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Production Technology Dynamics of Manufacturing Industries in Turkey[1]

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Abstract

This study analyzes the firm level productivity to clarify the differences among manufacturing sectors. We provide estimates of regional and sectoral total factor productivity (TFP) using firm-level data on Turkish manufacturing industry provided by TURKSTAT as survey data over the 2003-2015 period to understand firm heterogeneity across sectors and regions. Based on the results obtained from different estimation methods as ordinary least square, fixed effect and Levinshon-Petrin TFP estimations, there is a significant heterogeneity across sectors and firms in the same sector in the micro-level and this results in different average TFP levels for regions at macro-level. Our findings suggest that discrepancies in regional TFP levels are determined by technological dynamics of the industries that are dense in those regions. Calculating sectoral TFP differences may guide policymaker not only to give incentives to most productive sectors in order to accomplish sustainable growth with high value-added production, but also differentiating between firms and regions while giving incentives according to the density of the sectors on those regions.

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1. Introduction

Many theorists try to model long run growth path of economies. Since the seminal work of Barro et al. (1991), convergence of income levels between countries or between regions of the same country draws the attention of many researchers. However, most of the time, heterogeneity across sectors and regions of the country remains in the background. The presence of such heterogeneity across sectors or regions could result in several outcomes, one of which is total factor productivity (TFP) differences among these sectors/regions and the other is misallocation of resources. These outcomes have been put forward as reasons for within-country income per capita differences (Restuccia and Rogerson, 2008; 716-720). In this paper, I will analyze dynamics of regional and sectoral production technology in the manufacturing industries in Turkey using a panel data approach in order to examine whether TFP levels provide insight about different degrees of development within Turkey. As in Prescott (1998) and Hall and Jones (1999), I will mainly focus on estimation of regional and sectoral TFP using data on Turkish manufacturing firms to observe whether the dominant source of differences in output per worker is caused by differences in TFP levels.

Total factor productivity calculations are frequently used for addressing questions of efficient utilization of inputs and factors of production. Analytics of TFP can be traced back to Solow (1957). In his seminal paper, Solow defined change in the technology as "any kind of shift" in the production

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function, nevertheless he focused on different saving rates to explain international income differences. As a follow-up, Lucas (1988) has taken the neoclassical approach a step further, and introduced the notion of "human capital" as schooling, experience or specializing to elucidate income differences between countries. In what follows, Prescott (1997) has argued that these works were virtually unsatisfactory, as evidence reveals that the same level of human capital fails to explain international income differences. That's why, he resorted to total factor productivity analysis to clarify international and within-country income differences.

After the seminal work of Prescott, the idea of "total factor productivity" issued to explain variations in developed and developing countries' income levels, and the TFP approach is utilized to compare per capita income differences among countries especially after trade-liberalization income experiences. Grossman and Helpman (1991), is one of the examples that model a close economy in which productivity increases after trade liberalization due to the interactions of knowledge and innovation spillovers across trading partners. Caselli (2005), in turn, endeavors to clarify cross-country income differences not only with factors of production but also with differences in efficiency levels using survey data from both OECD and non-OECD countries. He claims that differences in human capital or physical capital are not enough to explain income inequality, but that efficiency differences would be the biggest part of the question.

TFP measure is also used by policy makers for regulations and subsidies in order to distribute resources more efficiently on specific sectors and/or regions. Having a far-reaching data set, Gennaioli et al. (2014) analyze 83 countries regional growth and convergence rates, including Turkey, over the period 1975-2001. They conclude that regional growth is shaped ultimately by the aggregate characteristics of national growth, and countries with more effective regulation exhibit faster convergence. Atiyas and Bakıs (2013) provide an aggregate sectoral TFP growth analysis for Turkey. Their findings show that after 2000s TFP growth in Turkey is more than 3 percent, and agriculture sector exhibits strikingly higher TFP growth than industry. Furthermore, in his empirical work Filiztekin (2000) analyzes the productivity growth in Turkish manufacturing sectors after trade liberalization of 1980. He finds a significant effect of openness to trade on productivity and growth using data up until year 2000.

