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Productivity analysis by using firm-level data: the case of Macedonia

Abstract

Productivity, the efficiency by which firms convert inputs into output is a central concept in growth-related discussions. This research is focused on analyzing productivity on a sample of Macedonian firms. The goal is twofold – first, to construct productivity indicators by using firm-level data, with special emphasis on construction of total factor productivity (TFP), and second, to identify productivity determinants specific for Macedonian firms. Results are in line with the global productivity trends – there is a significant slowdown in productivity growth in 2016. This is true for labor productivity, as well as for the TFP measure. However, the period is relatively short to conclude that this shift is of permanent, structural nature, especially having in mind the trend of reducing unemployment in the economy. As productivity determinants are concerned, econometric research confirms the importance of financial health, human capital and firms' size as significant factors that affect the productivity of Macedonian firms.

JEL Classification Numbers: D22, D24
Keywords: microdata, productivity, total factor productivity

[1] National Bank of the Republic of Macedonia. The views expressed in this paper are those of the author and do not necessarily represent the views of the National Bank of the Republic of Macedonia. Part of the analysis was prepared during a working visit at the National Bank of Belgium. The author is grateful to Ms Catherine Fuss for her assistance in preparing the codes for productivity estimation, helpful comments and suggestions regarding the design of the research and preparation of the dataset. Also, the author would like to thank Marko Josimovski and colleagues from the external sector in the Monetary Policy and Research Department at the NBRM for their help in preparing the dataset.

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Introduction

Productivity, the efficiency by which firms convert inputs into output is a central concept in growth-related discussions. It was Nobel Laureate Paul Krugman who stated “productivity isn’t everything, but in the long run it is almost everything”. And in line with this, there is a bulk of empirical evidence that confirms that differences in total factor productivity can explain the cross-country differences in income per capita (Hall and Jones, 1999; Easterly and Levine, 2001).

However, since 2004 there has been a general trend of slowdown in productivity growth across all advanced economies (Baily and Montalbano, 2016). Moreover, recent OECD report on productivity concludes that “this slowdown has extended to emerging economies”, as well. The average growth rate of labor productivity (LP) in Macedonia in the last five years is around 0.8%. Nevertheless, same as in other economies, one can notice slowdown in LP growth in 2016 and even decline in 2017. In other words, in these two years, employment, which increased at a stable and solid rate (average growth of 2.4% in 2016/2017), failed to generate more dynamic increase in production (average growth rate of GDP of 1.5% in the same period). Of course, this result should be interpreted with caution given that more time is needed to evaluate whether this change means permanent shift in productivity trend or it is due to temporary factors. The picture is even grimmer when total factor productivity (TFP) dynamics is observed - the average rate of change of TFP in the last five years is negative. With productivity being between the most important determinants of economic growth, the challenge ahead is to better understand the sources of productivity dynamics.

The objective of this research is to analyze productivity-related issues by using a firm-level database. Microdata is rich in information that might explain behavior of firms and individuals and it is an efficient way to fill “aggregate data gaps”. The goal of the research is twofold. First, to use firm-level data to construct productivity indicators, and second, to identify productivity determinants specific for Macedonian firms. The paper is organized as follows. The first section discusses the original database obtained from the Central Registry of the Republic of Macedonia. Next, we present the approaches used to calculate productivity indicators. We calculate LP and three alternative TFP indicators. The second section presents descriptive analysis of productivity dynamics. The third section tries to identify productivity determinants. More specifically, we estimate the impact of financial conditions, firms’ size, exporting status and human capital on firms’ productivity. We use few estimation methods and switch between alternative dependent variables in order to check the stability of the results. Discussion regarding future developments of the project and the concluding remarks are given in section four.

1 Data

1.1 Dataset

The analysis is carried out using an initial sample of large and medium-sized firms[2] that submitted financial accounts (balance sheet and income statement) to the Central Registry of the Republic of Macedonia in the period 2013-2016. In total, the sample consists of around 900 firms each year and it is an unbalanced sample. Financial sector and the public sector are not included in the sample. The structure of the sample is presented in Table 1.

The sample excludes agriculture because of the specific characteristics of this sector. In addition, “mining and quarrying”, “electricity, gas, steam and air conditioning” and “water supply; sewerage, waste management and remediation activities supply” were excluded from the sample because of small number of observations. Another characteristic of the sample is the size of the firms. Namely, the sample consists of medium-sized and large firms, whereas micro and small firms are not included. The reason behind this is the questionable quality and reliability of the data extracted from financial statements submitted by micro and small firms. First, they do not have legal obligation for preparation of audited financial statements. Second, as stated by Mitreska et al. (2017), it turns out that “the primary motivation of their financial reporting is connected with the taxation process or the need for fulfillment of certain legal requirements”.

Table 1. Sample Coverage by sectors, by year

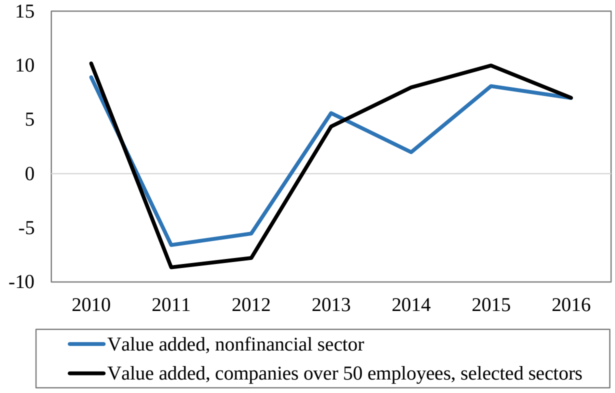
	2013	2014	2015	2016	Total 2013-2016
manufacturing	255	255	263	279	1052
construction	87	87	95	117	386
trade	346	346	356	368	1416
transport	64	64	70	72	270
other services*	136	136	135	143	550
	888	888	919	979	3674

*The group other services includes: accommodation and food service activities (I), information and communication (J), real estate activities (L), professional, scientific and technical activities (M) and administrative and support service activities (N).

According to the State Statistical Office (SSO) data for 2016, large and medium-sized firms (firms that employ over 49 workers) from the sectors as defined in our sample, constitute only 1.2% of the total number of non-financial companies in 2016. Though not representative in terms of numbers of companies, the selected sample is relevant in terms of the overall activity, dynamics and performance in the economy. Namely, these firms account for 52%[3] of the total turnover, 45% of the total value added and employ around 40% of the employees in the non-financial sectors in 2016. More importantly, these are the companies that determine the dynamics of the activity in the non-financial sector. Figure 1 shows the value added growth, in nominal terms, of the non-financial sector as an aggregate and the value added of the firms with more than 50 employees and from the sectors as defined in our sample.

[2] The classification regarding the size of the company in the Central Registry database is based on three criteria – number of employees, revenues and assets as defined in the Law on Trade Companies, Article 470.
[3] State Statistical Office, “Structural business statistics, 2016 – preliminary data”.

