Workforce skills and firm productivity

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January 2022

Abstract
We study the relationship between workforce skills and firm's productivity using Portuguese data for the period 2006-2018. We use a multi-dimensional index that incorporates worker's education, age, and unobserved ability to measure workers' skill. The analysis shows that the average skill of the workforce is positively associated with productivity. However, we find a negative relationship between the dispersion of the workforce skills and the value-added per worker. We also estimate quantile regressions and observe that the positive association between average skill and productivity is increasing across the conditional productivity distribution, while the negative association with skill dispersion is stable. (JEL: C23, J24)

Keywords: labour productivity, skill index, quantile, workforce heterogeneity.

1. Introduction

The differences in productivity levels across firms have been a central theme in economic research (Syverson 2011). The literature has pointed out several internal sources to the firms for these differences, including product innovation, investments in information technology and R&D, firm structure decisions, or human resource management practices, such as pay incentives, teamwork and investment in training (e.g., Acemoglu and Pischke 1998, Ichniowski *et al.* 1997). This article contributes to the literature that assesses how the workforce skill composition impacts productivity (e.g., Ilmakunnas and Ilmakunnas 2011).

If, on the one hand, a more heterogeneous workforce composition can positively affect productivity through the knowledge transfer effect, on the other hand, it can lead

Acknowledgements: We would like to thank Fernando Alexandre, João Amador, António Antunes, Hélder Costa, Paulo Guimarães, Attila Gyetvai, Pedro Duarte Neves, Pedro Portugal, Hugo Reis and participants at NIPE's seminar and an internal seminar of the Economics and Research Department of Banco de Portugal for helpful comments and suggestions. The analyses, opinions and conclusions expressed herein are the sole responsibility of the authors and do not necessarily reflect the opinions of Banco de Portugal or the Eurosystem. This paper is financed by National Funds of the FCT - Portuguese Foundation for Science and Technology, projects UIDB/03182/2020 and PTDC/EGE-ECO/29822/2017 ("It's All About Productivity: contributions to the understanding of the sluggish performance of the Portuguese economy").

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to opportunistic or free-riding behaviour from the part of the labour force, impacting negatively on average productivity (Hamilton *et al.* 2003). Although the literature has presented several approaches to assess which is the dominant effect on productivity, there are some limitations that this article intends to address.

Hamilton *et al.* (2003) analyse how teams' heterogeneity, computed considering the ratio between the maximum and the minimum individual productivity levels among all team members, impacts productivity. The authors conclude that the introduction of teams by the firm increases worker productivity and that more heterogeneous teams are, on average, more productive. Additionally, Mas and Moretti (2009) argue that not only do the most productive workers directly contribute to an increase in firms' output, as they also contribute indirectly through the increase of their co-workers productivity. However, since those studies are focused on specific firms, their findings may not be valid across a broad set of firms or sectors.

The literature that analyses the relationship between the workforce composition of a firm and its performance typically uses workers' observed characteristics, such as age, gender, educational attainment and race (e.g., Haltiwanger *et al.* 1999, Hellerstein *et al.* 1999, Mendes *et al.* 2010, Pfeifer and Wagner 2014). Although the observed characteristics may explain differences in productivity across workers and firms, it is restrictive to assume they entirely account for worker and firm idiosyncrasies. It is plausible that there is unobserved heterogeneity for both workers and firms, which conditions individual and firm-level productivity. Bender *et al.* (2018) and Iranzo *et al.* (2008) are examples of the literature that addresses this limitation and uses a measure that is not observed by standard variables. Both articles estimate the skill as the worker's fixed effect obtained from the AKM model – which decomposes wages into worker and firm fixed effects – proposed by Abowd *et al.* (1999). This worker specific component measures wages due to the worker's pure ability, regardless of the firm and net of the personal time-variant characteristics included as controls. Bender *et al.* (2018) use the average of the estimated worker fixed effects as a proxy for the average human capital at the firm and find that firms with a more skilled workforce have higher productivity. Torres *et al.* (2018) also rely on worker fixed effects to proxy for the workforce quality and highlight the importance to consider job title (i.e. occupational tasks) fixed effects as another source of labour heterogeneity in the production function.

Although the dispersion measure most commonly used in the literature is the standard deviation of the workers' skill level, several studies have proposed alternative measures. Kremer and Maskin (1996) propose a segregation index by skill proxied by wages, education or occupational categories. Ilmakunnas and Ilmakunnas (2011) and Parrotta *et al.* (2014) add other measures of dissimilarity and Herfindahl diversity indexes to infer how the dispersion in specific workforce characteristics affects firm's productivity. Ilmakunnas and Ilmakunnas (2011) find that age diversity impacts positively on total factor productivity (TFP), while educational diversity has a negative impact. Conversely, Parrotta *et al.* (2014) find that educational diversity significantly enhances firm productivity, while ethnic and demographic heterogeneity have the opposite effect. Finally, Iranzo *et al.* (2008) decompose the total skills dispersion into within-firm and between-firm components, showing that skill dispersion within occupational status groups (production and nonproduction workers) is positively related to firm's productivity. In contrast, the dispersion between these groups is negatively related to firm's productivity.

In this paper, and given that the one-dimensional skill measures may have limitations in capturing the overall impact of workforce composition on productivity, we use the multi-dimensional skill index developed by Portela (2001). This index measures worker's skill combining several observed components, such as schooling, age and worker's unobserved ability in line with Bender *et al.* (2018) and Iranzo *et al.* (2008). In this regard, our strategy compares with that used by Rocha *et al.* (2019) which also uses this skill index to evaluate the effect of the initial workforce average quality on firm's performance.

Our analysis further explores the relationship between firm's productivity and two moments of the workers' skill distribution, the average and the dispersion. We use the standard deviation of the workforce skills computed within the firm to assess the heterogeneity in each year. Our measure of firms' productivity is the value-added per worker. [1]

This article presents novel evidence for the Portuguese economy about the relationship between the workforce composition and firm's productivity. Using a very rich linked employer-employee dataset, we compute a composite index to study the relationship between workforce skills and productivity not only at the mean but also across the productivity distribution. We find a positive and significant relationship between the average workforce skills and firm's productivity. Moreover, this relation appears more relevant at the top than at the bottom half of the conditional productivity distribution. We also report a negative association between a more heterogeneous workforce and value-added per worker, conditional on the average workers' skill, which is relatively stable across the conditional productivity distribution. Our results align with the literature and provide additional evidence on the importance of considering the complementarity between several dimensions of worker's skill when assessing its effects on firm outcomes.