Focusing on capital accumulation to explain sources of economic growth, Saygılı et al. (2005) ascertain that there is a positive correlation between economic growth and capital accumulation. They also claim that productivity indicators are weak for agriculture and services, whereas they are high for industry. They draw attention to the increase in productivity with structural transformation after 2000s. In their work, Taymaz et al. (2008) use establishment-level data where they determine the factors effecting producitvity increase taking sector heterogeneity into account. While all the papers reviewed above give a general idea about TFP levels, usage of aggregated data, and methodological problems warrant that there is an acute need to estimate regional and firm-level TFP micro-data, as well as more robust techniques, a gap that this paper aims to fill.

Background data requirements for this research are production, employment and firm dynamics on Turkish economy. Publicly available data by TURKSTAT indicate that with 54.3% of the production share at the enterprise level, industry has the biggest portion. Moreover, 81% of the production level of industry is supplied by manufacturing. For this reason, we direct our attention to the manufacturing industry specifically. In addition, 97% of the firms in Turkey has less than 20 people employed but their share in aggregate production is comparably small. Therefore, we concentrate on the production dynamics of the large enterprises.

It is an inevitable fact that regional and sectoral analysis of Turkey at firm-level is significant that is missing in the literature. Awareness of firm heterogeneity and availability of detailed data provide us to analyze dynamics of regional and sectoral production technology in the manufacturing industries in Turkey.

2. Data and Methodology

The data set used in this paper is provided by Turkish Statistical Institute (TURKSTAT) available for use only in the data research center of the institute. Data are collected as annual surveys from enterprises which have 20 or more employees or if the firm is a significant producer in its sector. The time interval used in the paper is restricted due to the data provided by TURKSTAT as a survey for manufacturing firms covers until 2015. Beginning from 2016, TURKSTAT has changed methodology and started to use administrative data provided by Turkish Revenue Administration instead of collecting survey answers from firms. However, the differences in the calculations between two series made it necessary to revise administrative data for the time before 2016 to make it compatible with the earlier series. Nevertheless, these differences between calculations and structure of the dataset make it impossible to involve new series with the same methodology due to missing variables in the new series.[2] For this reason, this paper covers between survey years 2003 and 2015. Table-1 gives data on the number of enterprises.

Table 1: Number of Enterprises

years	all firms	manufacturing	sample obs.
2003	77592	31198	12396
2004	78463	33536	15005
2005	63304	25318	17760
2006	85016	34020	19354
2007	83963	33285	18744
2008	82662	32842	18883
2009	99921	35043	17025
2010	106715	33890	20932
2011	138013	41194	23596
2012	147916	43281	26268
2013	168676	46998	27754
2014	159433	45316	24916
2015	161716	45978	25286

Here the first column displays observations for all sectors, second column is the observations for manufacturing firms. we eliminate some of these observations that have less than 20 employees that are drawn randomly from the sample since their capital stock estimation becomes problematic for them due to missing values for some years, however our reduction for the sample size does not ruin unbiasedness thanks to random draw. We find that, production value and added value for the omitted sample are around 1% of the overall volume. Lastly, we have omitted the firms that operate only once over the 13 years analysis period in order to estimate capital stock with perpetual inventory method, which will be mentioned in detail below.

Production value of the firms included in the data set is measured as the sum of annual sales and changes in the stock value of final products for that year. Other dependent variable used in the estimations is value added with factor prices provided by TURKSTAT. According to reported sectoral inflation rates by TURKSTAT at the 2-digit level, production value and value added are deflated in base year (2003). Deflating the values with own sector prices is particularly important since variation in sectoral prices is quite substantial with, for instance, a 500% inflation over a period of 13 years such as petroleum and coal, whereas in some sectors price level decreases, e.g pharmaceuticals. Labor, as an indispensable factor of production, is given for firms in every year as "total number workers engaged". Unfortunately, there is no information about the skills, education level or service area of the employees as white collar or blue collar. Therefore, we had to resort only one type of labor in our estimations.

Another main factor for production, capital, is not reported in the survey data. Hence, it is estimated using investment data of firms which is reported separately as investments on machinery/equipment, patents/computer programming and building/structure.[3] Another independent variable included in the estimates is material input calculated as value of purchases on intermediate inputs plus the change in the material input stock for that year, as deflated by the corresponding sectoral price indices. Summary statistics of these variables for our sample are reported in Table-2 yearly.