Figure 1. Value added growth in the non-financial sector (all firms) and in companies with above 50 employees from selected sectors*



*manufacturing, construction, trade, transport and other services (I,J,L,M,N)
Source: State Statistical Office and author's own calculations.

1.2 Calculation of productivity indicators

This section describes the methods used for calculating the productivity indicators. Labor productivity (LP) is defined as units of value added per worker. When it comes to total factor productivity (TFP), methods for calculation can be divided into two groups: index number approaches and estimation methods. This research generally relies on the first approach; estimation methods are used only partially to estimate the production function parameters because of the short time span of the dataset.

Firm-level data is often distorted by outliers. Therefore, before construction of the productivity indicators the dataset was cleaned from extreme values. The outlier cleaning was applied to ratios. In this way, the probability of penalizing a firm that has high capital, labor costs or productivity just because it is big or successful, is minimized. More specifically, we were looking at the labor and capital ratio of individual firms and if these ratios were more than five interquartile ranges above or below the median of that sector in a specific year then that firm is eliminated from the sample. After the trimming the total number of observations for the period 2013-2016 decreased to 3364 observations from a total of 3674.

In order to calculate productivity of individual firms one needs a measure of the value added by individual firms. We followed the production approach where the value added is computed as the difference between the value of production and intermediary consumption. The value of production for all economic sectors (except trade) equals sales revenues plus inventory changes. For trade, the value of production equals the gross margin (sales revenues plus inventory changes minus cost of goods sold). Intermediary consumption by definition includes purchases, changes in input stocks, insurance and renting expenses and taxes. The production approach was used by López-García, Puente, & Gómez (2007) in their research on firm productivity dynamics in Spain. To get the real values, nominal value added was deflated using sector value added deflators from the National Accounts.

TFP indicators are derived following the index number approach where the output is related to a weighted sum of inputs. We assume Cobb-Douglas production function of the following form:

$$Y = AL^{\alpha}K^{\beta} \quad (1)$$

$$logY = logA + \alpha \text{logL} + \beta \text{logK} \quad (2)$$

$$logA = logY - \alpha \text{logL} - \beta \text{logK} \quad (3)$$

Y stands for the value added, labor input (L) is the total number of employees as reported by the firms in their income statements and the capital input (K) is equal to the net book value of fixed assets. The biggest challenge in this method is the calculation of the production function parameters α and β. We followed two alternative approaches.

In the first alternative, we assume constant returns of scale and we calculate production function parameters from the data. The labor share α is equal to the ratio of labor costs to value added, whereas the capital share β is one minus the labor share $(1-\alpha)$. By using this approach we obtained different parameters for each firm. In the next step, we calculate sector specific shares which are obtained by averaging the firm specific shares in each of the five sectors (defined as in Table 1).

In the second alternative we estimate the production function parameters by using the Ackerberg, Caves and Frazer – ACF (2006) [4] approach to production function estimation. This method belongs to the family of control function approaches that try to overcome the endogeneity problem connected with the existence of positive correlation between the observable input levels and the unobservable productivity shocks. The ACF method follows the two step Olley and Pakes - OP (1996) estimation methodology and uses observed input decisions (investment or intermediary inputs) to “control” the unobserved productivity shocks. However, unlike OP methodology which estimates the labor coefficient in the first stage, the ACF methodology estimates this coefficient in the second stage. In this way, the ACF method addresses additional collinearity problem connected with the identification of the labor coefficient in the first stage. After estimating the production function we apply the estimated coefficients on labor and capital to our data for the whole period (equation 3) in order to obtain measure for the TFP, with implicitly assuming stability of the production function parameters over the whole sample period[5].

Alternative values for the production function parameters - alpha and beta are presented in Appendix 1, Table 1. Our preferred measure is the first alternative in which different sectors have different capital and labor shares. Namely, we choose this measure over the second alternative (where all sectors have the same shares), because in reality different economic sectors have different degree of labor and capital intensity, and therefore, different labor and capital shares in value added. In addition, the sum of the capital and labor share for the whole economy is estimated to be close to one, which is consistent with the assumption of constant returns of scale.

[4] Estimation was made for the whole sample. We tried to estimate different parameters by sectors but results were volatile due to small number of observations.

[5] The usual approach is to derive the TFP directly from the estimated equations. However, by following this approach we would lose half of the time dimension (given that in our sample T=4) which will limit further analysis of the TFP dynamics.

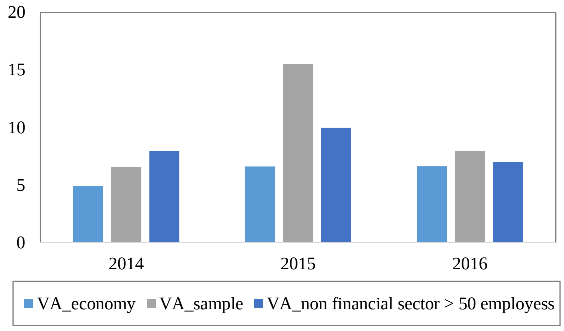
LP is calculated as units of value added per worker. Value added-based labor productivity is better measure compared to gross output-based labor productivity because it controls intermediate input usage (Gal, 2013).

$$LP = \log(VA/L) \tag{4}$$

2 Descriptive analysis of productivity dynamics

As a starting point, we focus on dynamics of sample aggregate indicators and compare them with the whole economy aggregate figures. Figure 2 shows the dynamics of sample value added, the non-financial sector and the whole economy. In general, growth rates of the three components are similar for 2014 and 2016. In 2015, value added of sample firms grew faster than the whole economy and non-financial sector value added suggesting that there are other companies and institutional sectors that might explain this discrepancy between different measures.

Figure 2. Nominal value added growth rate (%)



Source: State Statistical Office, Central Registry and author's own calculations.

Growth rates of different productivity measures are presented in Figure 3 and Figure 4[6]. Figure 3 shows the constructed productivity indicators from our sample of firms, whereas Figure 4 shows productivity indicators calculated from aggregate, macro data. One can see that the evolution of the compiled productivity indicators is very similar. There are differences in the intensity of the growth but the pattern of growth, in general, is consistent across measures. The results from the correlation matrix given in Appendix 1, Table 2 are also in line with this finding. Regarding the pattern of growth, it is evident that there is a downward movement in productivity in the last year of the analyzed period. Constructed productivity indicators show a significant slowdown in growth, whereas the productivity measure for the whole economy shows even a decline in TFP in 2016. This unvaforable movement in productivity, in fact explains, why, in 2016, when employment increased at a stable and solid rate and investment increased by double digits, GDP growth slowed down (by one percentage point in 2016 as opposed to 2015).

[6] Before analyzing productivity dynamics we aggregate individual firms' productivity by using firms' share in value added as weights. This is very important because productivity dynamics is driven by the most productive firms. In this case, using median or simple average as a represent for the whole sample could lead to wrong conclusions.