We assess the sensitivity of our results to an alternative measure of productivity (i.e., the value-added per hour worked), different proxies for skill (i.e., composite index with education and age, and each variable included in the skill index individually) and different measures of within-firm skill heterogeneity (i.e. percentile ratios, coefficient of variation and variance). The estimates remain qualitatively similar in all specifications.

The article is organised as follows. Section 2 describes the worker skill index and the heterogeneity measure used in the analysis, Section 3 introduces our econometric methodology. Section 4 describes the main data sources and presents some descriptive statistics. Then, Section 5 discusses the main results and Subsection 5.2 assess the sensitivity of our findings. Section 6 concludes.

1. The option of not using Total Factor Productivity as a proxy for productivity is because the data do not contain a precise measure of capital stock for the entire period under analysis.

2. Skill index and workforce heterogeneity

The search for the most accurate measure of worker's skill has been at the core of the most recent debates in the empirical labour economics. It should capture several individual characteristics, ranging from formal education, to general aptitudes obtained in the labour market, combined with innate or developed capacities, which are often unobservable.

In the vein of Portela (2001), we construct an aggregate skill index which will be at the core of our empirical analysis. The main advantages of this index, over the ones typically used in the literature, are that it allows us to integrate in a composite measure several skill dimensions, as well as variables measured in different units.

We compute the worker skill index, $Skill_{it}$, using the dimensions education, age and (unobserved) ability, according to the following specification,

$$Skill_{it} = a_{it,school} \times a_{it,age} \times a_{it,unobserved} \tag{1}$$

where the subscripts i and t denote the worker and the year, respectively. Each skill component $a_{it,school}$, $a_{it,age}$ and $a_{it,unobserved}$ represents the worker's position in the education, age and (unobserved) ability distribution in each year, respectively.

To compute each component we consider the cumulative logistic distribution, corrected by the factor 0.5. This functional form ensures that the main changes occur around the mean, while changes far from the mean have smaller impacts. The correction factor 0.5 ensures that each component is bounded between 0.5 and 1.5. The specification for each component is given by equations (1a), (1b) and (1c).

The contribution of education to the skill index is defined by,

$$a_{it,school} = 0.5 + \frac{e^{(school_{it} - mschool_t)/sschool_t}}{1 + e^{(school_{it} - mschool_t)/sschool_t}} \tag{1a}$$

where $school_{it}$ corresponds to the years of schooling of worker i in year t. The $mschool_t$ and $sschool_t$ correspond to the average and the standard deviation of schooling in year t, respectively. By definition, $a_{it,school}$ is higher than 1 when the number of years of schooling is above the average in the economy, while years of schooling below the average are associated with a value of less than 1.

Similarly, age's component is computed as,

$$a_{it,age} = 0.5 + \frac{e^{(age_{it} - mage_t)/sage_t}}{1 + e^{(age_{it} - mage_t)/sage_t}} \tag{1b}$$

where age_{it} corresponds to the age of worker i in year t. $mage_t$ and $sage_t$ correspond to the average and the standard deviation of age in year t, respectively. As before, a worker older than the average in the economy has a value for $a_{it,age}$ greater than 1.

Finally, worker's (unobserved) ability contribution to this estimated overall skill is formulated as,

$$a_{it,unobserved} = 0.5 + \frac{e^{(FE_i - mFE_t)/sFE_t}}{1 + e^{(FE_i - mFE_t)/sFE_t}} \tag{1c}$$

where FE_i corresponds to the unobserved skill of worker i. mFE_t and sFE_t correspond to the average and standard deviation of the unobserved ability in year t, respectively.

To obtain the worker's unobserved component we estimate a wage equation with high-dimensional fixed effects:

$$wage_{ift} = \psi + X'_{ift}\varphi + \tau_i + \mu_f + \lambda_t + \omega_{ift} \tag{2}$$

where $wage_{ift}$ corresponds to the logarithm of real hourly wage for worker i in firm f and year t. X is a vector with the time-varying worker's observed characteristics (schooling years, a second order polynomial on both age and tenure) and firm's observed characteristics (logarithm of firm size and its square); τ_i is the worker fixed effect, μ_f is the firm fixed effect; λ_t corresponds to year-dummies and ω_{ift} is the usual white noise error-term.[2] We use the estimated worker's fixed effects as a proxy for FE_i in equation (1c). This variable represents the worker's unobserved ability.

Having computed the worker's skill index, $Skill_{it}$, we are able to measure the workforce skills and heterogeneity for each firm/year. Table 1 summarizes some of the alternative measures of workforce heterogeneity proposed in the literature. In this article we use the within-firm standard deviation of the skill index to capture the firm's skill diversity.

3. Econometric methodology

We estimate the following regression model to assess the impact of the average and dispersion of the workforce skills on firms' productivity,

$$y_{ft} = \alpha + \bar{s}'_{ft}\gamma + \theta'_{ft}\delta + X'_{ft}\beta + \eta_f + \vartheta_t + \varepsilon_{ft} \tag{3}$$

where y_{ft} is the logarithm of the gross value-added per worker of firm f in year t. $\bar{s}_{ft}$ and θ_{ft} represent the average and the standard deviation of the skill index for firm f in year t, respectively. The parameters of interest are γ and δ which capture the effect of the average and dispersion of the workforce skills on firms' productivity, respectively.

The control variables in X_{ft} include a second order polynomial of firm size, measured by the logarithm of the number of workers, the share of part-time workers, the share of female workers, and a second order polynomial of the average firm tenure. The model

2. The model is estimated using the algorithm of Guimarães and Portugal (2010) through the Stata command *reghdfe* (Correia 2016). To identify the worker fixed effect we restrict the data to the largest connected set of workers and firms dropping approximately 0.4% of the observations. We report the estimates of this model in Table A1 and present the density of the worker fixed effects in the Figure A1 of the Appendix. Note that the age coefficient is not identified due to the inclusion of worker fixed effects and year dummies.