Table 2: Summary Statistics

years	produciton value	number of workers	estimated capital	added value
2003	162	1179726	107	40.6
2004	200	1382613	118	48.0
2005	219	1583688	131	42.9
2006	252	1723300	146	51.4
2007	260	1809293	171	51.6
2008	273	1839605	180	57.0
2009	242	1648004	186	51.7
2010	292	1918892	205	58.9
2011	339	2101980	218	67.6
2012	356	2352571	237	67.5
2013	389	2489306	243	79.6
2014	391	2516514	249	81.1
2015	413	2597823	252	83.7

[2] The variables used in the estimation is not available in the new series starting from 2016, since this study covers survey data results. For the detailed information, please check "Yıllık Sanayi ve Hizmet İstatistikleri, Metodoloji" document provided by TURKSTAT.

[3] After deflating the investment series with relevant price deflators, capital stocks for each item is constructed with perpetual inventory method. Before applying the method, an assumption is needed for the initial capital stock estimation, that is firms' are regarded to remain at their balanced growth path. Considering K_{i0} as initial capital stock of firm i and δ as depreciation rate, we can write

$K_{i1} = (1 - \delta)*K_{i0} + I_{i0}$

Dividing both sides of equation 1 with K_{i0}, we get;

$K_{i1} / K_{i0} = (1 - \delta) + I_{i0} / K_{i0}$

Since we have assumed that firms are at their balanced growth path,

$K_{i1} / K_{i0} = Y_{i1} / Y_{i0} = 1 + g_i$

where g is the real growth rate of the firm calculated as growth of deflated production value. Thus, we get

$K_{i0} = I_{i0} /(g_i + \delta)$

In the data set, not all firms report positive investment for their first year they appear in the data set. For this reason, we have taken the first year reported with positive investment to calculate the initial capital stock levels, and iterated back for the former years with deflated by the depreciation rate 1/(1-δ) for each type of capital stock.

TURKSTAT also reports summary statistics according to firm size annually on their website and our sample captures most of the firms operating in manufacturing industry with at least 20 employees in Turkey. Sector information for the firms are given at NACE-4 level, but we used 2-digit sector specification. Finally, region information of these firms is given as the headquarter of the enterprise in the dataset.

We start with the common assumption that the production technology of the firms s represented in the Cobb-Douglas production function form:

$$Y_{it} = A_{it}\ K_{it}^{\beta k}\ L_{it}^{\beta l}\ M_{it}^{\beta m} \quad (1)$$

where Y_{it} stands for output of firm i at time t and K_{it}, L_{it}, and M_{it} are capital, labor, and material inputs of firm i at time t, respectively. Ait stands for the productivity level which is unobserved while other variables are observable.

Taking the natural logarithm of the production function in equation 1, and expressing in econometric format:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l\, l_{it} + \beta_m\, m_{it} + \varepsilon_{it} \quad (2)$$

we get logarithmic form of production function where lower-case letters correspond to natural logarithms of each variables. Natural logarithm of A_{it} is equal to the summation of mean efficiency level, β_0 and time and firm specific measurement error of TFP, that is, ε_{it}.

Estimating TFP as residual from OLS estimation can create simultaneity since choices of inputs, such as labor, can be correlated with the unobserved productivity shock to the firm. Also in the balanced panel data, we only observe surviving firms over time, which may cause a selection bias. Therefore, estimating TFP with OLS method can cause endogeneity or selection bias problems (Van Beveren, 2012). There are some methods to get rid of simultaneity problem like instrumental variable (IV) estimation, fixed-effect (FE) (Mundlak, 1961; Hoch, 1962) or random-effect panel estimation. However, they all have some drawbacks in estimation process. For example, in fixed-effect estimation needs the assumption of strict exogeneity, unless it causes inconsistency and bias towards to zero in the estimation and this assumption does not hold in practice (Van Beveren, 2012). Whereas, IV method does not need strict exogeneity assumption for consistent estimation. In this method a variable correlated with inputs and uncorrelated with the shock such as input prices is essential, but most of the time input prices are not observed or even if it is observed, firms with market power set their input prices according to their productivity and sales, so input prices become endogenous. Lagged levels of inputs can also be used as instruments. But this approach introduces a downward bias in the estimates of the coefficient of the capital input (Van Beveren, 2012). Therefore, Blundell and Bond (2000) introduce generalized method of moments (GMM) for more accurate estimates defining AR(1) process for a part in error term. Although GMM is a proper solution for endogeneity problem, it is not sufficient to deal with selection bias issue since it does not take survival probability of firms into account.

