Is Labour Diversity Good for Firms' Productivity?

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1 Introduction

Workforce diversity has increased in many developed countries. There are many factors that contribute to this development. The ongoing population ageing in most developed countries increases the diversity of the labor force[1] as differences in terms of age between workers become larger. Increases in female labor participation and social pressure to enhance it further in the next years are also another force to increase labor force diversity in terms of gender[2]. Immigration plays a role as well, especially as a broader diversity of immigrants with respect to their countries of origin has been documented (Adsera and Pytlikova, 2012). Additionally, general levels of educational attainment have improved.
Over the past 30 years there has been a significant increase in the educational attainment of populations in almost all OECD countries and this is having effects in terms of diversity of education at workplace[3]. To ensure the emancipation of minorities, policymakers have been active in promoting diversity through enacting affirmative action policies.
And this has additionally influenced firms' hiring decisions as they had been under social pressure to be more diverse. Even the share of part-time workers in the workforce has increased in the last two decades in most developed countries[4]. As a result of these changes, the diversity of the workforce with respect to gender, education, age, ethnicity and working time (part-time vs full-time) have increased.

In this context, this work intends to investigate the effects at the firm level of a more diverse labor force. The literature suggested that mixing diverse workers can increase overall productivity. Nevertheless, the empirical evidence has so far been lacking and not always addressing it structurally. This is a problem because we do not know if the theory suggested by the literature, whose implications have been followed at the policy level, is supported by empirical evidence. So this empirical work is useful to provide further evidence on the effect of labor force diversity. The main channel of transmission between workforce diversity and firm productivity has been identified in the literature to happen through knowledge spillover and complementary skills of diverse workers. This is represented by building a model where diverse workers have different levels of labor productivity. With this framework in mind, this research aims is to verify the presence of any changes in firm productivity as a result of increasing labor force diversity. Through this approach, the diversity of labor force matters to the extent that it is associated with a difference in labor productivity by category of workers. And the purpose is to see if there is evidence of a spillover effect of any changes in firm productivity when less-productive workers are mixed with more productive workers. Consequently, two are the main pillars of the research strategy.
The first is to find evidence of differential of productivity across diverse workers.

[1] Throughout the paper the term workforce and labor force are used interchangeably to designate workers of the firm
[2] See OECD (2021): Labor Force Statistics (LFS)
[3] OECD: Education at a Glance 2016 - Indicators
[4] See OECD (2021): Part-time employment rate

The second pillar is to investigate the presence of any gains in firm productivity due to diversity. Accordingly, workforce diversity is broken down by gender, educational attainment and working time at the firm level.

To pursue the research goal, the following is implemented. Firstly, a model is specified which integrates labour diversity and labor productivity differences into firm's production function alongside the overall level of labor and capital. Secondly, a solution is proposed to estimate a labor-diversity-enhanced production function using firm-level panel evidence. The latter requires some non-standard procedures as there are some fundamental econometric problems to take into account in order to produce reliable estimates.

In answering the research question, this paper makes three contributions to the literature. First, it proposes a complete model to estimate the impact of labor force diversity which can be used also for other types of labor force diversity. Second, it presents empirical evidence on the impact of labor force diversity which is useful as there is still an unconsolidated view within the field. And the main findings point to a negative impact of education diversity and working time diversity on firm productivity. Third, it offers an alternative method to look at the effect of part-time work at the firm level.

The remainder of the paper has the following structure. Section 2 reviews the related literature. Section 3 proposes a model specification. Section 4 presents the econometric analysis including a brief description of data. Section 5 presents the results from the main model and also results from sensitivity analysis. Section 6 concludes. Finally, in the Appendix, some additional tables and computations are reported.

2 Related Literature

There are two branches of economic literature to which this paper is related.
The first one, and the main one, concerns the economic impact of labor force diversity. The second one is on the effect of part-time workers. Part-time work literature deserves an additional focus due to the lack of studies on labor-force diversity which consider working time diversity. However, through the approach used in this study, there are no big differences as I will show later. Therefore, both problems are addressed with the same methodology.

2.1 Labor force diversity

Economic theory agrees that there are opposing forces underlying the relationship between workforce diversity and productivity. And which force prevails is likely to depend on the type of diversity being considered, as there are major differences between demographic diversity (e.g gender and age characteristics) and education diversity.
Some works have established the microfoundation of the relationship. The mechanism under which labor force diversity positively affects firm productivity is identified through knowledge

spillover and complementary skills which arise out of the disjoint relevant information sets that diverse workers have (Lazear, 1999). Moreover, cultural diversity is found to benefit firm performance as it enhances its overall problem-solving ability (Hong and Page, 2001). However, there are negative consequences due to additional communication costs incurred by a more diverse labor force, especially if workers are somehow prejudiced (Becker, 1957). And also lower social ties and trust are induced by diversity (Lang and Lehmann, 2011; Lazear, 1999). It has been argued that the benefits outweigh the costs for education diversity (Lazear, 1999; Jehn et al., 1999), while this is less likely to hold for demographic diversity. In addition, several studies argue that the nexus between labor force diversity and productivity is expected to vary across working environments, especially between high-tech or knowledge-intensive sectors and more traditional or labor-intensive sectors (Garnero and Rycx, 2014). An interesting argument has been put forward through the lenses of team theory (Prat, 2002). A firm's attitude to innovate is expected to be greater if researchers do not share the same backgrounds and information sets. Therefore, some degree of diversity should be optimal. Similar conclusions have been reached by other studies (Parrotta et al., 2012a, Ozgen et al., 2013 and Jehn et al., 1999). The latter additionally highlights that education diversity is more likely to have a positive role when the tasks are complex rather than routine.

