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Uncovering Productivity Puzzles in Thailand: Lessons from Microdata

by

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Uncovering Productivity Puzzles in Thailand: Lessons from Microdata

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Abstract

The Asian financial crisis in 1997 has an impact on Thailand's productivity both in the short run and in the long run. The post-crisis productivity growth rate dropped to merely 1% per year in comparison to the pre-crisis level at 2% per year. Thus, a better understanding about the factors determining Thailand's aggregate productivity is a key to raising Thailand's output in the long run. Recent literature has identified resource misallocation as an important factor to explain the difference in the productivity levels between developed and developing economies. This paper uses the plant-level data to estimate the allocative efficiency and to identify the source of resource misallocation in the Thai manufacturing sector. The results suggest that the size-dependent policies could contribute to the factor misallocation and that market concentration, foreign investment, and financial deepening could help alleviate the misallocation problem at the sector level. However, R&D activities intensifies resource misallocation that calls for well-defined policies to promote knowledge spillover within industry and to reduce the frontier-laggard gap. Dynamic resource reallocation helps shore up TFP growth over the business cycle that emphasizing a set of policy to reinforce the mechanism of creative destruction.

JEL classification: L10, L60, O11, O12, O14, O32

Keywords: Total Factor Productivity, Resource Misallocation, Allocative Efficiency, Firm Dynamics, Creative Destruction, Manufacturing, Services, R&D, Financial Friction, Thailand

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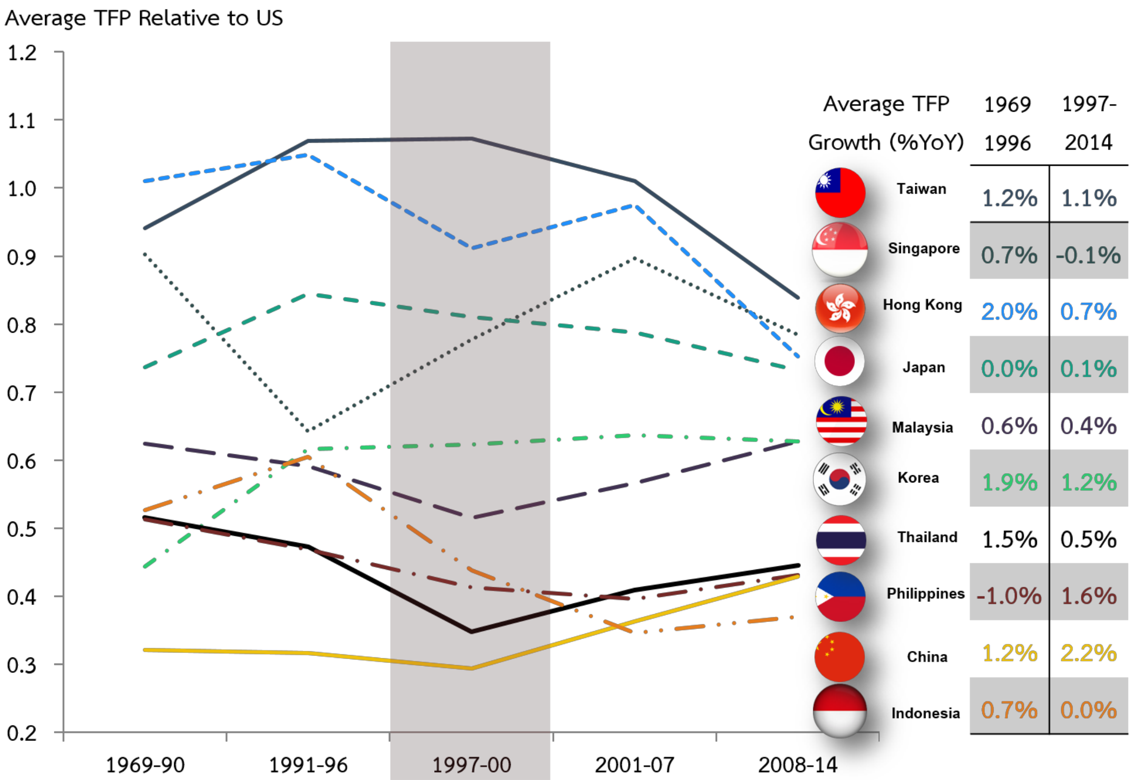
1. Introduction

It is widely believed that the Advanced Economies and Developing Countries dispersion in Total Factor Productivity (TFP) plays a key role in explaining their difference in the levels of income per capita, a proxy of population's capacity to produce goods and services in each country. Measuring and understanding the TFP's underlying is, thus, matter to enhance each country development as TFP is a significant factor to boost the nation's competitiveness along with raising population's income.

