wage dispersion on productivity dispersion, with controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<i>Univariate</i>									
log LP (90-10)	0.422*** (0.072)	0.259*** (0.083)	0.227** (0.088)						
log MFP_W (90-10)				0.143** (0.062)	0.096* (0.057)	0.072 (0.057)			
log MFP_SW (90-10)							0.074* (0.041)	0.073* (0.037)	0.058 (0.036)
<i>Multivariate</i>									
log LP (90-10)	0.422*** (0.072)	0.277*** (0.081)	0.240*** (0.081)						
log MFP_W (90-10)				0.143** (0.062)	0.100* (0.058)	0.084 (0.054)			
log MFP_SW (90-10)							0.074* (0.041)	0.075* (0.038)	0.063* (0.036)
% hrs by skilled workers		-0.773* (0.407)	-0.408 (0.316)		-0.627 (0.431)	-0.281 (0.337)		-0.599 (0.430)	-0.244 (0.332)
log Avg Firm Age			0.051** (0.025)			0.052** (0.025)			0.047* (0.025)
N	3563	2265	1786	3456	2191	1711	3536	2250	1771
Adj. R-Square	0.968	0.970	0.976	0.965	0.969	0.974	0.965	0.969	0.975
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country-sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Nb Sectors	22	22	22	22	22	22	22	22	22
Nb Countries	13	11	9	13	11	9	13	11	9

Data is at the country-sector-year level, weighted by the number of firms in each cell.

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: .

Comparing across specifications in the “univariate” panel shows how the coefficient of interest (on productivity dispersion) changes when the sample reduces. Overall, restricting samples drops point estimates roughly by half, e.g. from 0.143 to 0.072 between columns 4 and 6. (Since standard errors remain more or less unchanged, coefficients tend to lose statistical significance.)

For a given specification, comparing the “Univariate” panel (without controls) and the “Multivariate” panel (with controls) shows that, for a given sample, the coefficients do not vary much with the inclusion of controls. For instance, in column 6, including the share of high-skill workers and the log of average firm age changes the coefficient on MFP dispersion from 0.072 to 0.084.

These two elements taken together suggest that workers’ skill composition and firm age composition do not appear to be relevant confounding factors in the link between productivity dispersion and wage dispersion. Including them cuts our estimates of interest by half, but this is because of the induced change in sample. Changes in workforce composition and business dynamism do not drive a spurious correlation between productivity dispersion and wage dispersion.

Finally, to confirm the robustness of the estimates of Equation (4), we perform two exercises. First, we estimate the following regression:

$$WD_{cjt} = \alpha + \beta \cdot PD_{cjt} + \mathbf{y}_t + \varepsilon_{cjt} \quad (\text{C.8})$$

Table C.5: Regressing wage dispersion on productivity dispersion (pooled regression)

	(1)	(2)	(3)
	log Wage (90-10)	log Wage (90-10)	log Wage (90-10)
log LP (90-10)	0.696*** (0.096)		
log MFP_W (90-10)		0.176*** (0.030)	
log MFP_SW (90-10)			0.547*** (0.082)
N	3564	3456	3537
Adj. R-Square	0.501	0.258	0.310
Year FE	YES	YES	YES
Country-sector FE	NO	NO	NO
Nb Sectors	22	22	22
Nb Countries	13	13	13

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, NLD, NOR, NZL, SWE.

The results, given in Table C.5, show that the pooled regression of Equation (C.8) obtains qualitatively the same results as the regression with country-sector fixed effects of Equation (4). Unsurprisingly, estimates for β are higher without the inclusion of these fixed effects; this shows that sectoral and country characteristics, which also affect productivity dispersion, are still important determinants of wage dispersion. That estimates for β remain positive and significant when these fixed effects are included shows however that an important “within” variation is not captured by time-invariant characteristics, and justifies our initial analysis.