The empirical works regarding the effects of workforce diversity, to which this paper is more strictly related, are still inconclusive. Four main streams can be identified within this literature.

The first stream utilizes field and experimental studies to investigate the impact. While this type of study may fit to shed light at a micro level, there are some fundamentals problems concerning this methodology. For instance, Kurtulus (2011) criticizes the small sample size of these works and that they do not account for the longitudinal component of units. Moreover, Garnero (2014) objects that they rarely control for reverse causality which is considered to be important for the topic.

A second stream investigates the diversity-performance nexus through case studies of single companies. As Garnero (2014) observes, the advantage of this approach is the use of detailed data concerning firm characteristics. For instance, this allows to control for many variables and also to account for the time-invariant unobserved firm heterogeneity, which is expected to be relevant (Syverson, 2011). The work of Mas and Moretti (2009) is quite representative of this approach. They study the productivity of cashiers in a large supermarket chain in the U.S. They find that that less skilled workers become significantly more productive in the presence of highly productive co-workers, while the productivity of skilled workers is not hampered by the presence of less-skilled workers. Instead, Kurtulus (2011), using records of a U.S. firm in the health service industry finds that demographic and skill diversity within divisions is associated with lower worker productivity. However, there is a main drawback of this approach due to the poor external validity of these results.

There is a third stream in the empirical literature which looks at the impact of workforce diversity from a more macro perspective. Diversity is examined for its impact on aggregate output and results mostly regard how efficiently diverse individuals should be allocated across firms. Or, referring to Grossman and Maggi's work (2000), whether cross-matching, that is when each type of worker is dispersed across firms, is socially preferable to self-matching, where each type of worker is concentrated in homogenous firms. For this type of works, the evidence being used is mostly at the regional level or at least at a larger level than the firm. Alesina et al. (2013) find that birthplace diversity is positively related to long-run income. Ottaviano and Peri (2006) also find positive effects of cultural diversity on the productivity of native workers using US metropolitan data.

Finally, there is a fourth stream of literature of particular interest for this paper.
In general, these works (Garnero and Rycx, 2014; Vandenberghe, 2016; Parrotta et al., 2012b; Iranzo et al., 2008 and Ilmakunnas and Ilmakunnas, 2011) share the features of estimating the impact of diversity at firm level and they often use longitudinal data about workforce merging information from accounting databases and social security records.
While this may reduce the type of diversity being analyzed, these works have the advantage of being largely representative of the economy. In a certain way, they complement the weaknesses of the case studies mentioned earlier. Firm productivity in these studies is often measured as added value (log). Another common feature of these studies is that they provide results that are more robust to other approaches as they include estimation
techniques developed by Ackerberg et al. (2015) and Levinsohn and Petrin (2000), that allow taking into account for unobserved heterogeneity and endogeneity which was invalidating previous approaches. However, in terms of results, there are some differences.
Most of these studies (Iranzo et al., 2008; Garnero and Rycx, 2014 and Parrotta et al., 2012b) find that education diversity is beneficial for firm productivity.
To the best of my knowledge, only Ilmakunnas and Ilmakunnas (2011) show that firm's performance (looking at TFP) depends negatively on education diversity.
As for gender diversity, Parrotta (2012b) documents it hampers firm productivity.
For Garnero (2014) the negative impact of gender diversity on firm productivity is limited to traditional sectors, while in high-tech sectors gender diversity generates significant gains. Instead, Vandenberghe (2016) finds no compelling evidence that gender and educational diversity have any effect on firm's efficiency. However, there is a main caveat of this fourth stream. As Vandenberghe (2016) observes, these empirical studies tend to suffer from three limitations. First, they are not sufficiently connected with standard production function theory and the corresponding specifications. Second, and perhaps more importantly, they do no sufficiently distinguish the impact of labour heterogeneity (and the fact that not all labour types are equality productive) from that of labour diversity (the effect of mixing different types of workers per se). Parrotta et al. (2012b) for instance just add a diversity

indicator to a loglinearized Cobb-Douglas production function with only capital and overall labour. Third, many of the studies do not properly account for the fact that firm's labour mix is endogeneous, and for instance be heavily driven by short-term (unobserved) demand shocks. This paper relates to this fourth last stream of empirical literature but it additionally includes a complete specified model to accommodate for these problems.