Papers	Measure of heterogeneity
Hamilton *et al.* (2003)	Ratio between the maximum and the minimum individual productivity levels among all team members
Pfeifer and Wagner (2014); Haltiwanger *et al.* (1999)	Share of workers by category (e.g., age, gender, education, qualification)
Kremer and Maskin (1996)	Segregation index equal to 0 if all firms have the same workforce skill composition and 1 in the case of complete segregation. Skill is measured with observed variables, such as wages, education, or occupational categories
Ilmakunnas and Ilmakunnas (2011)	Standard deviation and dissimilarity, variety and diversity indexes for age and education
Parrotta *et al.* (2014)	Herfindahl indexes to measure the cultural, educational and demographic (age and gender) diversity
Iranzo *et al.* (2008)	Total within-firm skill dispersion decomposed into within and between-occupations. The skill is measured by the worker's fixed effect obtained from a wage equation

TABLE 1. Measures of heterogeneity discussed in the literature

also includes year-dummies (ϑ_t) to account for the macroeconomic conditions and firm fixed effects (η_f) to control for time-invariant unobserved factors that are specific to the firm and can impact productivity. This term also helps to mitigate the potential bias arising from the fact that the firm may endogenously select the optimal workforce mix to maximize productivity (e.g., Parrotta *et al.* 2014). ε_{ft} is an *i.i.d.* error term.

This specification allows us to conclude about the effect of the workforce skills composition on the productivity of the average firm. However, this effect may differ across the productivity distribution. In order to assess whether the effect is heterogeneous, we expand our analysis by estimating the specification above at selected quantiles of the conditional firm productivity distribution using the Method of Moments Quantile Regression estimator proposed by Machado and Santos Silva (2019). As argued by the authors, this approach has the advantage of allowing the fixed effects to have different effects over the conditional productivity distribution instead of being just a location shift as most of the other methods available.

4. Data

4.1. Data sources

The main data source of this article is the linked employer-employee data *Quadros de Pessoal* (QP) collected by the Portuguese Ministry of Labour, Solidarity and Social Security since the 1980s. The report of these data is mandatory for all Portuguese firms with at least one employee. Besides the high coverage, this dataset provides detailed information at the firm and establishment-level (location and main sector of activity, for example) and at the worker-level (such as age, gender, schooling, wage, occupation, tenure and hours of work) with reference to the month of October.

We match this dataset with *Sistema de Contas Integradas das Empresas* (SCIE), which provides economic and financial information for non-financial firms operating in Portugal. This dataset is collected through the Simplified Corporate Information since 2006 and compiled by Statistics Portugal. These data report to the whole fiscal period and allows us to compute the value-added per worker as a proxy for firm's productivity. Since this information is only available for corporations we restrict the analysis to this type of firm. Both QP and SCIE provide unique identifiers that allow us to match them and follow the same firm over time.

Our sample covers the firms located in Mainland Portugal for the period between 2006 and 2018. The least representative sectors are excluded.[3] To calculate the skill measures of the workforce we consider employees with non-missing information on the main variables of interest, aged between 16 and 64 years old, and with contracted weekly hours of work between 10 and 40. Since our study focuses on skill heterogeneity at the firm-level, we only consider the observations of the firms with at least five employees.

The final panel dataset includes information for 136,709 unique firms for the period 2006-2018. Table 2 describes the variables and the corresponding data sources.

4.2. Descriptive statistics

Table A2 in the Appendix presents summary statistics for the variables included in the analysis for the period 2006–2018. These statistics are obtained in the sample of our main econometric specification, i.e., without missing values in the variables included in the regression (first column of Table 3). We also split the sample into sector categories and show the statistics for the two most representative, i.e., manufacturing and services.

3. The excluded sectors are the primary sector (sectors 1-9, according to NACE Rev. 3); the manufacture of tobacco products (sector 12); remediation activities and other waste management services (sector 39); the activities of households as employers of domestic personnel (sector 97); undifferentiated goods and services-producing activities of private households for own use (sector 98) and activities of extraterritorial organizations and bodies (sector 99).

Variable	Description	Source
Workforce characteristics		
Wage	Real hourly wage (base wage and regular benefits divided by the normal monthly hours of work) in 2019 euros	QP
Schooling	Number of schooling years [a]	QP
Tenure	Number of years at the firm	QP
Age	Worker's age	QP
Firm characteristics		
Log of value-added per worker	Logarithm of gross value-added [b] in 2019 euros divided by the number of workers	SCIE
Log of value-added per hour	Logarithm of gross value-added in 2019 euros divided by the number of hours worked (normal and overtime monthly hours multiplied by the 11 months of work per year)	SCIE/QP
Percentage of female	Share of female workers at the firm	QP
Percentage of part-time	Share of part-time workers at the firm	QP
Log of firm size	Logarithm of the number of workers at the firm	QP
Average tenure	Average of workers' tenure at the firm	QP

TABLE 2. Variables' description and corresponding data source

a. The data reports the highest level of education completed by the worker which we convert in years of schooling. After correcting inconsistent values on this variable we attribute years of education to each worker according to the following rule: 0 years of education (workers who do not know how to read or write), 2 years (workers with less than 4 years of schooling), 4 years (first cycle of basic education), 6 (second cycle of basic education), 9 years (third cycle of basic education), 12 years (upper secondary education), 13 years (post-secondary education), 15 years of schooling (workers with polytechnic or bachelor degree), 17 years (master degree) and 21 years (PhD).

b. We apply the winsorize technique at the 1% and 99% for value-added in order to reduce the effect of outliers.

The two measures of the apparent labour productivity, i.e. value-added per worker and per hour, show that the average firm in the services sector is in general more productive than in manufacturing, which is in line with the official statistics for Portugal.

The average firm in the services sector has more skilled workers, as measured by the multi-dimensional skill index presented in Section 2. These results remain unchanged when we use different skill measures, as the skill index using the two observed characteristics: education and age.[4] Nevertheless, the average firm in the services sector is slightly more heterogeneous in terms of skills than in the manufacturing, as measured by the standard deviation of both skill indices. This is also an expected result, as the services include highly differentiated activities.