Figure 1 – Asian's Total Factor Productivity (TFP)



Source: Feenstra, Robert C., Robert Inklaar and Marcel P. Timmer (2015), "The Next Generation of the Penn World Table" American Economic Review, 105(10), 3150-3182, available for download at www.ggdc.net/pwt

Looking back on the Asian's history of economic growth since 1969, each country's TFP relative to that of United States is an appropriate indicator of a country's development in terms of productivity. Figure 1 illustrates that all countries' TFPs, but Taiwan, Japan and China, are hurt by the Asian Financial Crisis (AFC) in 1997. The crisis had stalled Asian countries' momentum of capabilities to catch up with the US's technology. Over this four decades, there are only Korea and China among the discussed ten Asian countries whose TFPs get closer to US, while Malaysia can only maintain her relative TFP to US's. The right panel of the previous figure states each country's average TFP growth at the pre and post AFC. All countries except Japan, Philippines and China have lower TFP growth. For

Thailand, The post-crisis TFP dropped to 0.5% per year in comparison to the pre-crisis level at 1.5% per year. It is, thus, this paper's intention to figure out factors behind Thailand's productivity slump.

Figure 2 – Thailand's source of economic growth

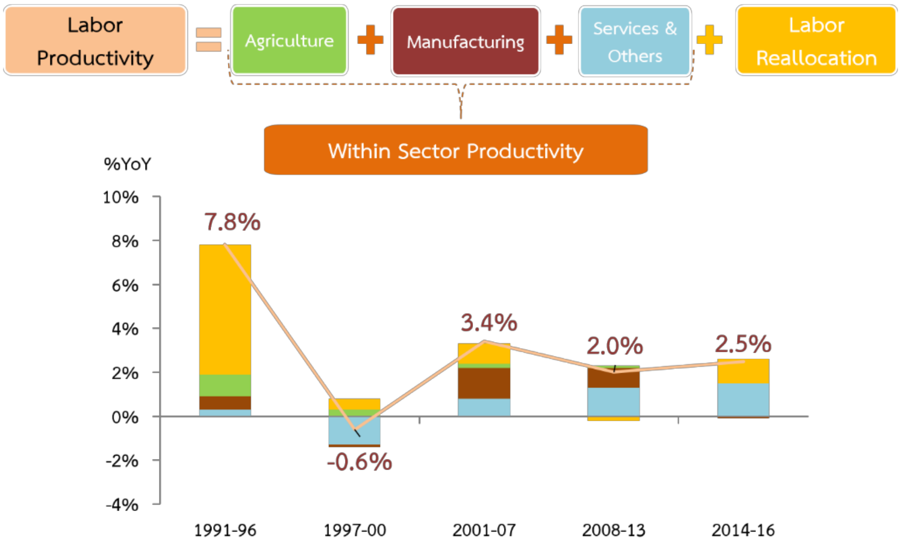
Source: National Statistical Office (NSO), National Economic and Social Development Board (NESDB) and calculated by authors

Thailand's economic growth, measured by the growth of Gross Domestic Product (GDP), has been gradually slowed down from 5.4% on average after the country fully recovered from the AFC in 1997 to 1.9% on average. Partially, the downturn of global business cycle since the Global Financial Crisis (GFC) in 2008 and the domestic issues such as the great flood in 2011 and series of political unrests have contributed to Thailand's slow growth. However, it is equally important to discern the structural cause of the country's slow pace of growth, which can be done by discussing the longer-term issue rather than focusing on cyclical factors, namely productivity issue.

Figure 2 does not only illustrate the slower step of Thailand's economic growth, but also decompose the source of economic growth into the employment and labor productivity: from both within sector and labor reallocation. For the first part, it is noticeable that employment slightly contributed to growth in the decade of 1990's, before turning to be an important driver after Thai labor market had absorbed both unemployed and migrant workers. Thailand's demand for labor seemed to grow in the opposite direction to the supply of labor as seen from continual tightened labor market with bottom-low unemployment rate, even relative the international standard. This implies the less likelihood for Thailand to rely only on labor input to boost her economic growth from now on. Indeed, the employment had contracted, on average, in the last few years.