Second, fixed-effects models might be affected by measurement error, as they might be contaminated by temporary fluctuations: the ‘signal’ of structural changes in productivity dispersion might be overwhelmed by the ‘noise’ of transitory changes, causing the variation left for identification to largely reflect transitory and idiosyncratic changes, rather than longer term changes (McKinnish, 2008). Therefore, to confirm the robustness of the estimates of Equation (4), we estimate the first-difference equation:

$$\Delta WD_{cjt} = \alpha + \beta \cdot \Delta PD_{cjt} + \mathbf{y}_t + \varepsilon_{cjt} \quad (\text{C.9})$$

where Δ in Equation (C.9) denotes long differences. Equation (C.9) estimates the link between changes in wage inequality and in productivity dispersion using long differences between 2005 and 2012, the period for which we can compute long differences for a significant number of countries.

Long difference estimates reported in Table C.6 similarly confirm that, for our two main measures of productivity LP and MFP_W, and whether controls for skills are included or not, an increase of the dispersion in labour productivity correlates with a significant increase in wage dispersion.

Table C.6: Regressing wage dispersion on productivity dispersion (2005-2012 change)

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta \log \text{ Wages (90-10)}$	$\Delta \log \text{ Wages (90-10)}$	$\Delta \log \text{ Wages (90-10)}$	$\Delta \log \text{ Wages (90-10)}$	$\Delta \log \text{ Wages (90-10)}$	$\Delta \log \text{ Wages (90-10)}$
$\Delta \log \text{ LP (90-10)}$	0.433*** (0.071)			0.310** (0.152)		
$\Delta \log \text{ MFP_W (90-10)}$		0.422*** (0.060)			0.392*** (0.109)	
$\Delta \log \text{ MFP_SW (90-10)}$			0.110 (0.096)			0.244*** (0.090)
$\Delta \%$ hrs by skilled workers				0.570 (0.539)	0.702 (0.433)	0.833* (0.494)
Constant	0.042*** (0.004)	0.047*** (0.003)	0.062*** (0.005)	0.021 (0.019)	0.015 (0.017)	0.016 (0.020)
N	1688	1643	1667	774	754	770
Adj. R-Square	0.125	0.122	0.013	0.059	0.099	0.048
Year FE	NO	NO	NO	NO	NO	NO
Country-sector FE	NO	NO	NO	NO	NO	NO
Nb Sectors	22	22	22	22	22	22
Nb Countries	12	12	12	9	9	9

Clustered standard errors at the country-sector level in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The number of observations reported is for all years, but the regression is run on long differences, with one observation per country-sector.

Data is at the country-sector-year level, weighted by the number of firms in each cell.

Countries: AUS, BEL, DNK, FIN, FRA, HUN, ITA, JPN, NLD, NOR, NZL, SWE.

D. THE ROLE OF STRUCTURAL FACTORS AND POLICIES: ADDITIONAL RESULTS

D.1 Structural factors: additional results for Labour Productivity

Table D.7 replicates Table 8 in the main text for the case of labour productivity. The role of globalisation is confirmed also in the case of LP, especially its role in reinforcing the effect of productivity dispersion (estimates for the interaction terms are positive and significant). When we include both ICT and openness at the same time (column 6 in Table D.7), ICT remains significant when considering LP while this was not the case for MFP. In fact, in the case of labour productivity, ICT has the strongest direct link with wage dispersion, as well as a significant although smaller effect via a tighter link between wage dispersion and productivity dispersion. This result might be partially explained by the fact that LP does not control for capital including some forms of tangible ICT capital. In fact in the case of MFP, Table 8 was showing that MFP dispersion was not strengthened at high levels of ICT (the interaction term is insignificant). The share of high-skill in total hours worked strengthens the link between between LP and wages, suggesting that sectors that become more skill intensive over time will also tend to experience a stronger connection between productivity dispersion and wage dispersion. This result was not present in the case of MFP, possibly highlighting a complementarity between high skills and capital, which is already captured by MFP.

The results of estimating Equation (5) shown in Tables 8 and D.7 can help us quantify the relative importance of productivity dispersion versus structural factors in explaining the increase in wage dispersion. We can do so by performing a simple quantification exercise, similar to that of Section 5.3.