2.2 Part-time workers

There is another branch of economic theory to which this paper is related. This one concerns the impact of part-time workers on firm performance.

The theoretical literature mostly presents two categories of theories on how part-time workers can affect firm productivity (Devicienti et al., 2015). The first one looks at the impact of part-time work through the lenses of individual labor productivity. The final effect is expected to depend on the nature of the relationship between individual labor productivity and the number of hours worked during the day (Barzel, 1973). In presence of start-up costs, the average labor productivity of part-time workers is expected to be lower than full-time workers. On the other hand, if labor productivity exhibits decreasing marginal return (i.e it increases during the working day up to a certain point, then it starts to decrease), it turns out that the average labor productivity of part-timers is higher than full-time workers.

For instance, Brewster et al. (1973) argue that the latter is the case, given that long working hours cause stress and tiredness, and they result in lower marginal labor productivity. Some other authors highlight the role of incentives to accumulate human capital. Part-timers are expected to face fewer incentives to invest in firm-specific human capital, while full-timers are more interested in developing their skills in order to achieve higher career goals (Brewster et al., 1994). As a result, from the perspective of human capital, part-time workers are expected to be less productive. The second category of theories focuses on the impact of part-time work on firms' organizational efficiency.

Similarly to gender diversity and demographic diversity, part-time work generates some additional coordination costs within the firm, which ultimately hamper firm productivity (Lewis, 2003). However, recurring to part-time work may also be a more efficient way for firms to better cover their needs along the production process, in particular for firms experiencing workload peaks or other sources of fluctuations of demand of work.

Therefore, economic theory does not agree on the final effect of the part-time worker on firm performance. Surprisingly, there are only a few empirical works concerning the impact of part-time work using firm-level measures in the context of production functions.

Garnero et al. (2014) and Kunn-Nelen et al (2013) find evidence that part-time workers are more productive than full-time workers, and that an increase in the share of part-time workers increases firm productivity. Instead, Vandenberghe and Specchia (2013) find that part-time workers are less productive than full-time workers and a larger share of share workers have

a detrimental effect on firm productivity. Francesco Devicienti et al (2015) also find that part-time work hampers firm productivity but they attribute this to a loss of organizational efficiency (e.g coordination costs), and not as a sign of differentials in productivity across workers. Interestingly, most of these works agree on the existence of differentials of labor productivity per category of workers. This is considered a valid reason to include working time diversity in the study of labor force diversity. A thorough research of the literature did not reveal any other studies which investigate the effect of part-time through this approach. However, also because of the complementarity and coordination costs that part-time workers are reported to generate, this is considered a promising methodological innovation that could open to additional evidence in the study of flexible working time.

3 Specification

The objective of this section is to specify a model which is rooted in standard production theory and allows identifying the impact of labor force diversity on firm production net of what should be simply be interpreted as labor heterogeneity (e.g. university-educated workers are expected more productive than non-educated ones). As to capturing the productivity differences characterizing different types of labor inputs, I capitalize on the previous works of Hellerstein and Neumark (1995) and Vandenberghe (2016).

In its essence, the proposed model is a log-linearized version of an augmented Cobb-Douglas production function in a Hellerstein-Neumark framework. In addition, a diversity index is included to track the presence of any gains/losses in efficiency due to diversity.

More precisely, the production function of a representative firm[5] starts from the following:

$$Y = AQL^{\alpha}K^{\beta} \tag{1}$$

Where Y is output, K is the capital and QL is the quality of labour index which reflects the workforce's heterogeneity.
In particular, assuming that each type of worker j is a substitutable input with different marginal product, QL can be rewritten as:

$$QL = \sum_{j} \mu_j L_j \tag{2}$$

where L_j is the the quantity of labor of worker type j

[5]All variables are at firm level at year t.

Plugging (2) into (1) , I get:

$$Y = A\left(\sum_j \mu_j L_j\right)^{\alpha} K^{\beta} \tag{3}$$

Note that marginal product of labor is :

$$\frac{\partial Y}{\partial L_j} = A\left(\sum_j \mu_j L_j\right)^{\alpha-1} \mu_j K^{\beta} \tag{4}$$

Therefore $\frac{\mu_j}{\mu_0}$ is the relative marginal productivity of worker type j with respect to a reference category of worker 0.
Transforming (1) in logarithm:

$$\ln Y = \ln A + \alpha \ln QL + \beta \ln K \tag{5}$$

Noting[6] that QL can be rewritten as

$$QL = \mu_0 L\left(1 + \sum_{j>0}((\mu_j/\mu_0 - 1)P_j)\right) \tag{6}$$

where $P_j = \frac{L_j}{L}$ i.e the share of worker type j within the workforce of the firm

Let $\lambda_j = \frac{\mu_j}{\mu_0}$ the relative marginal productivity or worker type j.
Taking log of (6) :

$$\ln QL = \ln \mu_0 + \ln L + \ln(1 + \sum_{j>0}((\lambda_j - 1)P_j)) \approx \ln \mu_0 + \ln L + \sum_{j>0}((\lambda_j - 1)P_j)) \tag{7}$$