Figure 3. Sample productivity indicators* (growth rates, in %)

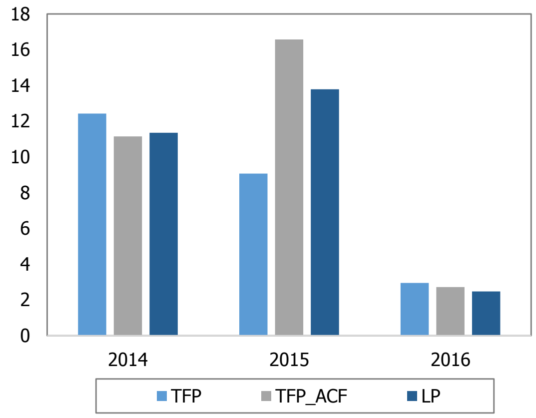
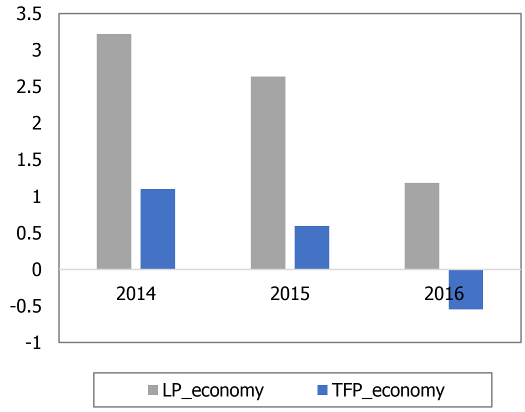


Figure 4. Economy productivity indicators** (growth rates, in %)



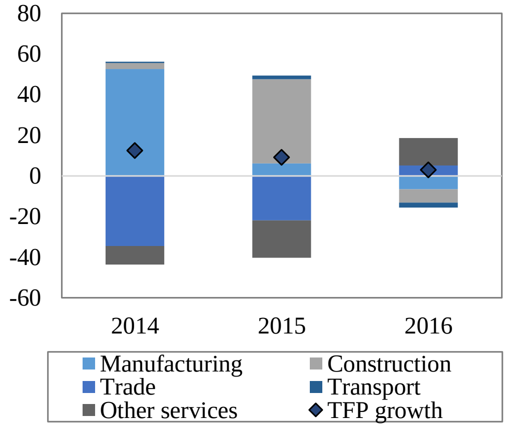
* TFP = first alternative with poduction function papameters derived from the data, TFP_ACF second alternative with production function parameters estimated with the ACF method

** TFP_economy is taken from the Conference Board, Total Economy Database, November 2017; LP_economy is constructed by the NBRM.

The aggregation of TFP allows for sectoral decomposition of the productivity growth. Contributions of different sectors to TFP growth are shown in Figure 5. The presented sectoral decomposition refers to the TFP indicator with different sectoral shares as our preferred measure; however, as a stability check, the sectoral decomposition of growth rates of productivity by sectors using the other TFP indicator (TFP_ACF) and the LP are presented in Appendix 2, Figure 1 and the results are very similar.

Looking at the contributions, manufacturing was leading sector of TFP growth in 2014, whereas construction had dominant share in 2015. The slowdown registered in productivity growth in 2016 can be attributed to the negative contribution of manufacturing, construction and transport. Generally, this is in line with macro data. In 2014, there was a high growth in manufacturing value added (and in line with this, a rise in labor productivity). After 2014, we saw significant decline in the growth which is in line with TFP dynamics shown in Figure 4. Construction was one of the key drivers of economic growth in the analyzed period, largely as e result of the implementation of publicly funded infrastructure projects. However, there is a significant slowdown in completed construction works dynamics in 2016.

Figure 5. Contributions of sectors (in percentage points) to aggregate TFP growth (in %) over time



Source: author's own calculations

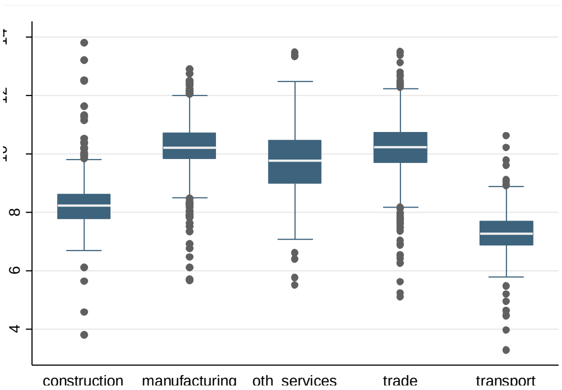
Looking at the level[7], manufacturing, trade and the group "other services" have similar level of productivity. The median firm in these sectors has TFP very close to the TFP of the median firm in the whole sample. The lowest level of TFP is registered in transport, where the median firm's TFP is smaller by 27% compared to the sample median firm's TFP. Figure 6 displays the evolution of the interquartile range[8] (IQR) for the TFP across different economic sectors. For the whole sample the dispersion measure for TFP is around 1.5 log points in the period 2013-2016 meaning that productivity of any firm in the top quartile of the distribution is 4.6 times higher than the productivity of any firm amongst the 25% of the least productive. This result is generally driven by the group "other services", whereas in all other sectors dispersion is smaller (the IQR is below or equal to one) and generally in line with the findings for other countries (Appendix 1, Table 3).

[7] Productivity indicator shown in Figure 5 is the TFP indicator with different sectoral shares. However, the results regarding the productivity dispersion are very similar across the other two productivity indicators – TFP_ACF and LP (see Table 3, Appendix 1 and Figure 2, Appendix 2).

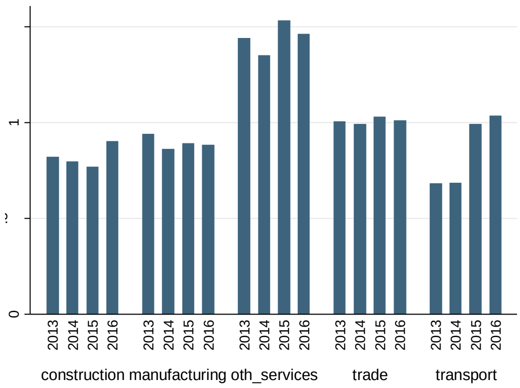
[8] The interquartile range (IQR) shows the relative difference between the productivity of the firm which is more productive than 75% of the firms (third quartile) and the productivity of the firm which is more productive than 25% of the firms (first quartile). It is calculated as the difference between the third and the first quartile of log measure of productivity (TFP and LP) as in Syverson (2011).

Figure 6. Productivity dispersion

median log-level for the 2013-2016 period



interquartile range by sectors, over time



Source: author's own calculations

Wide dispersion of productivity across firms, sectors and countries is a key stylized fact from empirical studies. Irrespective of the measure of productivity, empirical research showed that firms' productivity level varies a lot between different sectors and sub-sectors (see Bartelsman and Doms (2000) and Syverson (2011) for excellent review). When it comes to reasons, empirical research suggests different factors for explaining high productivity dispersion, but the general consensus is that firm-level factors are more important than macroeconomic or sectoral effects. Uncertainty connected with the development, distribution and regulation of new products and production techniques, managerial ability, quality of the workforce or human capital, firm-specific location, exporting activity and ownership structure are among firm-level, idiosyncratic factors that are found to have important explanatory power in different empirical studies (López-García, Puente, & Gómez, 2007). According to Hsieh and Klenow (2009) productivity dispersion is an indicator of misallocation of resources i.e. higher dispersion means more space for improving aggregate productivity and growth by re-allocating resources from the less to more productive firms.