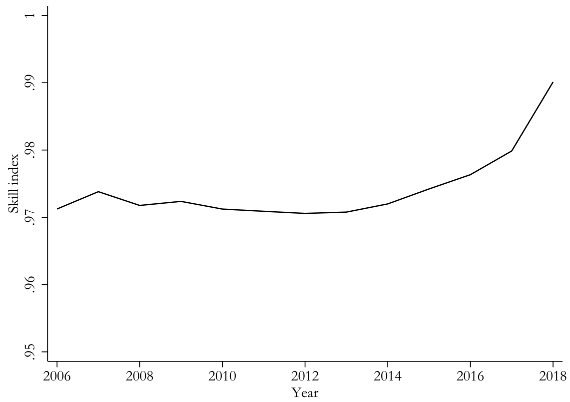
Considering the variables included in the skill index individually, the average number of years of schooling is also higher in services compared to manufacturing. The average workforce in services is also younger and stay at the firm for a shorter period of time.

4. We consider the first two components of equation (1): $a_{it,school} \times a_{it,age}$.

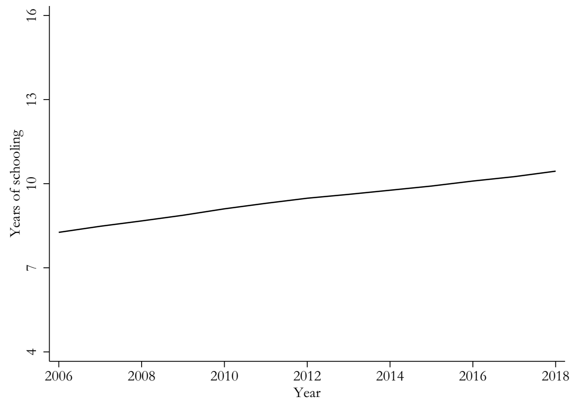
Regarding other control variables included in our econometric specification, the percentage of part-time workers and the percentage of female workers are higher in services than in manufacturing for the period under analysis. Also, manufacturing firms are, on average, larger than those in services sector.

Figure 1 shows the evolution of the skill index defined by equation (1) as well as its variables. Regarding the skill index, we observe a period of relative stability followed by an increasing trend. This occurs in parallel with an increase in the workforce average education and age over the period. The postponement of the entry into the labour market during the crisis period, as well as the progressive increase in the retirement age, may contribute to these patterns. In turn, the unobserved ability presents a subtle decreasing trend.

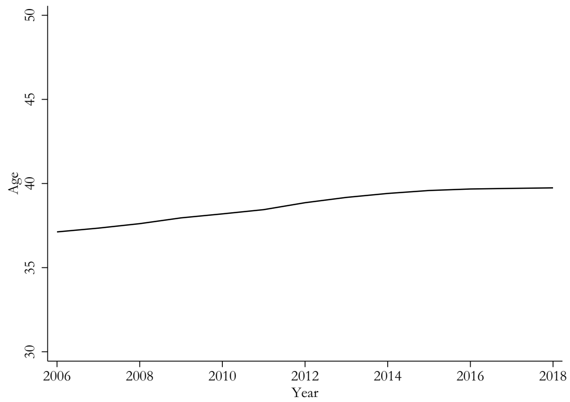
Figure 2 shows a positive correlation between the average workers' skill index and firm's productivity, which we analyse in detail in the following sections.



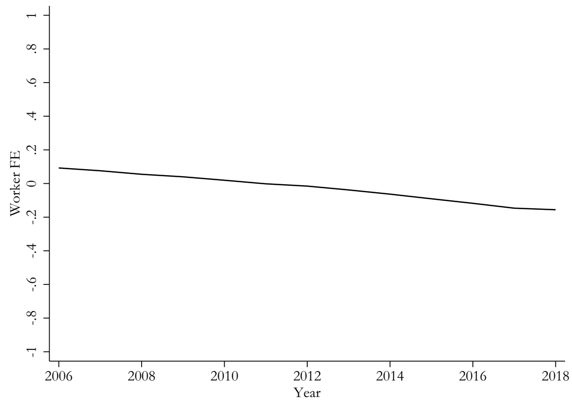
(A) Skill index



(B) Years of schooling



(C) Age



(D) Unobserved ability (worker FE)

FIGURE 1: Evolution of the skill index and its components (2006-2018)

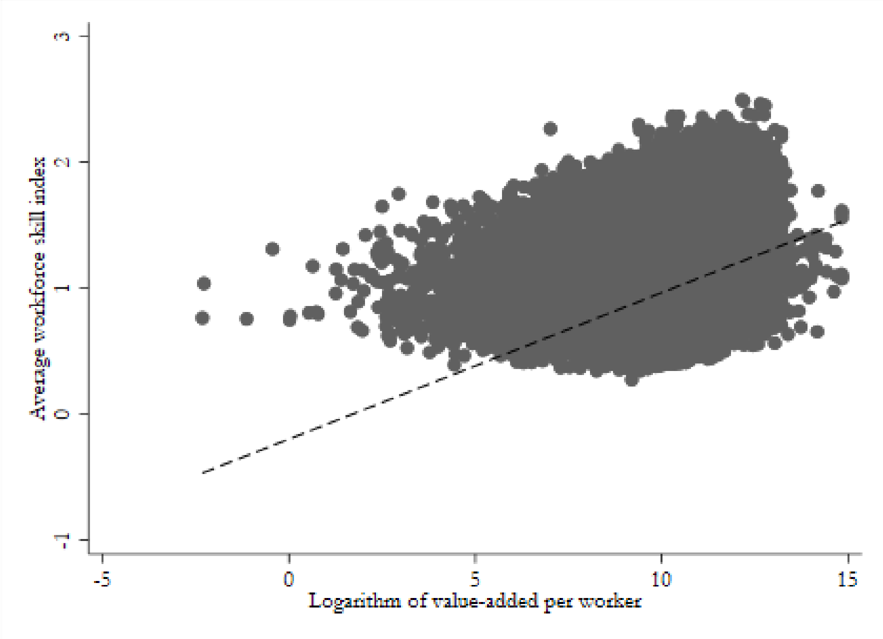


FIGURE 2: Relationship between firm's productivity and average workforce skill
Note: The dashed line represents the fitted values.

5. Results

5.1. Impact of workforce skills on firms' productivity

Table 3 presents the results of our main specification for the relationship between the two moments of workers' skill distribution, i.e., average and standard deviation, and firm's productivity, measured by value-added per worker. The first estimation column concerns the entire sample, while the second focuses on manufacturing and the last column refers to the services sector.