Substituting in (5), I obtain:

$$y = B + \alpha l + \beta k + \sum_{j>0} \eta_j P_j \tag{8}$$

where $B = \ln A + \alpha \ln \mu_0, \eta_j = \alpha(\lambda_j - 1)$ and y , l and k are respectively $\ln Y$, $\ln L$ and $\ln K$.
Finally I include in the model a measure of diversity of workers (e.g. Herfindahl index).

$$y = B + \alpha l + \beta k + \sum_{j>0} \eta_j P_j + \gamma DIV \tag{9}$$

The parameter of interest is γ. The idea is that it is likely to capture the marginal impact of diversity variations across firms and across time within firms, controlling for the intrinsic productivity differences across labour types that captured by the estimated η's. The next section will focus on how to correctly estimate this latter equation with available data.

[6]See Appendix for all steps

4 Econometric analysis

The econometric analysis comprises of two parts. The first part presents a brief description of the data and their source. Interestingly, descriptive statistics of the used dataset (e.g. Belgian economy) align with the global trend of increase in labor force diversity which was mentioned in the Introduction.

The second part proposes an estimation strategy that accounts for the possibility firms' mix of labor types (and thus the Herfindahl diversity index that we use) is endogeneous. The relevance of these issues has been mentioned in the literature review and in this subsection it is analyzed more extensively. The proposed estimation strategy relies on the previous works of Levinsohn and Petrin (2000) and Ackergberg et al. (2015). Essentially, they make use of the idea that the timing of some firms' decisions, such as the purchase of intermediate inputs, can be used to proxy unobserved productivity (TFP) developments that are generated by short-term demand shocks that are partially anticipated by firms – thus influencing labor decisions – but not observed by the statistician.

4.1 Data

The data for the analysis come from the Bel-first database containing annual account data on Belgian firms. The entire population of Belgian private firms employing more than 20 persons is considered. This allows documenting the capital of the firm (e.g. assets) and firm productivity (e.g. value-added). Additionally, these data provide information about the workforce composition at the firm level because, starting from 1996, Belgian companies are required to publish a social balance sheet as part of their annual accounts presenting characteristics of their employees[7]. As a result, it is possible to break down the workforce at the firm level in terms of gender (male or female), education attainment (beyond or below secondary education) and work-time (part-time vs full-time). As Vandenberghe (2016) made similar research on Belgian firms from the year 1998 to 2012, the study focuses on a panel of firms active between 2012 and 2019. Table 1 presents the main descriptive statistics as well as a measure of diversity (Herfindahl Index[8]).

It is of interest to see that over the years the share of female workers has increased but it is still below half. Consequently, gender diversity has increased over the years. Also, the average level of education within workers has increased as the share of less-educated people (e.g maximal educational attainment not above secondary school degree) has decreased. As a result, education diversity has increased. Finally also diversity of working time has increased, since the share of part-time workers has raised. In general, these data confirm the trend in the most developed economies concerning workers' education, female labor participation and

[7] National Bank of Belgium.

[8] Herfindahl Index (HI): $HI = 1 - (x_1^2 + ..x_i^2... + x_N^2)$ where x_i is the share of worker of type i in the firm

working time mentioned in the Introduction. Therefore, they are a good candidate to test the specified model.

Table 1: Descriptive statistics

Year	Value added (log)	No. of empl. (log)	Capital (log)	Share of female	Secondary or less	Share of part time	Herf gender	Herf educ	Herf work time
2012	11.145	6.812	11.963	0.362	0.695	0.216	0.322	0.264	0.230
2013	11.134	6.789	11.694	0.362	0.688	0.218	0.327	0.267	0.234
2014	11.256	6.894	12.011	0.357	0.690	0.222	0.325	0.273	0.236
2015	11.287	6.967	12.029	0.360	0.681	0.224	0.326	0.276	0.244
2016	11.281	6.915	12.023	0.361	0.675	0.232	0.329	0.279	0.240
2017	11.266	6.911	11.969	0.364	0.674	0.243	0.329	0.286	0.243
2018	11.291	6.907	12.000	0.365	0.681	0.240	0.331	0.282	0.238
2019	11.342	6.929	12.031	0.363	0.683	0.238	0.332	0.286	0.239

Notes: Weighted average of main variables. Weights are equal to the firm's number of workers
Source: Bel-first, 2021

4.2 Estimation

The purpose is to estimate equation (9) using available firm-level panel evidence. This requires non-standard regression techniques as there are fundamental problems of endogeneity.

In particular, as noted in the literature of production functions (Parrotta et al., 2012b) a major issue concerns the fact that there are productivity shocks that influence production which are unobserved by the econometrician, but they are observed by the firm and anticipated by managers. Therefore, firms' input decisions will reflect these situations. For instance, when positive shocks are observed, it can be expected that managers will be willing to hire more workers (and also of less productive category type). This means that the error terms and regressors are correlated and standard OLS regression is inadequate. Failure to consider this would ultimately give inconsistent estimates due to the fact that regressors are not exogenous.