3 Firm-level determinants of productivity

This section tries to identify the firm-level determinant of productivity. Our empirical strategy is based on the standard model of firm productivity, in which productivity measure is regressed against productivity determinants. In addition, we control sector and firm specific characteristics. The dependent variable is the TFP indicator with different sectoral shares[9].

[9] As a robustness check we present the estimated models with different dependent variables (TFP_ACF and LP) in the next section.

3.1 Definitions and descriptive statistics of the variables

Literature on productivity determinants is extensive and multidimensional. Our empirical research focuses on four wide groups of determinants - internal firm features, trading status, financial health and human capital. The correlation matrix and the summary statistics of the variables are given in Appendix 3 (Table 1 and 2).

Internal firm features are usually described through two variables: firm's age and size. Given that in our dataset we do not have data regarding the age of the firms, we included only firm size indicator. Firm size can have two opposing influences on productivity. Larger firms have access to a larger pool of technology which positively impacts firms' productivity. On the other hand, they tend to be less flexible in their operations, which might have a negative impact on TFP. As a proxy for the firm's size, we use the log level of the firm's revenues.

Theory and empirical work indicate that the firm's *trading status* is an important determinant for the firm's performance. This research focuses on the exporting activity of the firms[10]. There is a general consensus that exporters have superior characteristics compared to firms producing only for domestic markets. Exporters are more productive and more capital and technology-intensive. To investigate this effect, we have created two variables describing the exporting status of the firm. The first one is a dummy variable being equal to one if the firm is an exporter and zero otherwise. The second variable is the ratio between export and sales revenues and describes the export intensity of individual firms. Around 40% of the firms in our sample are exporters.

Firms with better *financial health* tend to exhibit superior productivity level. These firms are more resilient to financial and non-financial shocks and have access to external finance with more favorable conditions which, in turn, have a positive impact on their performance and productivity.

We include two financial variables to describe the financial health of firms. The first one captures the financial distress. Following Klein (2016) we include a dummy variable equal to one if the firm has an interest cover ratio[11] (ICR) bellow two and zero otherwise. Low ICR indicates that the firm approaches a financial distress, thus resources are likely to shift away from productive activities towards servicing the debt. In line with expectations, productivity distribution of firms with lower ICR ratio (or financially distressed firms) is shifted to the left indicating that these firms have lower TFP as compared to firms with higher ICR ratios (Figure 7). Around 28% of the firms in our sample are financially distressed.

The second variable measures the impact of leverage. We model this variable following the trade-off theory of capital structure that predicts decline in net benefits of debt financing on the firm's performance as the level of debt increases. Coricelli et al. (2012) investigated the relationship between leverage and TFP and, in line with the trade-off theory, found evidence of non-monotonic relationship between leverage and firm-level productivity. We construct sector specific dummy variable equal to one if the firm is considered to be highly leveraged and zero otherwise. More precisely, first we calculate the firm's level of leverage defined as total liabilities to total assets. In the second step, we compare individual leverage to the sectoral leverage threshold, the threshold being defined as the 75th

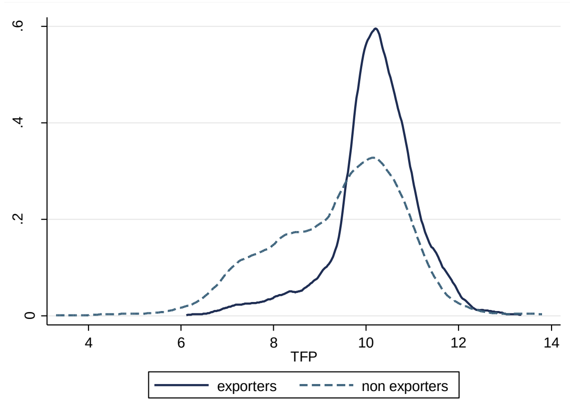
[10] Another group of the literature focuses on the effect of imports on firm's productivity. See JaeBin Ahn and Moon Jung Choi (2016).

[11] Interest cover ratio is calculated as the ratio between the earnings before interest and taxes and the interest payments.

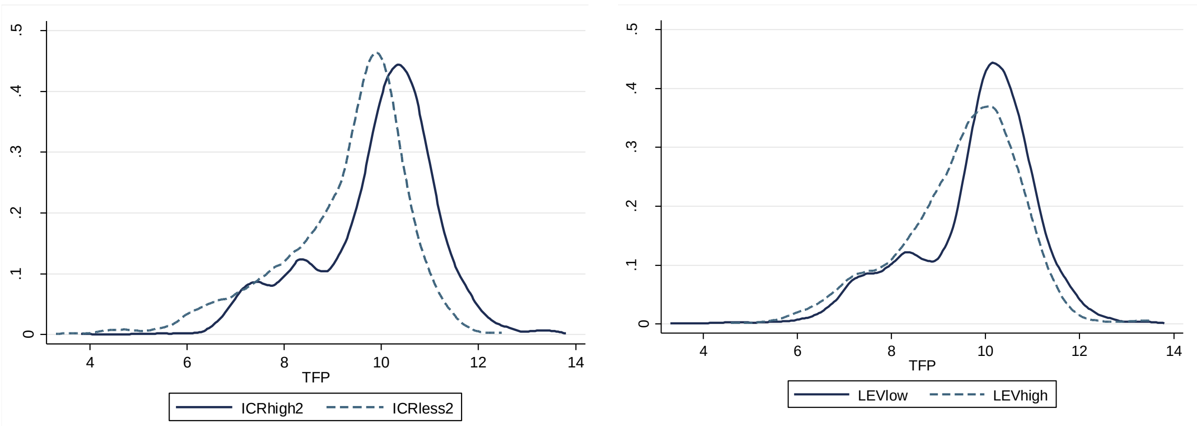
percentile in each sector[12]. Following this definition, around 25% of the firms are considered to be highly leveraged. The productivity distribution of highly leveraged firms is slightly shifted to the left, indicating lower productivity, though the difference is not that evident as in the case of the ICR variable (Figure 6).

Figure 7. Kernel density distribution of firm-level productivity (in logs)

Trading status



Financial health*



*ICRhigh2 refers to firms with ICR ratio above 2, ICRless2 refers to firms with ICR ratio below 2; LEVlow refers to firms with leverage below the tresholds, LEVhigh refers to firms that have leverage higher than the treshold.