We find that the average workforce skills within the firm is positively related to its productivity. More specifically, a one standard deviation increase in the average worker skill is associated, on average, to an increase in firm's productivity by approximately 3.5% (product of the standard deviation of average skill index in Table A2, 0.23, by the estimated coefficient in Table 3, 0.1514, by 100%).[5] This is a consistent result in the literature that suggests that firms with a high-skilled workforce are also more productive, regardless of how skills are measured (e.g., Bender *et al.* 2018; Haltiwanger *et al.* 1999). There is also another strand of literature that corroborates this result, but considering on-the-job training. Barron *et al.* (1987), Dearden *et al.* (2006) and Konings and Vanormelingen (2015) are part of the research that found that workers' training increases firm's productivity.

5. Multiplying the standard deviation of the explanatory variable by the estimated coefficient gives an interpretation of the coefficient independent of the scale.

Regarding the standard deviation of the workers' skill index within the firm, our estimates indicate that more heterogeneous firms are also less productive. Specifically, a standard deviation increase in the dispersion of the skill index within the firm is associated to a decrease in firm's productivity by approximately 0.6%.[6]

	All	Manufacturing	Services
Average worker skill	0.1514***	0.1397***	0.1306***
	(0.0121)	(0.0256)	(0.0153)
Worker skill dispersion (SD)	-0.0523***	-0.0551**	-0.0389**
	(0.0130)	(0.0280)	(0.0166)
Share of part-time workers	-0.0023***	-0.0021***	-0.0022***
	(0.0001)	(0.0004)	(0.0002)
Share of females	-0.0009***	-0.0011***	-0.0009***
	(0.0001)	(0.0002)	(0.0001)
Average worker tenure	0.0064***	0.0105***	0.0076***
	(0.0010)	(0.0025)	(0.0012)
Average worker tenure squared	-0.0002***	-0.0004***	-0.0002***
	(0.00004)	(0.0001)	(0.00005)
Firm size (log)	0.4988***	0.5422***	0.4686***
	(0.0109)	(0.0212)	(0.0138)
Firm size (log) squared	-0.0855***	-0.0836***	-0.0873***
	(0.0020)	(0.0037)	(0.0025)
Adjusted R^2	0.714	0.705	0.730
Number of observations	722,494	192,578	415,134

TABLE 3. Workforce skills and firm's productivity (2006–2018)

Notes: Standard errors clustered at the firm level in parentheses. Significance levels: ***, 1%; **, 5%. The dependent variable is the logarithm of gross value-added per worker. The regressions include year dummies and firm fixed effects. Manufacturing corresponds to 2-digit NACE Rev. 3 codes 10 to 33; Services corresponds to NACE Rev. 3 codes 45 to 96. "All" stands for all firms in the sample. "SD" represents the standard deviation.

6. Since we cannot exclude the possible bias resulting from the simultaneity between the firm's workforce selection and productivity maximization decision, we also estimate the model with all the independent variables lagged by one period. The results for the main variables of interest are qualitatively similar in this specification.

Comparing the estimates of the main parameters between manufacturing and services, the positive relation between the average worker skill and the value-added per worker is slightly higher for manufacturing than for services. Also, the coefficient associated with skill dispersion is statistically significant for both sectors, despite being slightly larger, in absolute terms, for manufacturing.

Table A3 in the Appendix presents the results considering only the firms with at least 10 workers in all periods. Although this condition is very restrictive considering the small average size of the firms in Portugal (e.g., Braguinsky *et al.* 2011; Banco de Portugal 2021), the impact of the average worker skill on firm's productivity remains significant and is even higher. Regarding the impact of the worker skill standard deviation, it is negative in all samples and loses significance in manufacturing.[7] The lowest worker turnover levels in the manufacturing sector or the smaller number of firm observations in the sample comparing to the services sector may contribute to explain this result. It is also important to highlight the large heterogeneity, within and between manufacturing and services, in terms of the activities and the occupational composition. For example, in the manufacturing sector engineers and skilled technicians coexist with workers performing repetitive tasks. The effect of skill heterogeneity on productivity may differ for white and blue-collar workers depending on the level of substitutability between them (e.g., Iranzo *et al.* 2008; Parrotta *et al.* 2014).

Regarding the control variables, the share of part-time workers is negatively related to the firm's value-added per worker. Furthermore, the lower level of productivity in firms with a higher share of female workers is also a common result in the literature (e.g., Ilmakunnas and Ilmakunnas 2011; Parrotta *et al.* 2014; Pfeifer and Wagner 2014). Finally, the average tenure at the firm is positively related to its productivity, which is in line with previous studies (e.g., Parrotta *et al.* 2014), and we also observe a concave tenure-productivity profile. The firm size has also an inverted U-shaped relation with productivity as found by Pfeifer and Wagner (2014).

5.2. *Sensitivity analysis*

In this subsection, we assess the sensitivity of our estimates to an alternative measure of productivity, different proxies for skill and different approaches to quantify within-firm skill heterogeneity.

5.2.1. *Productivity measure*

We re-estimate equation (3) with the gross value-added per hour worked as the dependent variable.[8] The results shown in Table 4 are qualitatively similar to those obtained for the value-added per worker. On average, a standard deviation increase

7. This result also holds if we consider small and medium firms with at least 10 and up to 249 workers in all time periods.

8. SCIE data do not provide information on hours worked. Therefore, we use the total number of normal and overtime hours reported with reference to the month of October in QP data multiplied by the 11 working months assuming that each worker is absent from the firm, on average, for one month.

in the average worker skill is associated with an increase of approximately 2.9% in value-added per hour worked, while skill dispersion is associated with a decrease of approximately 0.9%. We also confirm the previous conclusion that these effects tend to be larger in manufacturing than in the services sector.

	All	Manufacturing	Services
Average worker skills	0.1274***	0.1893***	0.0875***
	(0.0123)	(0.0277)	(0.0154)
Worker skills dispersion (SD)	-0.0761***	-0.0925***	-0.0705***
	(0.0135)	(0.0300)	(0.0170)
Adjusted R^2	0.705	0.696	0.725
Number of observations	722,494	192,578	415,134

TABLE 4. Sensitivity analysis – Productivity measured by value-added per hour worked

Notes: Standard errors in parentheses are clustered at the firm level. Significance levels: ***, 1%. The dependent variable is the logarithm of gross value-added per hour worked. The regressions include the following controls: percentage of female and part-time workers, tenure and tenure squared and the logarithm of size and its square, year dummies and firm fixed effects. "All" stands for all firms in the sample. "SD" represents the standard deviation.