As mentioned earlier, estimating coefficients with OLS can cause problems of endogeneity since the time and firm specific shocks to productivity are observed to the firm, and can lead them to choose their inputs accordingly resulting in correlation between the coefficients and the shock. In addition to endogeneity, firms with lower productivity have higher probability to exit the market and average productivity increases when they exit. As a result, entering to market afterwards become more difficult for new entrants (Melitz, 2003) and this situation causes selection bias in OLS estimation.

To overcome those problems, Olley and Pakes (1996) propose a model in which investment is chosen as proxy variable in order to get rid of endogeneity problem. They also suggest a solution to selection bias problem. While other balanced panel data methods require the existence of all firms in all years, Olley and Pakes argue that exit or entry decisions of firms depend on their future productivity. Therefore, they develop an algorithm in which at every period each firm decides whether to exit or continue according to their expected productivity level and if it exits it never re-enters. However the assumptions needed for Olley and Pakes method are too restrictive that only firms with non-zero investment levels can be included in the sample. Since in most of the developing countries data, including Turkey, firms report zero investment, it is not a suitable method for the survey data provided by TURKSTAT.

Olley and Pakes suggest a model where ε_{it} is decomposed into an observable or forecastable component, w_{it} as a function of productivity and capital, and unobservable component n_{it}. Thus, the production function takes the form below:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l\, l_{it} + \beta_m\, m_{it} + w_{it} + n_{it} \quad (3)$$

Let's denote, $\beta_0 + w_{it} = a_{it}$. To solve for ait OP use exit variable, X_{it} following a first-order Markov process to prevent the selection bias problem in addition to a proxy variable as "investment levels of firms". They claim that investment as a function of capital and productivity is strictly increasing in productivity so that its inverse exists. Taking the inverse of function $i_{it} = h_t(k_{it}, a_{it})$, productivity as an unobservable variable can be written as a function of observables as $a_{it} = g_t(k_{it}, i_{it})$, where $h_t(.) = g_t^{-1}(.)$. Setting $f(k_{it}, i_{it}) = \beta_0 + \beta_k k_{it} + g_t(k_{it}, i_{it})$, OP estimate the following regression using OLS method to consistently estimate β_l *and* β_m at first stage.

$$y_{it} = \beta_l l_{it} + \beta_m m_{it} + f(k_{it}, i_{it}) + n_{it} \quad (4)$$

Using the estimated coefficients and taking survival probability into consider- ation, OP estimate βk in the second stage. Estimated productivity in OP method can be constructed as residual from the following equation.

$$\hat{\alpha}_{it} = y_{it} - \beta_k k_{it} - \beta_l l_{it} - \beta_m m_{it} \quad (5)$$

After taking the exponential of $\hat{\alpha}_{it}$, TFP is calculated at firm level for each year. However, a sizable truncation in the data was needed for the OP method since a quarter of the firms in our data set report zero investment, and this fact could cause another type of selection bias.

While Olley and Pakes suggest using investment as a proxy variable so as to prevent endogeneity problem, Levinsohn and Petrin (2003) are aware of the fact that developing countries' data contains a significant amount of zero investment entries. Since firms report non-zero material input such as electricity and gas consumption, they suggest material input as a proxy in estimation. It is also possible to get healthier results than investment as a proxy since materials such as electricity can respond better to productivity shock.