Table D.7: Divergences and structural factors (LP)

	(1)	(2)	(3)	(4)	(5)	(6)
<i>Univariate</i>						
Log LP (90-10)	0.405*** (0.083)	0.405*** (0.083)	0.405*** (0.083)	0.394*** (0.074)	0.259*** (0.083)	0.182** (0.089)
Log LP (90-10)	0.400*** (0.085)	0.346*** (0.080)	0.376*** (0.082)	0.362*** (0.070)	0.260*** (0.073)	0.119 (0.083)
Log Import (goods)	-0.007 (0.049)					
Log LP (90-10) × Log Import (goods)	0.164*** (0.045)					
Log Export (goods)		0.065* (0.036)				
Log LP (90-10) × Log Export (goods)		0.229*** (0.051)				
Log Openness			0.048 (0.043)			0.008 (0.039)
Log LP (90-10) × Log Openness			0.221*** (0.051)			0.052 (0.061)
Sh. of ICT in fixed assets				1.069* (0.552)		2.503* (1.377)
Log LP (90-10) × Sh. of ICT in fixed assets				0.636* (0.342)		1.688 (1.669)
Sh. high-skilled (in total hours)					-0.639 (0.433)	
Log LP (90-10) × Sh. high-skilled (in total hours)					1.028*** (0.267)	
N	1817	1817	1817	2003	2263	1089
Adj. R-Square	0.928	0.932	0.931	0.966	0.972	0.949
Country-sector & year FE	YES	YES	YES	YES	YES	YES
Num. Countries	12	12	12	8	11	8

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 regressions include the logarithm of total gross output in the sector as extra control.

Regressions in columns (1), (2), (3), and (6) 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: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

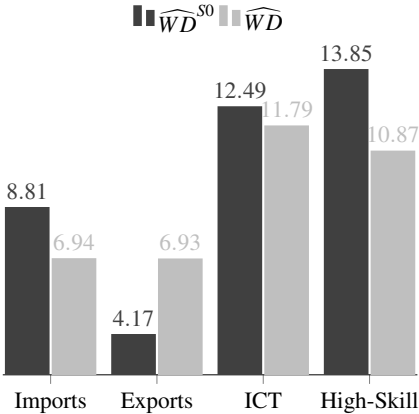
The largest set of countries include: AUS AUT BEL DNK FIN FRA HUN ITA JPN NLD NOR SWE.

NZL is missing from the regressions because sectoral data for gross output are not available.

In Table D.7, all regressors are in deviation from the mean. The coefficient of each variable can be interpreted as the effect at the mean of the other variable, since the interaction term is then zero. For instance in column (1) of Table D.7, the coefficient of Log LP can be interpreted as the effect of an increase in productivity dispersion on wage dispersion, in a counterfactual country-sector where Log Import is held at its mean value. This allows us to estimate how much of the increase in labour productivity dispersion translates into increased wage dispersion, holding imports constant. Within each country-sector, dispersion in labour productivity has increased on average by 14.5% between 2001 and 2012. Holding imports at the mean, this would translate into an increase in wage dispersion of $0.387 \times 14.5\% = 5.6\%$ between 2001 and 2012, explaining 44% of the actual variation observed.

Figure D.6 replicates for LP the formal quantification exercise of Figure 8 in the main text. Contrasting the two predictions for wage dispersion we are able to gauge the contribution of structural factors and their interaction with productivity dispersion to the total increase in wage dispersion. A large difference between the predicted and the counterfactual increase in wage dispersion indicates that structural factors play an important role in explaining the increase in wage dispersion, either via their direct effect or the interaction with productivity dispersion. For LP, the direct effect of the increase in productivity dispersion accounts for most of the predicted increase in wage dispersion over the period. The counterfactuals that keep the factors fixed at their initial levels actually predict an even higher increase in wage dispersion. This is explained by the fact that Imports and the share of high-skilled have a negative point estimate for labour productivity, while the ICT share has slightly decrease over time within the country and sectors analysed.