5.2.2. *Skill measure*

In this subsection we analyse to what extent the findings discussed in the previous section are sensitive to some alternative skill measures.

The estimation of the worker's unobserved ability using the procedure described in Section 2 hinges upon having enough variability in the observed characteristics to disentangle the observed and unobserved effects. In order to alleviate this restriction we compute the skill index defined in equation (1) with the two observed components of skill: education and age. The results are shown in Table 5. The coefficients remain qualitatively unchanged but lose statistical significance in the services sector using this alternative skill index. The statistical significance is kept unchanged, however, if we consider only firms with at least 10 workers in all periods.[9] Ilmakunnas and Ilmakunnas (2011) find that a two-dimensional age-education diversity measure is not significantly correlated with productivity using Finnish data.

The choice over the skill variable matters for the empirical evidence, as shown by Ilmakunnas and Ilmakunnas (2011). They find that productivity is negatively associated with educational diversity but positively correlated with age diversity. Therefore, it is relevant to understand the association between firm's productivity and each one of the variables that are used in the skill index proposed in Section 2.

9. These results are available upon request.

	All	Manufacturing	Services
Average worker skills with education and age	0.0781***	0.0822**	0.0348
	(0.0168)	(0.0342)	(0.0219)
Worker skills dispersion with education and age (SD)	-0.0767***	-0.1133***	-0.0337
	(0.0195)	(0.0404)	(0.0255)
Adjusted R^2	0.713	0.705	0.730
Number of observations	722,725	192,630	415,276

TABLE 5. Sensitivity analysis – Skill index with observed characteristics

Notes: Standard errors in parentheses are clustered at the firm level. Significance levels: ***, 1%; **, 5%. The dependent variable is the logarithm of gross value-added per worker. The regressions includes the following controls: percentage of female and part-time workers, tenure and tenure squared and the logarithm of size and its square, year dummies and firm fixed effects. "All" stands for all firms in the sample. "SD" represents the standard deviation.

Table 6 shows the relationship between the average and standard deviation of the years of education at the firm and value-added per worker. As expected, the average years of education of the workforce are positive and significantly associated with firm's productivity – one standard deviation increase in the average worker education is associated with an increase of 2.8% in productivity.

The larger dispersion in terms of years of education is associated, on average, with a decrease in firm's productivity. However, this effect is relatively low – one standard deviation increase in the dispersion of the years of education is associated with a decrease of 0.3% in productivity – only statistically significant for the services sector.

	All	Manufacturing	Services
Average worker education	0.0109***	0.0084***	0.0107***
	(0.0012)	(0.0024)	(0.0016)
Worker education dispersion (SD)	-0.0028**	0.0039	-0.0045***
	(0.0013)	(0.0026)	(0.0017)
Adjusted R^2	0.713	0.705	0.730
Number of observations	722,725	192,630	415,276

TABLE 6. Sensitivity analysis – Education

Notes: Standard errors in parentheses are clustered at the firm level. Significance levels: ***, 1%; **, 5%. The dependent variable is the logarithm of gross value-added per worker. The regressions includes the following controls: percentage of female and part-time workers, tenure and tenure squared and the logarithm of size and its square, year dummies and firm fixed effects. "All" stands for all firms in the sample. "SD" represents the standard deviation.

Table 7 shows the impact of the firm's workforce age composition on value-added per worker. In line with the reported evidence of an inverse U-shaped relationship between age and productivity (e.g., Pfeifer and Wagner 2014, Cardoso *et al.* 2011), we consider a slightly different specification by including a second order polynomial for the average workers' age. The results confirm a concave relationship between the workforce average age and productivity. The workers' age dispersion is negatively associated with firm's productivity – one standard deviation increase in the age dispersion is associated with a decrease of 0.9% in productivity – although not statistically significant at the usual significance levels for manufacturing.

	All	Manufacturing	Services
Average worker age	0.0342***	0.0250***	0.0312***
	(0.0023)	(0.0048)	(0.0030)
Average worker age squared	-0.0004***	-0.0003***	-0.0004***
	(0.00003)	(0.0001)	(0.00004)
Worker age dispersion (SD)	-0.0036***	-0.0015*	-0.0043***
	(0.0004)	(0.0009)	(0.0006)
Adjusted R^2	0.714	0.705	0.730
Number of observations	722,725	192,630	415,276

TABLE 7. Sensitivity analysis –Workers' age

Notes: Standard errors in parentheses are clustered at the firm level. Significance levels: ***, 1%; *, 10%. The dependent variable is the logarithm of gross value-added per worker. The regressions include the following controls: percentage of female and part-time workers, tenure and tenure squared and the logarithm of size and its square, year dummies and firm fixed effects. "All" stands for all firms in the sample. "SD" represents the standard deviation.

Most recent papers also use worker fixed effects estimated in a first stage Mincerian wage equation as a proxy for worker (unobserved) ability (Iranzo *et al.* 2008). The results obtained with this measure are shown in Table 8 and are qualitatively similar to those obtained using the skill index. A one standard deviation increase in the average worker ability is associated with an increase of 6% in productivity. In comparison, a standard deviation increase in the dispersion of the workers estimated fixed effects is associated with a decrease in value-added per worker by 0.3% but not statistically significant at the usual significance levels. Although the coefficient of the dispersion of workforce ability within the firm is positive for the manufacturing sector, it is not statistically significant.

These results are consistent with the idea that workforce diversity can affect firms' productivity through different dimensions (Parrotta *et al.* 2014). Our results show that firms, and especially those in the services sector, may have productivity gains by hiring workers of similar ability, education and age. The skill index used in this article is a comprehensive measure that considers this evidence.

	All	Manufacturing	Services
Average worker FE	0.2227***	0.1899***	0.2159***
	(0.0103)	(0.0207)	(0.0133)
Worker FE dispersion (SD)	-0.0206*	0.0179	-0.0359**
	(0.0113)	(0.0220)	(0.0145)
Adjusted R^2	0.714	0.706	0.730
Number of observations	722,494	192,578	415,134

TABLE 8. Sensitivity analysis – Unobserved ability

Notes: Standard errors in parentheses are clustered at the firm level. Significance levels: ***, 1%; **, 5% *, 10%. The dependent variable is the logarithm of gross value-added per worker. The regressions include the following controls: percentage of female and part-time workers, tenure and tenure squared and the logarithm of size and its square, year dummies and firm fixed effects. "All" stands for all firms in the sample. "SD" represents the standard deviation.