The second source of growth is from the labor productivity or how much each worker produces. Since 1990, Thailand had transformed herself from an agricultural into industrial country and on her way to be a service country[1]. Such structural transformation triggers an important mechanism to boost growth as it shifts labor from low productivity sector, agriculture, to higher productivity sector such as manufacturing and services. The labor reallocation in Thailand was stalled for a while (seen from no contribution to growth during 2008-2013) after some agricultural subsidizing policies had attracted workers back from manufacturing and services to agricultural sector. Fortunately, this adverse effect has disappeared, and the reallocation mechanism seems to work fine in moving workers back into tourism-related services after the boom in tourism sector.

Figure 3 – Thailand's sectoral labor productivity growth



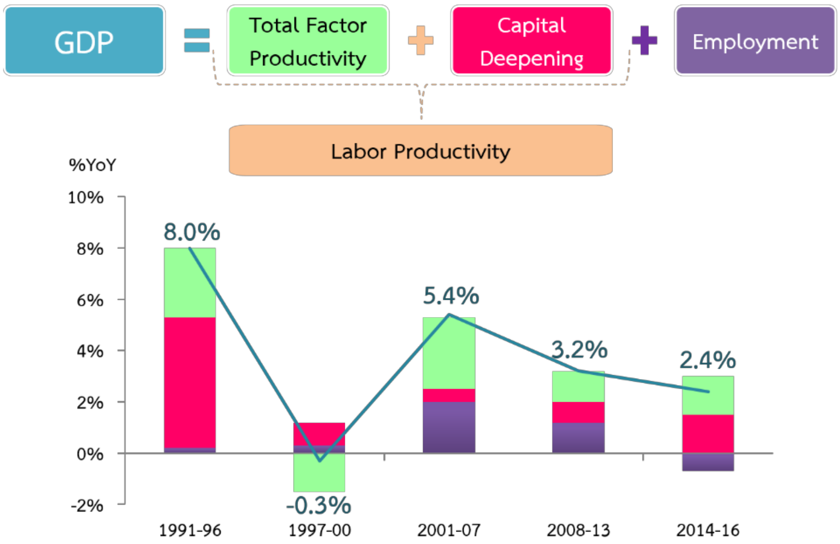
Source: NSO, NESDB and calculated by authors.

Figure 3 depicts the performance of each sector in contributing to labor productivity growth. As mentioned, services sector has a bright prospect to become a major source of Thailand growth. Reversely, manufacturing, used to contribute the most before the GFC, has faded away from its role as a main source of growth. This paper, therefore, aims to figure out the cause of this sector's productivity slowdown by exploring the micro data. It is also this paper's goal to provide policy recommendation to unblock bottlenecks in the process of reviving manufacturing's contribution to growth.

Having said that, the paper does not focus on only the labor productivity issue. TFP is authors' prime interest, as it also controls for how much capital input is used in the production process on top of usage of labor input. To provide audience a glimpse of how Thailand's TFP looks like in macroeconomic context, Figure 4 decomposes GDP into three elements: employment, capital deepening and TFP[2].

[1] Fully discussed in Chantapong et al. (2015).
[2] The Cobb-Doulas production function with a constant-return-to-scale assumption is implemented as discussed later in Section 3 of this paper. Detail of calculation is available upon request.

Figure 4 – TFP and capital deepening's contribution to Thai economic growth



Source: NSO, NESDB and calculated by authors

In the viewpoint of production function, Thailand's economic growth has based substantially on inputs, capital before the AFC and after 2013 as well as labor during 2000's decade. TFP, used to contribute around one third and half of economic growth in 1991-1996 and 2001-2007, respectively, has not much supported GDP growth since the burst of GFC, though. This event coincides with the lower productivity growth of manufacturing sector, and then motivates the authors to uncover productivity puzzles in Thailand, also chosen as the paper's title.

This paper consists of five parts. In addition to this introduction, the following four parts capture: overview of Thailand's firm-level productivity, resource misallocation and aggregate TFP, structural change of Thailand's productivity in manufacturing and services sectors, and conclusions, respectively.