Figure D.6: Counterfactual and predicted increase in wage dispersion (LP)



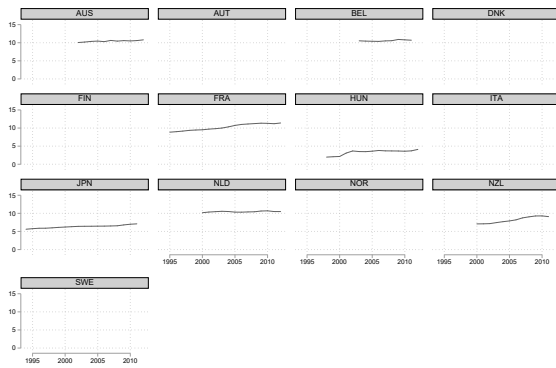
Note: Change in 90-10 log wage ratio between 2001 and 2012 (2009 for the share of High-Skill). The dark bars represent the counterfactual % increase in 90-10 ratio that would have occurred, holding Openness or Share of ICT constant at their value at the beginning of the period. The gray bars represent the wage dispersion predicted by the model as estimated in Equation (5). The predicted and counterfactual increases in wage dispersion differs across different factors because of sample differences.

D.2 Policy and their evolution

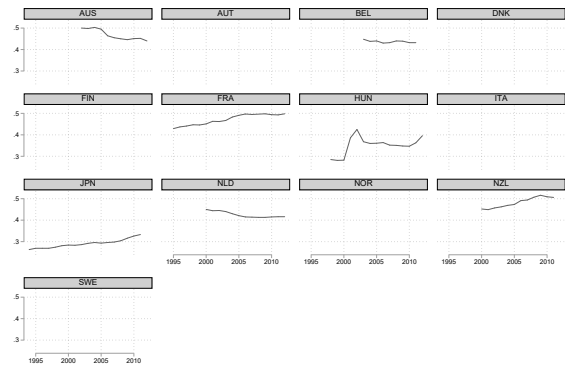
Figure D.7 depicts the policy variables used in the analysis of Section 6.3 on policies and their impact of wage and productivity dispersions.

Figure D.7: Changes in policies over time, by country

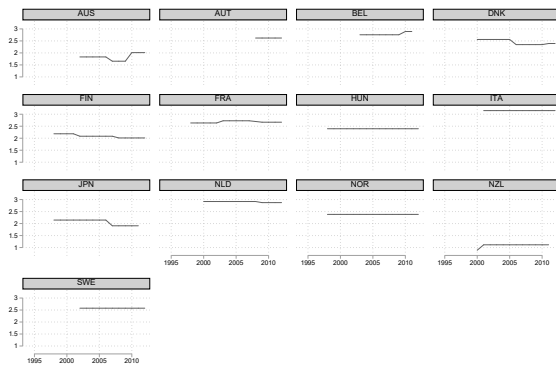
(a) Real Minimum Wage (hour)



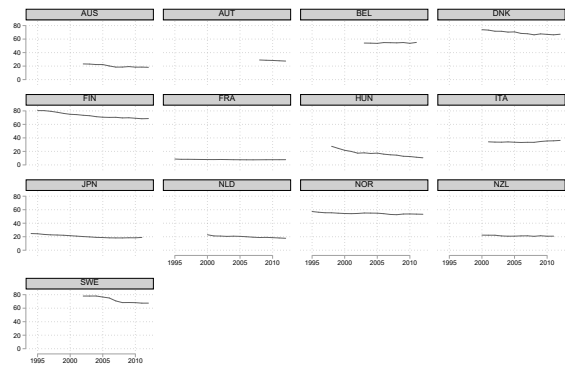
(b) Relative minimum wage (w.r.t. average)