Moreover, the estimation model must account for an unobserved fixed-effect component, because of substantial unobservable heterogeneity across firms as it is documented by Syverson (2011).

This amounts to say that the econometric version of the model is:

$$y_{it} = B + \alpha l_{it} + \beta k_{it} + \sum_{j>0} \eta_j P_{ijt} + \gamma DIV_{it} + \delta X_{it} + \omega_{it} \tag{10}$$

ω_{it} is a three-components error term s.t $\omega_{it} = \theta_i + \tau_{it} + \epsilon_{it}$ in which θ_i is an unobservable fixed effect, τ_{it} is a short-term shock unobserved by econometrician but observed by the firm and ϵ_{it} is a purely random shock. Finally X is a vector of controls[9].

[9]The province, the sector of activity (e.g nace) and the year are used as controls.

Taking into account these issues, the following estimation strategy composed of 5 models is used.

4.2.1 Model 1

In model 1 equation (10) is estimated through the standard OLS technique. This procedure disregards the three components of the error term and delivers inconsistent estimates but these estimates act as an initial useful reference.

4.2.2 Model 2

In model 2 the growth-equivalent of equation (10) is estimated. Using the panel structure of data, data are first-order differenced of 1 year and then an OLS regression is performed. Hence, in the regression Δy_{it} will replace y_{it} and so forth. As a result, time non-varying variables are dropped. This allows removing the bias due to the fixed-effect error component but not the bias due to the short-term unobserved shock.

4.2.3 Model 3

In model 3 the issue of endogeneity due to the short-term shock is addressed τ_{it} using the structural techniques suggested by Levinsohn and Petrin (2000) and Ackerberg et al. (2015). In particular, the procedure follows these steps.
Step 1.
A key component of this procedure concerns the timing of the firms decisions on inputs.
It is assumed that the intermediate input material is chosen by the firm after that the labor inputs (not only the quantity of labor l, but also the share of type j and diversity of workforce) are selected and after that the short-term productivity shock is observed by the firm. Therefore, intermediate material demand can be written as a function of capital, productivity shock and labor inputs. $int_{it} = f(k_{it}, \tau_{it}, l_{it}, P_{ijt}, DIV_{it})$
Note that without loss of generality I will consider the case in which there are only two types of workers (i.e $\sum_{j>0} \eta_j P_{ijt} = \eta_j P_{ijt}$)
Assuming that the intermediate material demand function is strictly increasing in the productivity shock v_{it} , hence its invertibility, then: $\tau_{it} = f^{-1}(k_{it}, int_{it}, l_{it}, P_{ijt}, DIV_{it})$
The function $f^{-1}(.)$ can be proxied with a 3rd order polynomial expansion in int_{it} ,k_{it},l_{it}, P_{ijt} and DIV_{it}. Then the first stage is to regress y_{it} on a composite term Φ that comprises a constant, a 3rd order polynomial expansion in int_{it} ,k_{it} , l_{it}, P_{ijt} and DIV_{it}.
Step 2
It is possible to generate implied values for τ_{it} using stage 1 regression estimated value of Φ and candidate values for the coefficients β , α , γ and η .

$$\tau_{it} = \Phi^{hat} - \alpha l_{it} - \beta k_{it} - \eta P_j - \gamma DIV \tag{11}$$

Assume that τ_{it} is a first-order Markov chain (i.e. $E(\tau_{it}|\tau_{it-1}, \tau_{it-2}, ...) = E(\tau_{it}|\tau_{it-1}$)

Then τ_{it} will depend on some function $g(.)$ of past realisation and an innovation term ν_{it} :

$$\tau_{it} = g(\tau_{it-1}) + \nu_{it} \tag{12}$$

Where $g(.)$ can be proxied by a fourth-order polynomial.

The timing of firm's decisions is used to identify some moments conditions.

In particular, the capital in period t is determined at least at period t-1 as it takes a full period for new capital to be ordered and ready to use. Therefore, k_{it} is uncorrelated with the innovation term ν_{it} :

$$E[\nu_{it}|k_{it}] = 0 \tag{13}$$

Moreover, labor inputs in t are probably chosen along with the observation in t of the innovation term ν_{it}. Thus l_{it} is correlated with ν_{it} But lagged labor inputs , e.g. l_{it-1}, l_{it-2} , DIV_{it-1} , DIV_{it-2} , P_{ijt-1}, P_{ijt-1} are uncorrelated with ν_{it}

As a consequence, the following holds:

$$E[\nu_{it}|l_{it-1}, l_{it-2}...] = 0 \tag{14}$$

$$E[\nu_{it}|P_{ijt-1}, P_{it-2}...] = 0 \tag{15}$$

$$E[\nu_{it}|DIV_{it-1}, DIV_{it-2}...] = 0 \tag{16}$$

Each of the above equation leads to an unconditional moment condition such as (for equation 13):

$$E[\nu_{it}k_{it}] = 0 \tag{17}$$

Substituting ν_{it} from equation (11) and (12) and using GMM method the parameters are identified.