5.2.3. Dispersion measure

Finally, we consider it is relevant to assess the robustness of our results to other dispersion measures. To this end, we re-estimate equation (3) replacing the standard deviation of the skill index by the variance, coefficient of variation and the ratio between different percentiles of the skills distribution in order to assess the consistency of the correlation of skills dispersion and firm's productivity (Table 9). The estimates are broadly consistent with those discussed above, irrespective of the dispersion measure used.

The ratio between the skill level of the worker at the 90^{th} percentile and that of the worker at the 10^{th} or the 50^{th} percentile of the skill index distribution is negatively associated with firm's productivity. However, the coefficient of the ratio between the skill level at the median and that at the 10^{th} percentile of the skill index distribution is not statistically significant. This provides evidence that the dispersion at the bottom is not as relevant as the dispersion at the top half of the skill distribution.

5.3. Workforce skills and productivity distribution

In this subsection, we intend to verify whether the estimated coefficients of our main econometric specification change across the productivity distribution. We, therefore, estimate regression quantiles with firm fixed effects using the Method of Moments Quantile Regression proposed by Machado and Santos Silva (2019). According to Machado and Santos Silva (2019) when the number of observations is large compared to the number of time periods we may face asymptotic bias issues. As such, the results in this subsection should be read with caution.

	All	All	All	All	All
Average worker skills	0.1363***	0.1344***	0.1337***	0.1353***	0.1489***
	(0.0111)	(0.0111)	(0.0111)	(0.0111)	(0.0120)
Worker skills dispersion (P90/P10)	-0.0067***				
	(0.0016)				
Worker skills dispersion (P90/P50)		-0.0156***			
		(0.0032)			
Worker skills dispersion (P50/P10)			-0.0019		
			(0.0030)		
Worker skills dispersion (Coeff. Var.)				-0.0388***	
				(0.0120)	
Worker skills dispersion (Variance)					-0.0645***
					(0.0185)

TABLE 9. Sensitivity analysis – Alternative dispersion measures

Notes: Standard errors in parentheses are clustered at the firm level. Significance levels: ***, 1%. The dependent variable is the logarithm of gross value-added per worker. The regressions include the following controls: percentage of female and part-time workers, tenure and tenure squared and the logarithm of size and its square, year dummies and firm fixed effects. The number of observations is 722,494. "All" stands for all firms in the sample. "P90" represents percentile 90; likewise for the other percentiles. "Coeff. Var." is "Coefficient of variation".

Table 10 presents the estimates for five percentiles (10^{th}, 25^{th}, 50^{th}, 75^{th} and 90^{th}) of the conditional productivity distribution.[10] We can observe that the coefficients associated with the average and dispersion of worker skill preserve the statistical significance in the five percentiles. Regarding the magnitude of the coefficients, the results are similar at the mean and median of the conditional distribution. However, the hypothesis that the coefficients are the same across all quantiles is rejected, i.e., the impact of the average worker skill on firm's productivity varies depending on the position of each firm in the productivity distribution.

We find an increasing positive association of the average worker skill with firm's productivity over the conditional quantiles of the distribution. Therefore, in more productive firms a marginal increase in the average workers' skill index is associated with a larger increase in productivity than in less productive firms, controlling for the share of females and part-time workers and average tenure at the firm, firm's size and firm and time fixed effects.

10. These estimates were obtained in the same sample of our main econometric specification.

	P10	P25	P50	P75	P90
Average worker skill	0.1235***	0.1358***	0.1534***	0.1672***	0.1766***
	(0.0141)	(0.0119)	(0.0097)	(0.0097)	(0.0107)
Worker skill dispersion (SD)	-0.0508***	-0.0514***	-0.0524***	-0.0531***	-0.0536***
	(0.0163)	(0.0137)	(0.0110)	(0.0108)	(0.0118)

TABLE 10. Workforce skills and firm's productivity distribution

Notes: These estimates are obtained in the sample of our main econometric specification. We use 1000 bootstrap replications to obtain estimates for standard errors in parentheses. Significance levels: ***, 1%. The dependent variable is the logarithm of gross value-added per worker. The regression includes the following controls: percentage of female and part-time workers, tenure and tenure squared and the logarithm of size and its square, year dummies and firm fixed effects. The number of observations is 722,494. "P90" stands for percentile 90 and the same applies to the other percentiles. "SD" represents the standard deviation.

The skill dispersion is negatively associated with firm's productivity in line with the estimates at the mean. The hypothesis of coefficient equality over the different quantiles cannot be rejected which provides evidence that the relationship between worker skill dispersion and firm's productivity is relatively homogeneous over the conditional productivity distribution.

6. Conclusion

We use Portuguese linked employer-employee data to investigate the relationship between firm's productivity (value-added per worker) and the two first moments of the workers' skill distribution (average and standard deviation) for 2006-2018.

Unlike most previous empirical studies, which focus on a single component of worker's skill, we use a multi-dimensional skill index to comprehensively measure three of the most debated dimensions of workforce skills: worker's formal education, age and unobserved ability. This last dimension corresponds to the worker fixed effect obtained from a Mincerian wage equation.

We find a positive and significant relationship between the average workforce skills and firm's productivity, both in the manufacturing and the services sector. This result is robust to different skill measures and increases across the conditional productivity distribution.

On the other hand, the standard deviation of workers' skill index, conditional on its average, is negatively associated with firm's productivity. This effect is roughly the same across firms with different productivity levels.

Our reduced-form analysis deserves further exploration to identify causal relations between skill composition and firm's productivity. Additionally, the skill index can be extended to include firm-specific human capital and managerial skills that the literature singles out to be relevant for firm's outcomes. Finally, it would also be pertinent to analyse the productivity dynamics in the post-COVID-19 period, since the pandemic represents a shock to the organisation of work, namely in terms of the technologies used and how the workers interact, which may have heterogeneous effects across sectors of activity.

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Appendix

	All
Schooling (years)	0.0058***
	(0.0002)
Age squared	-0.0003***
	(6.1e-06)
Tenure	0.0080***
	(0.0003)
Tenure squared	-0.0001***
	(0.00001)
Firm size (log)	0.0561***
	(0.0120)
Firm size (log) squared	-0.0020
	(0.0016)

TABLE A1. Estimates of the wage equation (2) (2006–2018)

Notes: Standard errors in parentheses are clustered at the firm level. Significance levels: ***, 1%. The dependent variable if the logarithm of real hourly wages. The regression includes firm, worker and year fixed effects. The number of observations is 24,643,358. "All" stands all firms in the sample.