2. Overview of Thailand's Firm-level Productivity

The macroeconomic data in the previous section has indicated Thailand's persistently lower productivity issues since the GFC. Although it seems to be the global phenomenon as the recent low productivity is widespread without full understanding of causes and persistence, according to Christine Lagarde[3], Thailand is unable to be complacent and simply waits until the phenomenon passes. This is because the recent phenomenon mostly affected Advanced Economies, not Developing Countries in general. Besides, when compared to other countries with labor productivity slowdown in the 2000's

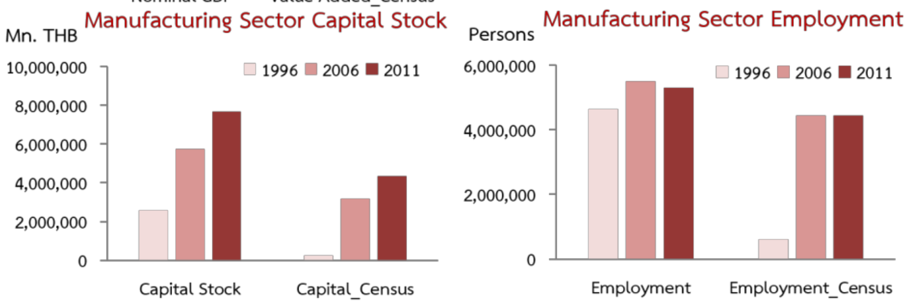
[3] Managing Director's Presentation to the International Monetary and Financial Committee (IMFC) in the meeting on October 8, 2016.

decade including Japan, Korea, Hong Kong, Malaysia, and Singapore, Thailand had the sharpest slowdown[4].

To shed some light on the productivity problem left unanswered from the macroeconomic data, this paper uses two sets of micro data: the Manufacturing Industry Census published in 1997, 2007 and 2012[5] (covering data of 1996, 2006 and 2011) along with the 2004th, 2006th, 2008th, 2010th, 2012th and 2014th edition of Business, Trade and Services Survey spanning over data of 2003, 2005, 2007, 2009, 2011 and 2013. The plant-and-shop level of data allows authors to unearth details of firms' performance in manufacturing and part of services sector[6]. This section plans to delineate these micro data with focus on TFP in particular.

Figure 5 – Coverage of Manufacturing Industry Census relative to macroeconomic data

	<10 workers	10-49 workers	50-199 workers	>=200 workers	Total Plants
1996	1,904	6,468	1,512	1,071	10,955
2006	412,537	29,138	7,276	6,595	455,546
2011	366,852	36,460	7,271	6,409	416,991



Source: NSO, NESDB and calculated by authors

To begin with, the manufacturing data are aggregated to compare with the macroeconomic data in three dimensions: value added, capital stock and employment. To be specific, the data of 2006 and 2011 are able to represent GDP, capital stock and employment quite well, although the value added change from 2006 to 2011 is unable to catch up with an increase in nominal GDP during the same period. Also, the 1996 data are obviously unmatched with the other two in terms of coverage as Figure 4 depicts (almost half a million in 2006 versus roughly ten thousand in 1996). This is partially due to

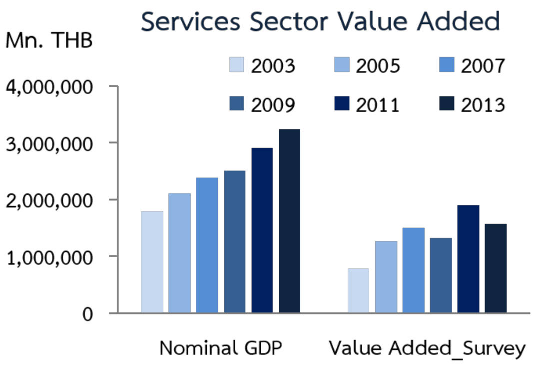
[4] The Monetary Policy Committee, 2013, "Labor constraints and economic growth", in Monetary Policy Report July 2013.

[5] The 2012th edition is the Business, Trade and Services Census, with coverage of manufacturing and part of services.