Again taking the same productivity function equation

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + w_{it} + n_{it}$$

and demand for material input positively depends on the firms state variable k_t and a_t

$$m_{it} = m_t(k_{it}, a_{it}) \quad (6)$$

Positive effect of a_{it} on demand of m_{it} allows the inversion of demand function as

$$a_{it} = n_t(k_{it}, m_{it}), \text{ where } m_t(.) = n_t^{-1(.)}. \quad (7)$$

Therefore, unobserved productivity function becomes function of two observable inputs. LP also allow us to estimate TFP taking value added, v_{it} as dependent variable where

$$v_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + w_{it} + n_{it} \quad (8)$$

and TFP can be calculated as taking the exponential of following equality.

$$\hat{\alpha}_{it} = v_{it} - \beta_k k_{it} - \beta_l l_{it} \quad (9)$$

The estimation process identified in the above includes two stages in which LP estimates first β_l consistently and at the second stage β_k is estimated and differs from OP as taking material input as proxy. Due to the structure of available data, LP estimation technique is used for the estimations.

3. Discussion and the Conclusion

We estimated TFP with three additional methods; OLS, fixed effect and LP with production approach to check the robustness of our results (Table-3).

Compared to other estimations' coefficients, OLS gives higher values for labor which is expected. Since the positive correlation between productivity shock and labor choice, OLS results are biased upwards confirming the theoretical results (Van Beveren, 2012).

Table 3: Estimation Results

	(1)	(2)	(3)	(4)
	OLS	GLS	FE	LP
	lnval	lnval	lnval	lnval
lnKtotal	0.146**	0.138**	0.134**	0.131**
	(0.00091)	(0.00123)	(0.00178)	(0.00589)
lnworkers	1.035**	0.952**	0.873**	0.814**
	(0.00200)	(0.0026)	(0.00328)	(0.00536)
Constant	7.420**	7.833**	8.222**	
	(0.0103)	(0.0152)	(0.0237)	
Observations	222506	222506	222506	215238
Chi2				56.89 (p=0.0000)
R-squared	0.7265			

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

When capital coefficients are examined, it is clear that OLS gives a downward bias that results underestimating the effect of capital in production[4]. The difference of fixed effect estimates with OLS and LP estimates can be explained by change in the magnitude of productivity shock of firms over time. According to firm-level TFP estimation, what we observe is that firms' productivity level changes over time but not with a constant rate. Therefore, our data does not properly fit to fixed-effect estimation model. We also used energy usage as a proxy for unobserved productivity shocks instead of material. Differences in referring these two variables as independent arise when executing the regressions. In the case where production value is dependent variable, LP are unable to identify coefficients of variables due to lack of variation in the data (Arnold, 2005). Therefore, our estimation relies on value added approach of LP estimation techniques tabulated in Table-4.

[4] Our results are robust to different depreciation rates for different investment types to construct capital for building using δ=5%, for machinery δ=10% and for patent δ=30% (Yılmaz and Özler, 2005). Table-4 includes estimates of capital with two different capital estimation and they give similar results.

Table 4: Levpet Estimation Results		
	(1)	(2)
	lnval	lnval
lnmaterial	0.488**	0.490**
	(0.00501)	(0.00529)
lnworker	0.403**	0.405**
	(0.00414)	(0.00503)
lnenergy	0.227**	0.234**
	(0.0744)	(0.0926)
lnK1	0.390**	
	(0.0203)	
lnK2		0.382**
		(0.0153)
Standard errors in parentheses		
*** p<0.01, ** p<0.05, * p<0.1		

This paper estimate TFP at the firm-level for manufacturing industry in Turkey and explores that TFP levels of sectors and their distribution among regions lead to heterogeneity within Turkey.

Sectors	Nace-2 Code
High technology industries	
Aircraft and spacecraft	28
Pharmaceuticals	21
Office, accounting and computing machinery	28
Radio, TV and communications equipment	28
Medical, precision and optical instruments	26
Medium-high technology industries	
Electrical machinery and apparatus, n.e.c.	27
Motor vehicles, trailers and semitrailers	29
Chemicals excluding pharmaceuticals	20
Railroad equipment and transport equipment, n.e.c.	30
Machinery and equipment, n.e.c	33
Medium-low technology industries	
Building and repairing of ships and boats	31
Rubber and plastics products	22
Coke, refined petroleum products and nuclear fuel	19
Other non-metallic mineral products	23
Basic metals and fabricated metal products	24
Low-technology industries	
Manufacturing, n.e.c.; Recycling	32
Wood, pulp, paper, paper products, printing and publishi	16,17,18
Food products, beverages and tobacco	10,11,12
Textiles, textile products, leather and footwear	13,14,15