4.2.4 Model 4

Model 4 consists of an integration of Model 3 and Model 4. First, data are first-order differenced as in Model 2 to remove the fixed-effect error component. Second, the econometric procedure of Model 3 is applied to these transformed data. This ultimately allows delivering consistent estimates for the parameters of interest.

4.2.5 Model 5

Model 5 uses an alternative data transformation to Model 4. In particular, data are firstly centered around its mean value over time, province and sector of activity. Secondly, the econometric procedure of Model 3 is applied.

5 Results

5.1 Main results

The main results of the analysis are reported in Table 2 for gender diversity, Table 3 for education diversity and in Table 4 for working-time diversity[10]. In each of these tables results are reported for the econometric Model 1 - 5. In general, different estimated models lead to non-identical results. And this highlights the importance of recurring to alternative models accounting for endogeneity biases. But there are some regularities. Results from Model 2 and Model 4, which both present estimates on First Order Differenced data across time, have similarities. Instead, the rest of the model (1-3 and 5) is more homogeneous, at least in the direction of the relationship between workforce diversity and firm productivity. Most of the estimated models show evidence of marginal productivity differences across selected workers categories. Female workers are estimated to be less productive than male workers in Models 1,3 and 5. Lower educated workers are estimated to be less productive than higher educated workers in Model 1,2 and Model 5. And part-time workers are estimated more productive than full-time workers in any econometric model except Model 4.

Focusing on where there is evidence of productivity difference, more detailed results can be highlighted on the impact of workforce diversity on firm productivity.

Gender diversity is found to positively affect firm productivity in this subset of models (Model 1,3 and 5). But in model 5 accounting for endogeneity, this relationship reduces of magnitude, and more importantly, it loses significance. For this reason, it can be concluded there is no strong evidence of any statistically significant effect of gender diversity on firm productivity.

As for education diversity, results are ambiguous for the subset of models exhibiting productivity differences. In Model 1 and Model 3 the education diversity is found to increase firm productivity. Conversely, the relationship turns negative in model 5 accounting for the unobserved fixed effect component. Even though all estimates in Model 5 are significant, this discrepancy of estimates ultimately limits the external validity of this finding. To solve this ambiguity, a richer division of the workforce is tested (Table 4) where education diversity is broken into 3 levels of education: lower than secondary, secondary and above secondary education. Interestingly, these estimates more consistently show that education diversity is negative for firm productivity. In light of these results, it is estimated[11] that a 10% increase of diversity index for education leads to a reduction in value-added between 0.27% and 0.36%.

Finally, working-time diversity leads to more robust results. In the majority of models, it is found that diversity in working-time hampers firm productivity, also when accounting

[10]For Working time and Gender labor hours are used to measure labor, while for education number of employee has been used because of lack of data at hour level

[11]Note that it is a log-linear model and HI takes value from 0 to 1

for fixed effect and endogeneity. It is estimated that a 10 % increase of diversity index for working time diversity [12] leads to a reduction of added value belonging to an interval from 2.7% to 5.3 % .

In summary, there is no evidence that gender diversity has any effect on firm productivity, while education diversity and working time diversity are found to have a negative impact on firm productivity. Moreover, working time diversity is reported to have a larger effect than education diversity. In addition, considering the entity of increases of labor force diversity reported so far (see Table 1), only working time diversity is found to have a relevant impact on firm performance.

Table 2: Gender diversity

	Model 1	Model 2	Model 3	Model 4	Model 5
$\beta(K)$	0.359***	0.160***	0.393***	0.145***	0.392***
	(0.00232)	(0.00630)	(0.00740)	(0.00620)	((0.00610)
$\alpha(l)$	0.628***	0.636***	0.652***	0.693***	0.601***
	(0.00285)	(0.00721)	(0.0109)	(0.0224)	(0.00731)
$\eta(P)$	-0.0751***	0.0503	-0.0602	-0.0128	-0.0374
	(0.0158)	(0.0497)	(0.0419)	(0.0877)	(0.0293)
$\gamma(DIV)$	0.165***	-0.147**	0.186***	-0.187**	0.0784
	(0.0232)	(0.0534)	(0.0538)	(0.0685)	(0.0412)
RMP^a	0.8804	1.07	0.908	0.981	0.8916
N	35018	29947	23617	19242	23617

[a] Implied relative marginal productivity of female workers (male workers are the reference category). For direct derivation see equation (8). Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: Bel-first, 2021

Table 3: Education diversity

	Model 1	Model 2	Model 3	Model 4	Model 5
$\beta(K)$	0.346***	0.223***	0.376***	0.191***	0.421***
	((0.00241))	(0.00662)	(0.00674)	(0.00858)	(0.00649)
$\alpha(l)$	0.613***	0.412	0.619***	0.437***	0.515***
	(0.00282)	(0.00751)	(0.00613)	(0.0177)	(0.00607)
$\eta(P)$	-0.356***	0.00496	-0.346***	0.0112	-0.282***
	(0.0106)	(0.0114)	(0.0104)	(0.00624)	(0.00964)
$\gamma(DIV)$	0.0322**	0.00976	0.0402**	-0.0000751	-0.0363**
	(0.01000)	(0.0190)	(0.0147)	(0.00945)	(0.0133)
RMP^a	0.42	1.01	0.44	1.03	0.45
N	36422	31342	24232	19821	24232