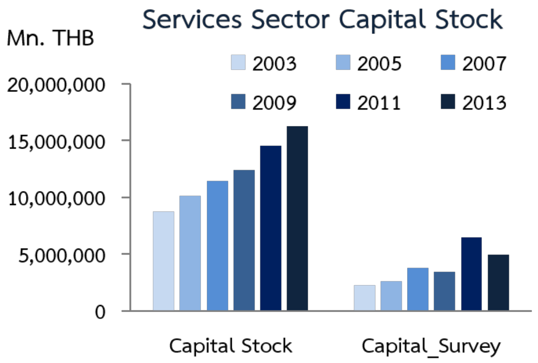
[6] The sectors of services covered in these data sets are trade, hotel and restaurant, real estate, and other services, categorized by the 3rd revision of International Standard Industrial Classification (ISIC3).

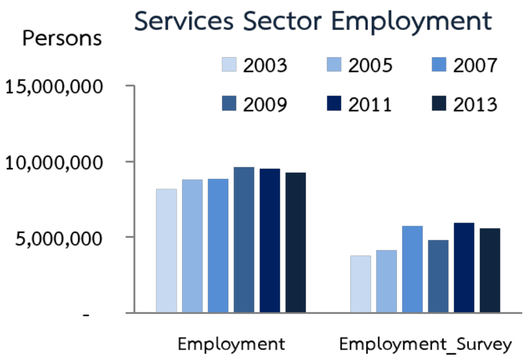
the different number of plants surveyed across the three (the data include approximately 73,000 and 80,000 observations after cleaned in 2006 and 2011, respectively, while there is left only around 10,000 plants for 1996). Also, there is no survey weight assigned in 1996 to show how much each observation represents in the population (the average survey weight of the 2006 and 2011 data is five to six). According to this issue, the authors decide to leave the 1996 data from analysis in some parts of the paper as it is see fit.

Figure 6 – Coverage of Business, Trade and Services Survey relative to macroeconomic data



	<10 workers	10-49 workers	50-199 workers	>=200 workers	Total Shops
2003	1,112,197	33,391	3,070	1,522	1,150,180
2005	1,121,331	37,326	3,624	1,775	1,164,056
2007	1,522,597	63,704	5,549	2,570	1,594,420
2009	1,522,509	50,538	4,858	2,673	1,580,577
2011	1,553,144	76,546	5,247	2,576	1,637,514
2013	1,625,117	46,111	5,302	2,501	1,679,031



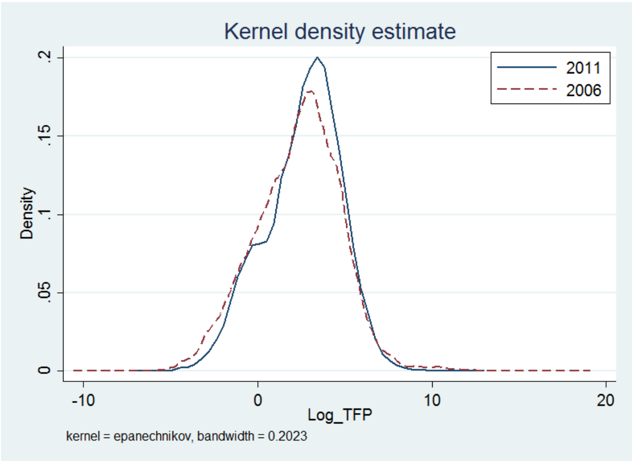


Source: NSO, NESDB and calculated by authors

As in the previous figure, Figure 6 shows the coverage of the data sets relative to their corresponding macroeconomic data. A few points should be addressed. First of all, the 2011 data are surveyed along with the industrial census, which may span over larger population and provide the higher aggregate value than the other surveys. Next, the capital stock data from survey are much lower than the official capital stock report. It is possible that the official report also includes capitals of whole business groups, while the survey data used in this paper reports only capital stock of each shop, not the capital stock of consolidated businesses.

For the rest of this section, TFP is estimated in both plant-and-shop level as well as in an industrial 4-digit-ISIC level. This task is roughly done to make it consistent with the macroeconomic TFP reported in the first section with the same assumption of Cobb-Douglas production function with constant-return-to-scale input. It is noteworthy that the labor share used here is the average ratio over data sets of total wage bill to total value added in each 4-digit-ISIC level, relative to the macroeconomic labor share equal to the compensation of employees in the National Income.