Source: OECD Science, Technology and Industry Scoreboard 2011

As seen in the table at the appendix estimating the TFP taking sector specific differences into account is signid. Classification of manufacturing industries according to technology intensity and the distribution of the sectors in Turkey at level-2 shows us firm and sector heterogeneity resulting in regional heterogeneity among Turkey. It is evident that the production function takes different coefficients for different sectors and the TFP level for those sectors vary significantly as seen in Table-5. The results are in line with OECD technology distinction of sectors, where the highest TFP levels are estimated in sectors 21 (manufacture of pharmaceuticals) and 26 (manufacture of computer and optical instrument).

TFP distribution of all firms between 2003-2015 behaves like pareto distribution, which is expected as many firms having low TFP and small number of firms having higher TFP levels. We observe a slight increase in TFP levels of firms by sector and also by region from year 2006 to 2015.

Figure 1: TFP distribution of **Textile** firms in region TR32

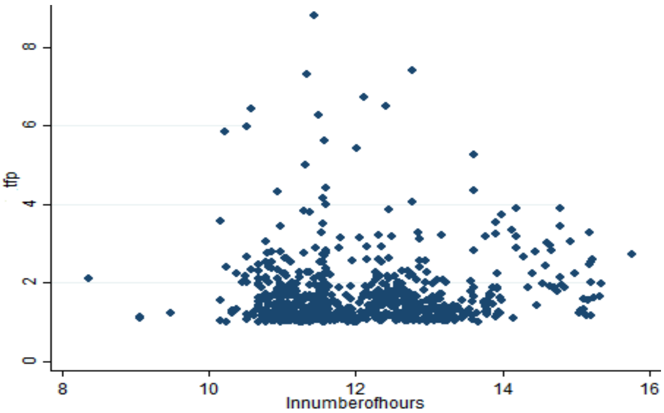
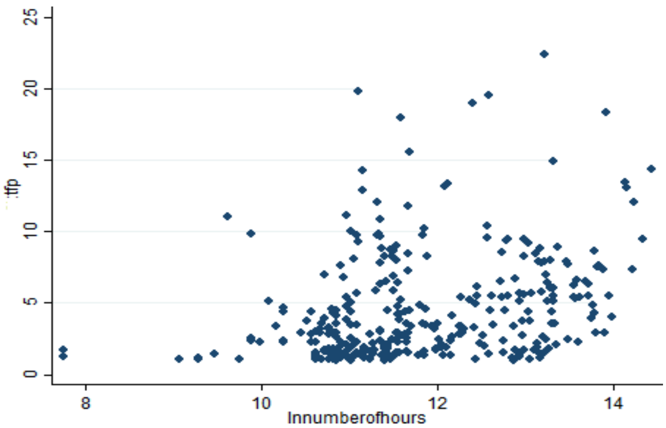


Figure 2: TFP distribution of **Chemicals and Chemical Products** firms in region TR42



Textile and chemical products are one of the examples that we can reproduce in order to show the TFP distribution and level differences among sectors. According to the figures and Table-5, TFP levels in high-technology sectors are well above the ones in the low technology sectors, like textiles. While analyzing each region's data specifically, it is observed that in Istanbul region (TR10) number of firms is high not only because of the existing firms in that region, but also it is high because of being the head of lots of local units. Therefore, Istanbul can be thought as the average TFP of the country. Although high productive sectors - manufacture of rubber-plastic and manufacture of non-metallic minerals- operate in regions like Tekirdağ (TR21) and Balıkesir (TR22), its TFP is not as high as expected since food products and textile products are produced in lots of small firms that have around 30 workers and these sectors are means of living for the big part of the population. Therefore, low levels of TFP is caused by the domination of low technology industries in these regions.