[a] Implied relative marginal productivity of low educated workers (more educated workers are the reference category). Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: Bel-first, 2021

[12] This is a large variation of HI, which has never been experienced so far, see Table 1

Table 4: Education diversity in 3 types

	Model 1	Model 2	Model 3	Model 4	Model 5
$\beta(K)$	0.347***	0.223***	0.370***	0.189***	0.419***
	(0.00240)	(0.00661)	(0.00584)	(0.00922)	(0.00574)
$\alpha(l)$	0.615***	0.412***	0.628***	0.438***	0.521***
	(0.00283)	(0.00751)	(0.00502)	(0.0191)	(0.00566)
$\eta_1(P_1)$	-0.348***	0.0103	-0.319***	0.0215***	-0.178***
	(0.0118)	(0.0119)	(0.00944)	(0.00619)	(0.0110)
$\eta_2(P_2)$	-0.379***	0.004	-0.359***	0.000389	-0.168***
	(0.0109)	(0.0123)	(0.0106)	(0.00710)	(0.0119)
$\gamma(DIV)$	-0.0421**	0.00433	-0.0383***	-0.00181	-0.0274*
	(0.0133)	(0.0152)	(0.0100)	(0.00738)	(0.0111)
RMP^1	0.43	1.03	0.49	1.05	0.66
RMP^2	0.38	0.99	0.43	1.00	0.68
N	36422	31342	24232	19821	24232

[1] Implied relative marginal productivity of primary educated workers (Tertiary educated workers are the reference category). [2] Implied relative marginal productivity of secondary educated workers (Tertiary educated workers are the reference category). Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: Bel-first, 2021

Table 5: Working time diversity

	Model 1	Model 2	Model 3	Model 4	Model 5
$\beta(K)$	0.364***	0.160***	0.394***	0.144***	0.402***
	(0.00230)	(0.00630)	(0.00673)	(0.00919)	(0.00778)
$\alpha(l)$	0.628***	0.635***	0.641***	0.695***	0.586***
	(0.00294)	(0.00630)	(0.0108)	(0.0240)	(0.0101)
$\eta(P)$	0.100***	0.109	0.137	0.0123	0.430***
	(0.0295)	(0.0624)	(0.0978)	(0.0626)	(0.126)
$\gamma(DIV)$	-0.277***	0.0308	-0.240**	0.157***	-0.528***
	(0.0295)	(0.0624)	(0.0978)	(0.0626)	(0.126)
RMP^a	1.16	1.17	1.21	1.02	1.73
N	35018	29947	23617	19242	23617

[a] Implied relative marginal productivity of part-time workers (Full-time workers are the reference category). Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: Bel-first, 2021

5.2 Sensitivity analysis

As a part of sensitivity analysis, some changes to the previous methodology are made to test the robustness of the results.

First, in alternative to Herfindahl Index, the Shannon Index [13] is adopted to measure labor force diversity. Note that this alternative index, like HI, is increasing in the evenness of the data. In Appendix Table 6 results for model 1 and model 5 are reported for each type of diversity measured with this alternative index. Most of the previous results are

[13] Diversity is measured with $H' = -p_i \sum \ln p_j$ where p_i is the proportion of worker of type j

confirmed after these robustness checks. In particular, gender diversity is again positively correlated with firm productivity. But once you account for endogeneity, this relation is no longer significant. For education diversity, estimated coefficients are aligned with the previous model which breaks downs the workforce by 3 education levels. Namely, this posits again for a negative effect of education diversity on firm productivity. As for working time diversity, the effect is confirmed negative like in the main model, despite diversity being measured differently.

Finally, another robustness check is conducted. In the ACF-LP algorithm it was used the purchase of raw materials as an intermediate input to approximate the short-term shock (main model). In alternative, now it is used the purchase of raw materials, consumables, services and other goods for the demand of intermediate inputs. In Appendix Table 7 results for model 5 are reported for the different inputs. Note that in comparison with estimates of the main model, these estimates are similar and more importantly they do not alter the direction of the relationship between diversity and firm productivity.

To conclude, the main model is robust to a change of the diversity index and a change of the intermediate input.

6 Conclusion

This study evaluates the impact of workforce diversity on firm productivity. The first part consists in developing a theoretical model that allows categories of workers, which are diverse in terms of labor productivity, to enter accordingly in the production function of the firm. As the main aim of the study is to verify the presence of gains/losses in firm efficiencies coming from a more diverse labor force, a measure for diversity has been included in the model. The second part consists in laying down an estimation strategy which accounts for the most relevant econometric problems out of the setting, namely unobserved heterogeneity and simultaneity bias.