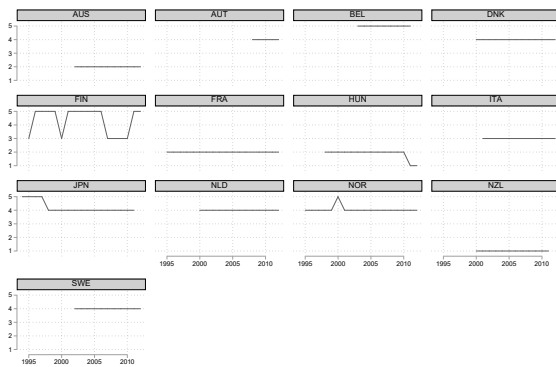
(c) Employment Protection Legislation (indiv. and coll.)



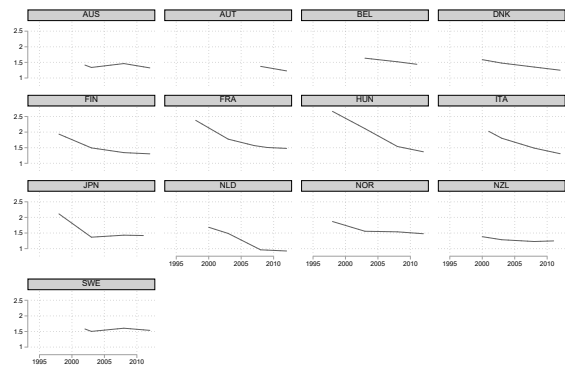
(d) Trade Union Density



(e) Coordination in Wage Setting



(f) Product Market Regulation



D.3 Policies: additional results for Labour Productivity

Table D.8 show the results of the regression of wage dispersion on labour productivity dispersion, each of the considered policies and their interaction. Compared to the results for MFP in the main text, the pattern is more mixed. The most robust result is the direct negative impact that policies have on wage dispersion over time. The effect of the minimum wage on the link between wage and productivity dispersion still changes sign between the cross-sectional and the within country-sector estimates, but

the effect appears to be insignificant. Similarly, the estimates of the interaction term between labour productivity and the other policies are smaller in magnitude and partially lose significance with respect to MFP. Labour productivity is driven by the level of capital intensity of the firms, and the impact of the policy will depend on whether firms substitute capital with labour, or whether capital and labour are gross complement.⁴⁴

Table D.8: Divergences and Policy (LP)

	(1)	(2)	(3)	(4)	(5)	(6)
Log LP (90-10)	0.237*** (0.072)	0.256*** (0.075)	0.277*** (0.042)	0.262*** (0.044)	0.237*** (0.045)	0.232*** (0.041)
Real Min Wage (hour)	-0.295*** (0.094)					
Log LP (90-10) × Real Min Wage (hour)	0.041 (0.033)					
Relative Min Wage (wrt av)		-0.097** (0.041)				
Log LP (90-10) × Relative Min Wage (wrt av)		0.022 (0.022)				
EPL (indiv. and coll.)			-0.021 (0.035)			
Log LP (90-10) × EPL (indiv. and coll.)			-0.079*** (0.030)			
Trade union density				-0.359*** (0.051)		
Log LP (90-10) × Trade union density				-0.005 (0.026)		
Wage Setting					-0.068*** (0.014)	
Log LP (90-10) × Wage Setting					-0.029** (0.012)	
PMR (interpolated)						-0.029 (0.020)
Log LP (90-10) × PMR (interpolated)						-0.022*** (0.005)
N	1889	1889	3289	3563	3563	3289
Adj. R-Square	0.970	0.969	0.971	0.971	0.969	0.973
Country-sector & year FE	YES	YES	YES	YES	YES	YES
Num. Countries	7	7	13	13	13	13

Data is at the country-sector-year level, weighted by the number of firms in each cell. Policy and institutional variables vary at the country-year level. The dependent variable is Log Wage (90-10); all regressors are standardised.

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 NLD NOR NZL SWE.

⁴⁴We cannot test these hypotheses with the data currently available in the MultiProd database. But we intend to collect information that might help shed further light on these results in the next wave of MultiProd.