Human capital is an important precondition for achieving higher productivity levels. Ilmakunnas et al. (2004) find that productivity increases in worker's education and age. Konings and Vanormelingen (2011) show that firm-level productivity is higher with the increase in the number of workers that received training. Empirical studies that investigate the impact of the human capital on productivity usually use data on education level, investment in on-the-job training, composition of the workforce (managers, blue-collar workers, white-collar workers) to describe the human capital of the firms (Beveren and Vanormelingen, 2014). In our dataset, we do not have detailed data on working force composition. In fact, the only labor market variable available to us is wages and therefore, we use wages as proxy for human capital. Though not optimally, this strategy is also used in other research on this topic. For example, Goncalves and Martins (2016) use wages as proxy for different education

[12] Leverage thresholds by sectors are presented in Appendix 3.

levels when trying to evaluate the impact of human capital on productivity. In addition, Konings and Vanormelingen (2011) find a significant positive impact of training on workers' wages, which, to a certain extent, justifies the use of wages as proxy for human capital.

3.2 Estimation results

This section presents the results of our assessment of the determinants of productivity. We start by estimating the following productivity model using pooled OLS:

$$lnTFP = f(size, export, ICR, leverage, wages) \tag{5}$$

In addition, we included year dummy variables and sector dummy variables to control sectoral heterogeneity. Our strategy is to include variable by variable in order to check the stability of each estimated coefficient. As an additional stability check, we estimated fixed-effect model (column 6) despite the small time dimension of our dataset. Even though some authors (Pontuch, 2013) argue that fixed-effect model is not appropriate when using firm-level explanatory variable, we wanted to see whether coefficients remain stable even after controlling firm heterogeneity. The results are presented in Table 2. Preferred models with all explanatory variables are presented in column 4 and 5.

Table 2. Productivity determinants – pooled OLS and fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	OLS	OLS	OLS	FE
Size	0.161***	0.149***	0.067**	0.065**	0.069**	0.395***
Leverage		-0.158**	-0.126**	-0.126**	-0.127**	-0.100
ICR		-0.603***	-0.609***	-0.609***	-0.610***	-0.221***
Wages			0.700***	0.698***	0.698***	0.328***
Export dummy				0.043		
Export intensity					-0.019	0.013
cons	7.120***	7.613***	0.574	0.606	0.558	-0.8584
year dummies	yes	yes	yes	yes	yes	yes
sector dummies	yes	yes	yes	yes	yes	yes
number of observations	3364	3364	3364	3364	3363	3363
R2	0.52	0.57	0.66	0.66	0.66	0.53

* p<0.05 ** p< 0.01 ***p<0.001

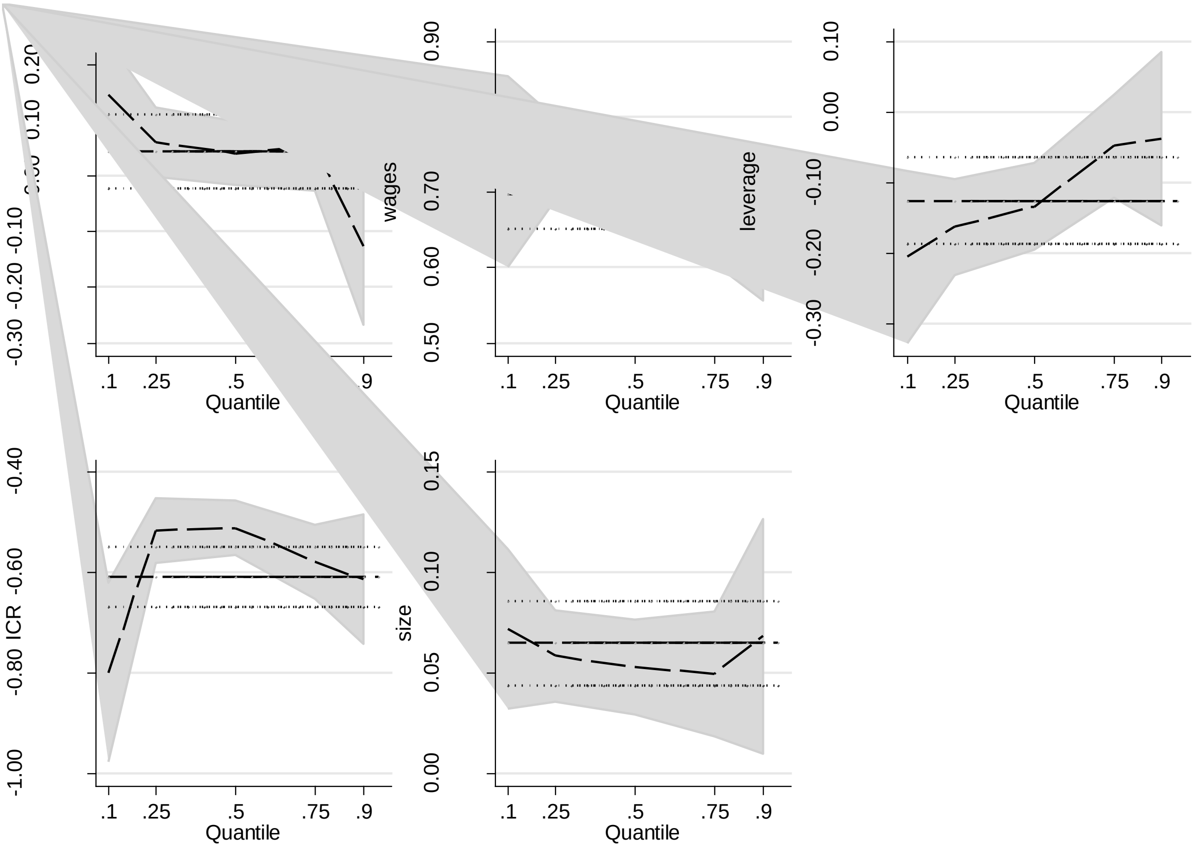
The estimation results indicate a positive and significant impact of size on firms' productivity – 1% increase in size would lead to around 0.1% increase in productivity (0.4% in the FE). Variables describing the financial health of the firms have the expected negative effect on productivity. Highly leveraged firms have lower productivity by 0.13% (the coefficient is not significant in the FE specification), whereas firms that have ICR lower than 2 will experience a decline in productivity of around 0.6% (0.2% in FE). Another important result is the positive and significant coefficient of workers' wages. Namely, results suggest that firms with 1% higher wages (indicating higher quality of human capital) will have 0.7% higher productivity, on average (the coefficient is estimated to 0.3 in FE). Given that there is a potential endogeneity bias between wages and productivity, in the next section, we control this problem and then compare the results. With respect to exporting status, contrary to our expectations, we did not find evidence of a significant impact of export on firms' productivity. Both variables that describe the exporting activity of firms turned out to be insignificant. This result requires further analysis of the relationship between export and productivity; for example, testing the "learning by exporting hypothesis" (Loecker, 2007).

As the productivity distribution is quite dispersed we wanted to check whether the estimated coefficients differ for firms with different productivity. To that end we estimated quantile regressions (QR) originally developed by Koenker and Bassett (1978). QR provide estimates of the linear relationship between explanatory variables and a specified quantile of the dependent variable. According to Mata and Machado (1996) QR is a more efficient estimator when dealing with large heterogeneous samples. Namely, instead of concentrating on a single tendency measure (the conditional mean of the whole sample), the QR method provides an overview of the overall conditional distribution of firms' productivity. This is especially true when the dependent variable is not identically distributed among firms. If this is the case then there will be significant discrepancies in the estimated slope parameters at different quantiles.