The main findings do not clearly show an unambiguous general effect of labor force diversity on firm productivity. But at the level of the specific type of diversity, more can be concluded. There is no evidence gender diversity has any effect on firm productivity as in Vandenberghe (2016). As for education diversity, most of the results point to a negative but of low magnitude effect[14]. This finding is consistent with Ilmakunnas and Ilmakunnas (2011), but it differs from most of the literature. Therefore, some caution is recommended and further evidence is advisable. Concerning working time diversity, results are more robust to alternative estimation techniques. And they show that working time diversity is harmful to firm productivity at a relatively important magnitude. This finding can be related to the existing empirical evidence arguing that there is a negative impact of part-time work on firm

[14]Especially once a threefold division of education attainment has been used

productivity (e.g. Devicienti et al., 2015). However, the adopted research strategy in this study is quite new in its approach to the spillover effect of part-time workers. This offers an innovative perspective on the study of part-time work.

In conclusion, three main contributions arise out of this work. First, it proposes a relatively simple but complete model to estimate the impact of labor force diversity on firm productivity, which can be ultimately adopted also for other types of diversity. Second, it challenges the evidence that education diversity is good for firm efficiency. Third, it offers an alternative method to look at the effect of part-time work at the firm level.

Further research should expand on the findings of this paper. For instance, it would be beneficial to investigate the labor force – productivity nexus through other research designs such as natural experiments. It would be useful also the use of another measure for firm productivity as only added value was used in this work. Moreover, it would be interesting to reconcile better the empirical evidence with the economic theory on the spillover effects. This study has attempted to do so by deriving a suitable production function. But further research could be done at the micro-level on identifying the channel of transmission, and a corresponding empirical strategy should be proposed.

Finally, in terms of policy implication, there are no strong prescriptions that can be made because of the ambiguous effect of labor force diversity on firm productivity. However, some minor remarks can be made following the results on education diversity and working time diversity. Affirmative policies seeking to encourage a more diverse labor force should consider that this may hamper firm productivity, especially when they incentivize the use of part-time work.

7 Appendix

Equation (6) is obtained from the following:
knowing that $QL = \sum_j \mu_j L_j$
rewriting QL s.t. $QL = \mu_0 L + \sum_{j>0}(\mu_j - \mu_0)L_j$
multiplying and dividing by $\mu_0 L$ the second addendum of rhs
$QL = \mu_0 L + \mu_0 L \sum_{j>0}(\mu_j/\mu_0 - 1)L_j/L$
Then $QL = \mu_0 L(1 + \sum_{j>0}(\mu_j/\mu_0 - 1)P_j$ as in equation (6)

Table 6: Workforce diversity measured by Shannon Index

	Gender diversity		Education diversity		Working time diversity	
	Model 1	Model 5	Model 1	Model 5	Model 1	Model 5
$\beta(K)$	0.351***	0.402***	0.331***	0.419***	0.352***	0.390***
	(0.00232)	(0.00628)	(0.00257)	(0.00826)	(0.00232)	(0.00639)
$\alpha(l)$	0.642***	0.602***	0.633***	0.518***	0.649***	0.599***
	(0.00290)	(0.00864)	(0.00307)	(0.00739)	(0.00303)	(0.00759)
$\eta(P)$	-0.0812***	0.0675	-0.459***	-0.412***	-0.0663*	0.390**
	(0.0156)	(0.0533)	(0.0130)	(0.0211)	(0.0290)	(0.125)
$\gamma(DIV)$	0.162***	-0.0236	0.00714	-0.141***	-0.0784**	-0.337***
	(0.0190)	(0.0496)	(0.0160)	(0.0187)	(0.0239)	(0.0719)
N	34513	23191	30501	19446	33828	22509

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: Bel-first, 2021

Table 7: ACF-LP algorithm with another input

	Gender diversity		Education diversity		Working time diversity	
	Main model[1]	other input[2]	Main model	other input	Main model	other input
$\beta(K)$	0.392***	0.378***	0.421***	0.406***	0.402***	0.389***
	(0.00610)	(0.00706)	(0.00649)	(0.00703)	(0.00778)	(0.00878)
$\alpha(l)$	0.601***	0.586***	0.515***	0.510***	0.586***	0.555***
	(0.00731)	(0.00920)	(0.00607)	(0.00536)	(0.0101)	(0.0166)
$\eta(P)$	-0.0374	-0.0848**	-0.282***	-0.226***	0.430***	0.378*
	(0.0293)	(0.0316)	(0.00964)	(0.0115)	(0.126)	(0.152)
$\gamma(DIV)$	0.0784	0.0609	-0.0363**	-0.00212	-0.528***	-0.525***
	(0.0412)	(0.0425)	(0.0133)	(0.0143)	(0.105)	(0.140)
N	23617	25971	24232	26651	23617	25971

[1] Reports the results for Model 5 of the main econometric models.[2] Presents results for model 5 using an alternative intermediate input. Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: Bel-first, 2021

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