The remaining regions of the West like Izmir, Bursa, Eskişehir and Kocaeli, etc. including Ankara have relatively higher TFP levels. The reason for higher TFPs in these regions is that their giant firms operating in high technology industries defined by OECD, such as chemical products, non-metallic minerals, basic metal industry, computer and optical instrument and transportation equipments or high value added sectors like petroleum and coal, like the ones in region TR42 shown in Figure 2. Additionally, the positive relationship between TFP level and the size of the firm, which can be inferred from the number of workers, is apparent in chemical products sectors. However, there is no significant relationship between TFP level and size in the textile sector. This difference also contributes to not only sector specific but also firm level heterogeneity. Therefore, calculating the sector specific TFP levels at firm level is prominent to canalize the subsidies into more procutive firms for the sake of sustainable growth.

Based on the results obtained from different estimation methods, there is a significant heterogeneity across sectors and firms in the same sector in the micro-level and this results in different average TFP levels for regions at macro-level.

However, the differences between the TFP levels of regions are originated from the fact that some sectors being conglomerated in some regions. Therefore, sectoral analysis becomes more prominent for a regional result. Calculating sectoral TFP differences may guide policymaker not only to give incentives to most productive sectors in order to accomplish sustainable growth with high value-added production, but also differentiating between firms and regions while giving incentives according to the density of the sectors on those regions.

Table 5: Sector and Region specific TFP results

Sectors	TFP Level		Regions	TFP Level
10	2.3		TR10	4.4
11	6.1		TR21	2.6
12	6.2		TR22	3.0
13	1.9		TR31	3.5
14	1.9		TR32	2.5
15	1.8		TR33	4.4
16	3.1		TR41	3.1
17	2.8		TR42	4.8
18	2.6		TR51	6.2
19	5.4		TR52	2.8
20	4.0		TR61	2.8
21	7.7		TR62	3.2
22	2.9		TR63	3.7
23	2.7		TR71	3.0
24	3.0		TR72	3.5
25	2.3		TR81	4.8
26	7.5		TR82	2.0
27	3.4		TR83	2.5
28	2.7		TR90	3.1
29	4.0		TRA1	5.1
30	6.3		TRA2	2.0
31	1.8		TRB1	1.6
32	2.9		TRB2	1.4
33	4.7		TRC1	3.0
			TRC2	2.0
			TRC3	4.4
Overall TFP				**3.0**

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Appendix

Table 6: Estimation Results for each Sector at 2-digit

NACE-2 Codes	lnworker	Standart Error	lncapital	Standart Error	N
10	0.776**	(0.014)	0.139**	(0.0313)	22685
11	0.668**	(0.0804)	0.338**	(0.0987)	1077
12	0.693**	(0.182)	0.239	(0.231)	178
13	0.868**	(0.0166)	0.208**	(0.017)	24082
14	0.882**	(0.00876)	0.0807**	(0.0312)	34189
15	0.865**	(0.0328)	0.175**	(0.0342)	5283
16	0.892**	(0.0336)	0.0554	(0.0864)	3577
17	0.979**	(0.0364)	0.105**	(0.0348)	4520
18	0.917**	(0.0519)	0.173**	(0.0465)	3061
19	0.903**	(0.11)	0.0537	(0.142)	450
20	0.921**	(0.0353)	0.155*	(0.0793)	5578
21	0.823**	(0.0887)	0.101	(0.0826)	1134
22	0.871**	(0.0214)	0.145**	(0.0499)	13584
23	0.820**	(0.0206)	0.277**	(0.0245)	15951
24	0.848**	(0.0292)	0.151**	(0.0206)	6740
25	0.905**	(0.0153)	0.212**	(0.0325)	19278
26	1.019**	(0.0536)	0.213**	(0.0719)	1929
27	0.874**	(0.0244)	0.134**	(0.0446)	7619
28	0.956**	(0.0187)	0.172**	(0.0233)	16127
29	0.927**	(0.0249)	0.153**	(0.0326)	7908
30	0.835**	(0.0394)	0.372**	(0.0727)	1813
31	0.887**	(0.026)	0.0549**	(0.0229)	9888
32	0.892**	(0.0346)	0.204**	(0.0534)	4504
33	0.738**	(0.0298)	0.269**	(0.103)	3086

TFP levels are the results of Levinsohn-Petrin estimation of production function where dependent variable is value added. Standard errors in parentheses, * $p<0.10$, ** $p<0.05$, ** $p<0.001$