The QR are estimated for five quantiles (10, 25, 50, 75, 90). Five graphs in Figure 8 correspond to the OLS coefficients for export, wages, leverage, ICR and size from the estimated model in Table 2, column 4[13]. Regarding the statistical significance, the results are generally in line with the OLS estimation. Also, the size of the coefficients is not dramatically different from the OLS coefficients. However, as expected, we find that the impact of explanatory variables on firms' productivity varies depending on the position of each firm in the productivity distribution.

[13] Appendix 3 presents the table with estimated QR coefficients.

Figure 8. Quantile regressions: TFP and TFP determinants*



* The dashed lines represent the estimated parameters for the individual quantiles (10, 25, 50, 75, 90). The shaded areas around the dashed lines delimit the 95 percent confidence intervals for the quantile regressions. The solid lines represent the respective OLS coefficient of each explanatory variable, whereas the dotted lines display the 95 percent confidence intervals of the OLS coefficients.

Export QR parameters, same as the OLS coefficients, are generally insignificant. We find a positive and significant impact only for the firms with lowest productivity. Regarding size and wages, QR estimates are very close to the OLS coefficient and similar across different quantiles. The interesting finding is related to the impact of firms' financial characteristics. The negative effect that was estimated in the OLS and FE model of the financial variables remains, but the impact is stronger for low productive firms i.e. productivity of the firms at the lower quantiles will decline more if firms are financially distressed and highly leveraged as compared to firms in the top quantiles. The estimated coefficient of leverage is not statistically significant for the most productive firms. Similar results regarding financial variables are found in Ku and Yen (2016) and Dimelis et al. (2017) who analyzed an effect of leverage on firms' performance.

Part of the explanation of this non-linear effect of financial variables on productivity might be connected with the so-called signaling effect (Ross 1977). Namely, being high productive usually goes together with having high performance and high capacity for debt servicing. If this is the case then new debt in high productivity firms will be used for productive investments and innovation which will offset the potential negative impact of debt on productivity. Also, the negative impact of the ICR will be less pronounced. Complementary explanation is connected with costs of debt issuance; debt issuance is connected with bankruptcy costs and costs of financial distress, as well as agency, moral hazard, monitoring and contracting costs. Lowest productive firms (firms in the left-hand side quantiles) most probably have higher costs connected with debt issuance compared to more productive firms (firms in the right hand-side quantiles) which in part explains the more pronounced negative impact of both financial variables on their productivity.

3.3 Robustness check

As a robustness check, we perform two exercises. First, we try to control potential endogeneity problem. Second, we re-estimate the models by changing the dependent variable.

When working with firm-level regressors we face potentially serious endogeneity problem given that all firm-level regressors are just like productivity observed at firm-level. To address this problem we start lagging the firm-level variables – wages, leverage, ICR and size in the pooled OLS regression following Pontuch (2013). As a further step, we run instrumental variable (IV) regression where we instrument the potentially endogenous firm-level variables with one and two period lags. While lagged values are not always the best instruments to use, the Hansen test confirms the exogeneity of the instruments, and the size and the sign of the coefficients remain stable (Table 3). The only exception is the leverage variable that is insignificant in the lagged OLS equation, as well as in the IV regression.

Table 3. Robustness check – lagged OLS and IV

	OLS	IV - gmm
Export dummy	0.093	0.112
$Wages_{(t-1)}$	0.670***	
Wages		0.743***
$Leverage_{(t-1)}$	-0.038	
Leverage		0.037
$ICR_{(t-1)}$	-0.548***	
ICR		-1.026***
$Size_{(t-1)}$	0.045*	
Size		0.023
cons	1.245*	0.859
year dummies	yes	yes
sector dummies	yes	yes
number of observations	2256	1356
R2	0.680	0.694
Hansen J test		p = 0.509

In IV regression wages, leverage, ICR and size were instrumented with t-1 and t-2 values.
* p<0.05 ** p< 0.01 ***p<0.001

As part of the robustness check, we vary the dependent variable i.e. instead of the TFP indicator with different sectoral shares, we estimate the model with the following productivity indicators: TFP_ACF and LP. The coefficients remain stable across models with different versions of the dependent variable and different estimation methods which confirms the robustness of our results (Table 4).

Table 4. Robustness check – different dependent variables

	(1)	(2)	(3)	(4)
	OLS		FE	
Dependent variable:	TFP_ACF	LP	TFP_ACF	LP
Export dummy	0.040	0.072		
Wages	0.669***	0.732***	0.359***	0.471***
Leverage	-0.176***	-0.246***	-0.085	-0.080
ICR	-0.540***	-0.472***	-0.218***	-0.223***
Size	0.121***	0.099***	0.387***	0.321***
cons	0.570	2.171***	-0.449	1.452
year dummies	yes	yes	yes	yes
sector dummies	yes	yes	yes	yes
number of observations	3364	3364	3364	3364
R2	0.426	0.390	0.223	0.231

* p<0.05 ** p< 0.01 ***p<0.001

4 Discussions and concluding remarks

The research was focused on analyzing productivity-related issues by using a firm-level database. The contribution of the research is twofold. First, this is the first time microdata to be used for calculation of productivity indicators in the case of Macedonia and second, this is the first analysis, at least to the knowledge of the author, which tries to identify productivity determinants specific for Macedonian firms.

In line with the general trend of slowdown in productivity growth across all advanced economies and, more recently, in some emerging economies, descriptive analysis for Macedonian economy shows a slowdown in productivity growth in 2016 largely as a result of the decline in productivity in manufacturing and construction. Looking at the aggregate macro data, this unvaforable movement in productivity in fact reflects stable and solid growth in employment, supported by active government policies, strong investment activity and relatively moderate GDP growth. However, as the time dimension of our analysis is rather small, it is difficult to conclude whether this downward trend will continue or it is driven by more temporary factors. When it comes to productivity determinants on micro level, econometric analysis confirmed that size, human capital and financial health are important for productivity of Macedonian firms. Moreover, for some of the variables this connection is not linear and this effect is most pronounced for the financial health variables. On the other hand, exporting activity of the firms is not a significant factor for firm-level productivity. This result requires future analysis of the relationship between export and productivity.

Having in mind the importance of productivity for achieving sustainable and inclusive economic growth, additional analyses are needed to explain the unfavorable developments in productivity. One future step should be decomposition of productivity dynamics on technical efficiency, reallocation and fixed costs terms following Petrin and Levinsohn (2012). This will answer the question whether the recent slowdown is the result of a slowdown in average firm-level productivity or resource reallocation among sectors.

References

Ackerberg, D., Caves, K., & Frazer, G. (2006). Structural identification of production functions. *MPRA Paper 38349*.

Ahn, J., & Jung, C. M. (2016). From Firm-Level Imports to Aggregate Productivity: Evidence from Korean Manufacturing Firms Data. *IMF Working Paper, WP/16/162*.