Figure 7 – Plant-level TFP distribution in manufacturing sector

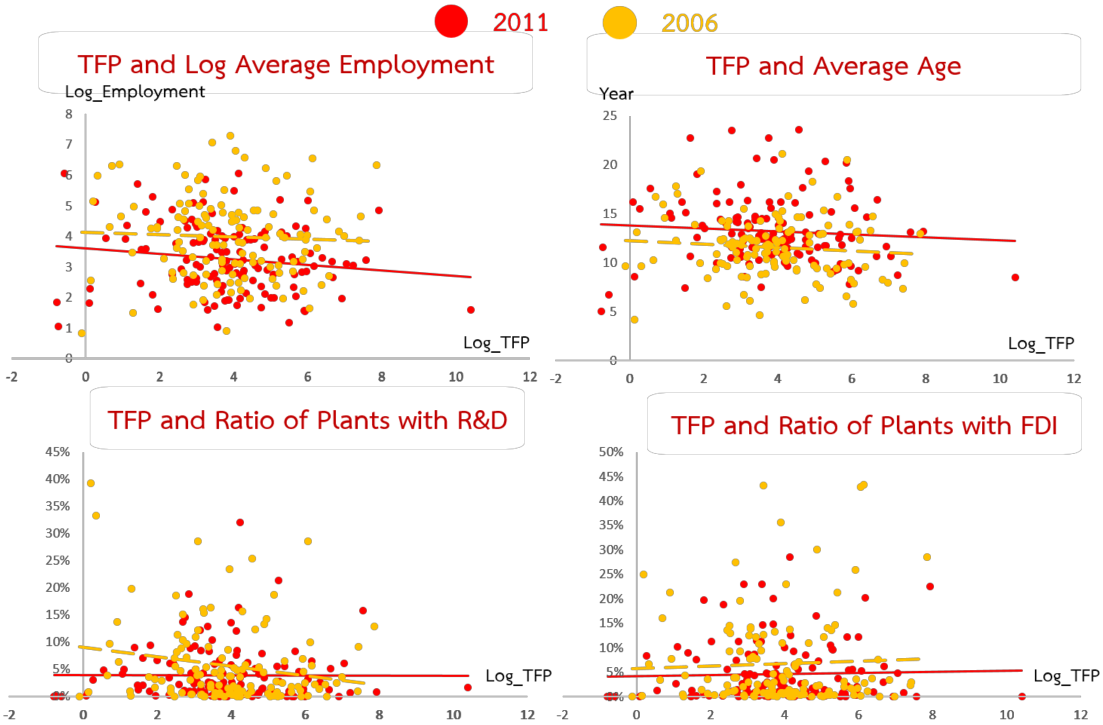


Source: NSO, NESDB and calculated by authors

Figure 7 illustrates natural logarithm of each plant's TFP in the 2006 and 2011 industrial census data. The shapes of both distributions differ a bit as mode of the 2011 data is a bit higher, while the 2006 data have more of the data with log TFP close to zero. The next step is to estimate TFP of manufacturing in the 4-digit-ISIC level, and then to seek some stylized facts to explain the slower growth of productivity in this sector.