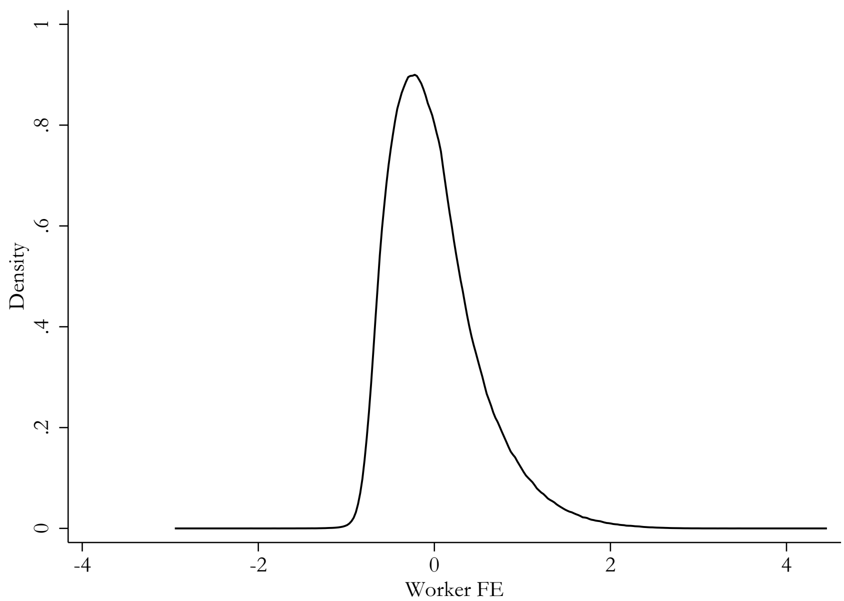

FIGURE A1: Density of the worker fixed effects

	All					Manufacturing					Services				
	Mean	SD	P25	P50	P75	Mean	SD	P25	P50	P75	Mean	SD	P25	P50	P75
Workforce characteristics															
Average skill index	0.95	0.23	0.79	0.91	1.08	0.87	0.18	0.74	0.85	0.97	1.01	0.25	0.83	0.97	1.15
Standard deviation of the skill index	0.31	0.12	0.22	0.29	0.38	0.29	0.11	0.21	0.28	0.36	0.32	0.12	0.23	0.31	0.39
Average skill index with education and age	0.95	0.14	0.85	0.93	1.04	0.89	0.11	0.81	0.88	0.96	0.99	0.15	0.89	0.98	1.09
Standard deviation of the skill index with education and age	0.19	0.06	0.15	0.19	0.23	0.18	0.06	0.14	0.18	0.22	0.20	0.06	0.15	0.19	0.23
Years of schooling	9.04	2.57	7.06	8.75	10.80	7.80	1.87	6.43	7.61	9.00	10.00	2.56	8.12	9.89	12.00
Standard deviation of the years of schooling	2.59	1.06	1.87	2.62	3.29	2.62	0.99	1.99	2.68	3.30	2.51	1.04	1.76	2.51	3.21
Age	39.19	5.68	35.21	39.20	43.13	39.78	5.35	36.10	39.77	43.43	38.65	5.79	34.54	38.60	42.67
Standard deviation of the age	9.22	2.62	7.51	9.30	10.93	9.50	2.38	7.99	9.55	11.03	9.04	2.75	7.18	9.10	10.88
Worker FE	-0.05	0.27	-0.23	-0.08	0.10	-0.11	0.23	-0.27	-0.13	0.04	-0.02	0.30	-0.23	-0.06	0.14
Standard deviation of the worker FE	0.35	0.14	0.25	0.33	0.43	0.34	0.13	0.25	0.33	0.42	0.36	0.14	0.26	0.34	0.44
Percentage of part-time workers	2.74	8.73	0.00	0.00	0.00	1.04	4.64	0.00	0.00	0.00	3.65	10.39	0.00	0.00	0.00
Percentage of female workers	39.78	31.86	12.50	33.33	66.67	41.19	32.17	14.29	33.33	66.67	47.26	30.69	20.00	43.75	72.81
Average tenure	6.62	5.33	2.50	5.36	9.55	8.20	5.89	3.57	7.11	11.75	6.28	5.10	2.35	5.00	9.00
Firm characteristics															
Log of value-added per worker	9.88	0.72	9.49	9.87	10.29	9.76	0.63	9.40	9.75	10.15	9.96	0.76	9.58	9.97	10.40
Log of value-added per hour	2.55	0.71	2.17	2.55	2.95	2.41	0.63	2.04	2.40	2.79	2.63	0.75	2.26	2.64	3.05
Log of firm size	2.55	0.92	1.79	2.30	3.00	2.80	0.98	2.08	2.56	3.33	2.47	0.90	1.79	2.20	2.83

TABLE A2. Summary statistics (2006-2018)

Notes: Manufacturing corresponds to 2-digit NACE Rev. 3 codes 10 to 33; Services corresponds to NACE Rev. 3 codes 45 to 96. “SD” stands for standard-deviation. “P25”, “P50” and “P75” represents percentile 25, median and percentile 75, respectively.

	All (>=10 workers)	Manufacturing (>=10 workers)	Services (>=10 workers)
Average worker skills	0.3322***	0.1677***	0.3343***
	(0.0285)	(0.0441)	(0.0390)
Worker skills dispersion (SD)	-0.1322***	-0.0555	-0.1254***
	(0.0310)	(0.0502)	(0.0433)
Adjusted R^2	0.785	0.768	0.802
Number of observations	232,122	87,373	115,821

TABLE A3. Workforce skills and firm's productivity – firms with 10 or more workers

Notes: Standard errors in parentheses are clustered at the firm level. Significance levels: ***, 1%. The dependent variable is the logarithm of gross value-added per worker. The estimation includes firms with at least 10 workers in all time periods. The regressions includes the following controls: percentage of female and part-time workers, tenure and tenure squared and the logarithm of size and its square, year dummies and firm fixed effects. "All" stands for all firms in the sample. "SD" represents the standard deviation.