Andrews, D., Criscuolo, C., & Gal, P. N. (2015). Frontier Firms, Technology Diffusion and Public Policy: Micro Evidence from OECD Countries. *OECD*.

Bartelsman, E. J., & Doms, M. (2000). Understanding Productivity: Lessons from Longitudinal Microdata. *Journal of Economic Literature, 38*(3), 569–594.

Beveren, I. V., & Vanormelingen, S. (2014). Human Capital, Firm Capabilities and Productivity Growth. *National Bank of Belgium, Working Paper Research No 257*.

Chen, M., & Guariglia, A. (2013). Internal Financial Constraints and Firm Productivity in China: Do Liquidity and Export Behavior Make a Difference? *Journal of Comparative Economics*, 1123-1140.

Coricelli, F., Driffield, N., Pal, S., & Roland, I. (2012). When does leverage hurt productivity growth? A firm-level analysis. *Journal of International Money and Finance*.

Dimelis, S., Giotopoulos, I., & Louri, H. (2017). Can Firms Grow Without Credit? A Quantile Panel Analysis in the Euro Area. *Journal of Industry, Competition and Trade*.

Easterly, W., & Levine, R. (2001). It's not Factor Accumulation: Stylized Facts and Growth Models. *World Bank Economic Review, 15*(2), 177-219.

Gal, P. N. (2013). Measuring Total Factor Productivity at the Firm Level Using OECD-ORBIS. *OECD Economic Department Working Papers* (1049).

Gonçalves, D., & Martins, A. (2016). The Determinants of TFP Growth in the Portuguese Manufacturing Sector. *GEE Papers 0062*.

Hall, R. E., & Jones, C. I. (1999). Why Do Some Countries Produce So Much More Output Per Worker Than Others? *Quarterly Journal of Economics, 114*(1), 83-116.

Hsieh, C.-T., & Klenow, P. J. (2009). Misallocation and Manufacturing TFP in China and India. *The Quarterly Journal of Economics, 124*(4), 1403-1448.

Ilmakunnas, P., Maliranta, M., & Vainiomaki, J. (2004). The Roles of Employer and Employee Characteristics for Plant Productivity. *Journal of Productivity Analysis*, 249-276.

Jovanovic, B., & Kabashi, R. (2011). Potential output and output gap. *NBRM working paper series*.

Klein, N. (2016). Firm-Level Productivity and its Determinants: the Irish case. *Selected Issues - Ireland, International Monetary Fund*.

Knings, J., & Vanormelingen, S. (2011). The Impact of Training on Firm Level Productivity and Wages: Evidence from Belgium. *KU Leuven*.

Koenker, R., & Bassett, G. (1978). Regression quantiles. *Econometrica, 46*, 33-50.

Ku, Y.-Y., & Yen, T.-Y. (2016). Heterogeneous Effect of Financial Leverage on Corporate Performance: A Quantile Regression Analysis of Taiwanese Companies. *Review of Pacific Basin Financial Markets and Policies*.

López-García, P., Puente, S., & Gómez, Á. L. (2007). Firm Productivity Dynamics in Spain. *Banco de Espana, Documentos de Trabajo, No. 0739*.

Mata, J., & Machado, J. (1996). Firm Start-up Size: a Conditional Quantile Approach. *European Economic Review*, 1305-1323.

Mitreska, A., Bojceva-Terzijan, S., & Debnikov, P. (2017). Corporate Sector Deleveraging in Macedonia in the Aftermath of the Crisis - Has it happened at all? *National Bank of the Republic of Macedonia*.

Ospina, S., & Schiffbauer, M. (2010). Competition and Firm Productivity: Evidence from Firm-Level Data. *IMF Working Paper*(WP/10/67).

Pontuch, P. (2013). Firm-level Productivity and Exporting: Diagnosing the Role of Financial Constraints. *European Commission Product Market Review 2013: Financing the Real Economy*, 30-46.

Syverson, C. (2011). What Determines Productivity? *Journal of Economic Literature, 49*(2), 326-365.

Wooldridge, J. M. (2009). On estimating firm-level production functions using proxy variables to control for unobservables. *Economics Letters*.

Јовановиќ, Б. (2017). *Вистинската цена на ефтината работна сила.* Институт за општествени и хуманистички науки - Скопје.

Appendix 1: Tables

Table 1. Production function parameters

	Labor α	Capital β
constant returns of scale		
manufacturing	0.80	0.20
construction	0.60	0.40
trade	0.77	0.23
transport	0.56	0.44
other services	0.71	0.29
ACF	0.78	0.17

Table 2. Correlation matrix

Productivity indicators, levels

	TFP	TFP-ACF	LP
TFP	1.00		
TFP-ACF	0.55	1.00	
LP	0.49	0.96	1.00

Productivity indicators, growth rates

	TFP	TFP-ACF	LP
TFP	1.00		
TFP-ACF	0.97	1.00	
LP	0.95	0.99	1.00

Table 3. Productivity dispersion in EU countries and in Macedonia

TFP (median log level) in selected EU countries (2002-2012)

	Manufacturing		Services	
	All	20+	All	20+
Belgium	0.72	0.52	0.72	0.51
Estonia	0.93	0.65	1.09	0.87
Finland	0.66	0.52	0.65	0.40
France	0.49	0.48	0.52	0.48
Germany	0.68	0.66	0.73	0.64
Italy	0.64	0.55	0.70	0.56
Latvia	0.98	0.83	1.23	0.78
Poland		0.82		0.87
Portugal	0.67	0.61	0.86	0.65
Slovakia		0.75		1.02
Slovenia	0.80	0.58	0.87	0.79
Spain	0.72	0.65	0.77	0.59

Source for the EU countries: Bartelsman, E. J. and Wolf, Z, "Measuring Productivity Dispersion", Tinbergen Institute Discussion paper, TI 2017-033/VI

Productivity indicators (median log level) in Macedonia (2013-2016)

	TFP	TFP-ACF	LP
construction	0.81	0.93	0.98
manufacturing	0.89	0.89	1.11
oth_services	1.47	1.29	1.36
trade	1.02	0.98	1.10
transport	0.81	0.71	0.78
all sectors	1.52	1.05	1.19

Appendix 2: Figures

Figure 1. Contributions of sectors (in percentage points) to aggregate TFP growth (%) and LP (%) over time

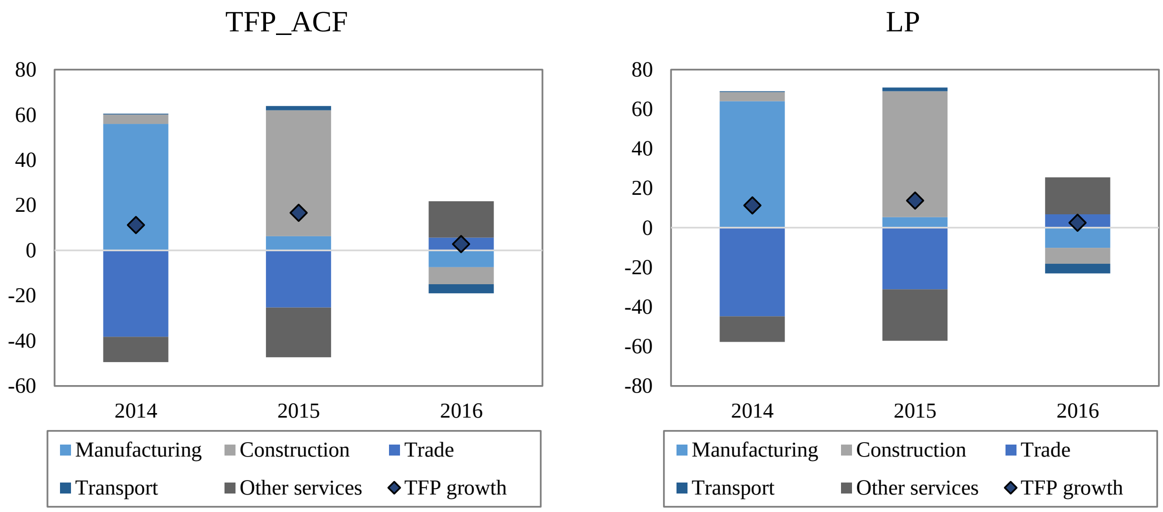
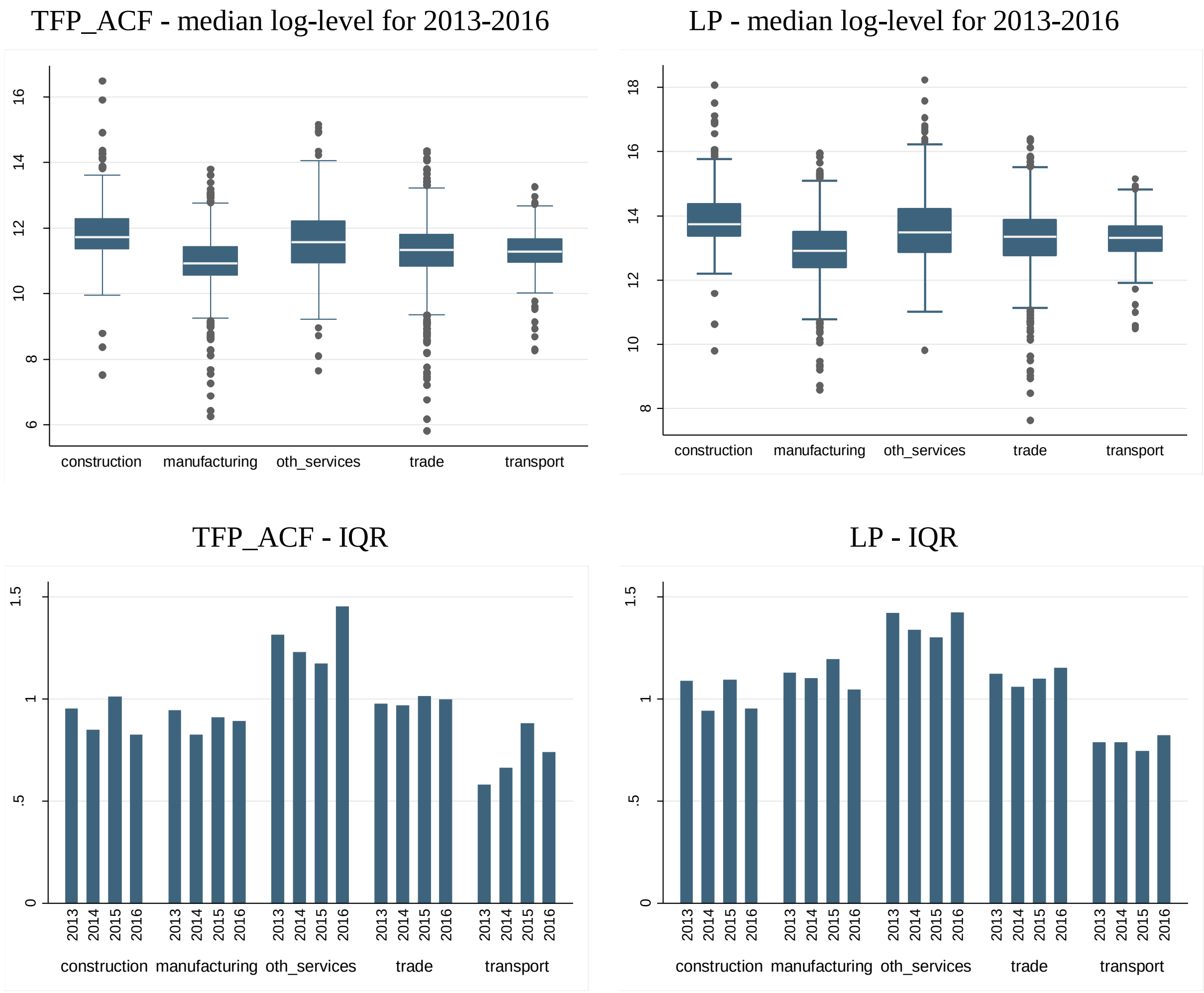


Figure 2. Productivity dispersion



Appendix 3: Econometric results

Table 1. Correlation matrix of the explanatory variables

	TFP	Export dummy	Export intensity	Wages	Leverage	ICR	Size
TFP	1						
Export dummy	0.2996	1					
Export intensity	0.1237	0.4442	1				
Wages	0.1286	-0.1127	-0.1234	1			
Leverage	-0.1067	0.0053	0.033	-0.0238	1		
ICR	-0.2202	0.0412	0.0325	-0.0133	0.2636	1	
Size	0.2113	0.2134	0.0618	0.1232	0.0255	-0.0769	1

Table 2. Summary statistics of the explanatory variables

	mean	sd	p25	p50	p75
TFP	9.72	1.29	9.05	9.98	10.57
Export intensity	0.19	0.50	0.00	0.00	0.08
Export dummy	0.40	0.49	0.00	0.00	1.00
Wages	12.60	0.62	12.16	12.49	12.95
ICR	0.28	0.45	0.00	0.00	1.00
Leverage	0.25	0.43	0.00	0.00	0.50
Size	19.33	1.35	18.77	19.34	20.03

Table 3. Leverage threshold levels by sectors

	P75
construction	0.73
manufacturing	0.66
other services	0.73
trade	0.66
transport	0.54
Total	0.67

Table 4. QR estimated parameters

	export dummy	wages	leverage	ICR	size
OLS	0.043	0.698***	-0.126**	-0.609***	0.065**
q10	0.146**	0.727***	-0.206**	-0.800***	0.072**
q25	0.061*	0.7442***	-0.163***	-0.517***	0.058***
q50	0.041	0.716***	-0.134***	-0.511***	0.053***
q75	0.053	0.663***	-0.048	-0.579***	0.050***
q90	-0.126	0.656***	-0.038	-0.615***	0.068*

* p<0.05 ** p< 0.01 ***p<0.001