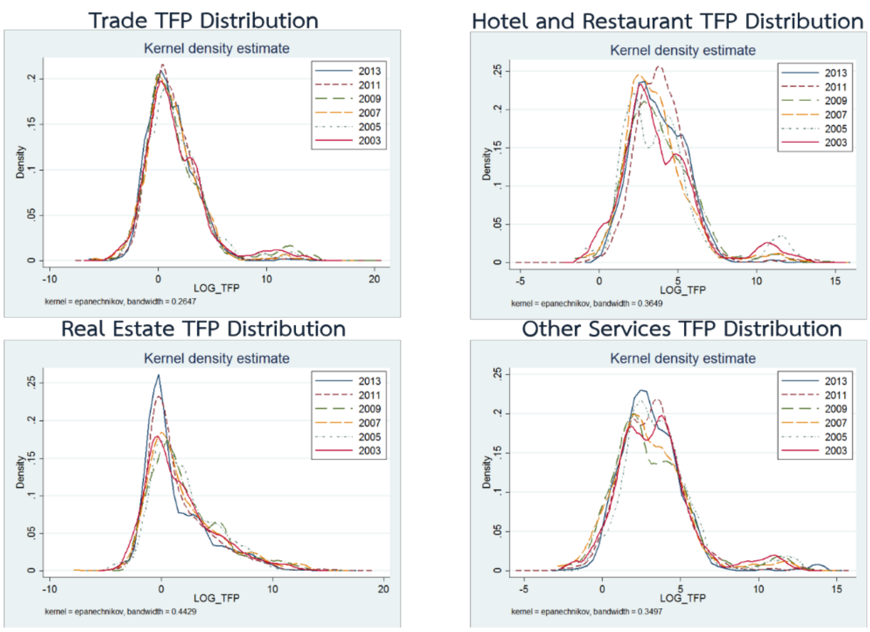
Each dot in Figure 8 represents each 4-digit-ISIC industry TFP compared with the natural log of average number of employees, the average age of shops, ratios of plants in industry with Research and Development (R&D) investment, and ratios of plants with Foreign Direct Investment (FDI). There is no clear relationship between TFP and these four variables, although it is quite surprised to find that the larger and older groups of industries tend to have a bit lower TFP. For R&D and FDI, the relationships are rather flat. Though, we do not yet have an answer to the productivity puzzle. In the next section, we will explore further on the allocative efficiency and the effects of these variables on the aggregate productivity. The idea is to determine whether the Thai manufacturing sector is as efficient as its international benchmark.

Figure 8 – Industry-level TFP in manufacturing sector



Source: NSO, NESDB and calculated by authors

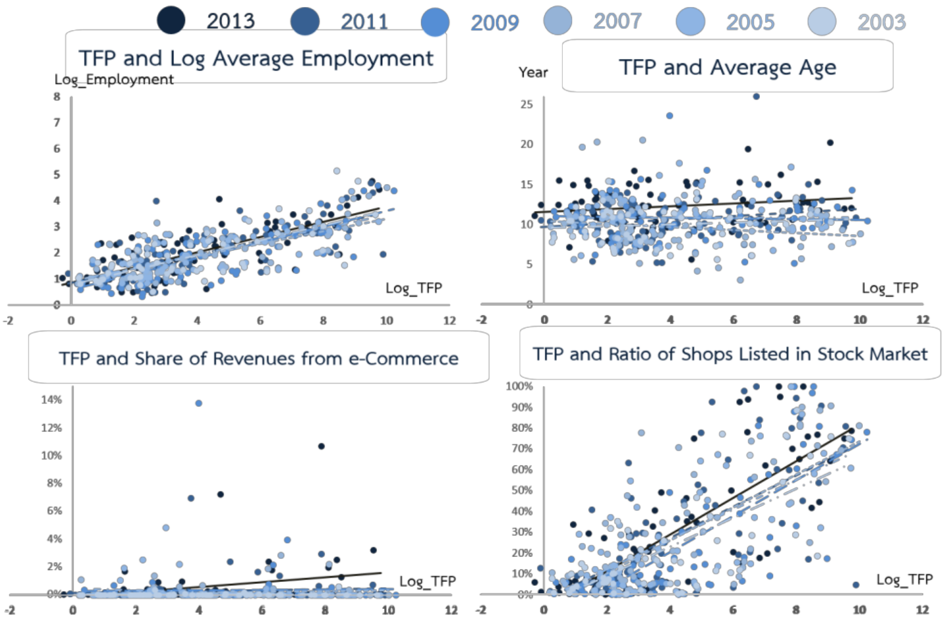
Figure 9 – Plant-level TFP distribution in Services Sector



Source: NSO, NESDB and calculated by authors

Figure 9, comparative to Figure 7, draws development of each sector's TFP distributions from 2003–2013. Basically, TFP distributions in trade sectors have not changed much across time. For hotel and restaurant, TFP distribute rather normally in 2011 and not skewed to the right as the rest especially those in 2003 and 2005. This may be thanks to more coverage of sample in 2011. Noticeable that the real estate sectors also cover professionals and consultants such as those in science, business, law and accounting. TFP in this sector is, then, not limited to represent performance of real estate companies. For both real estate and other services sectors, the density is more concentrated around its mode in 2013 compared with a decade ago. One interpretation is that firms' easier access to technology with lower costs allows them to raise their competitiveness. Nevertheless, technology would also make competition fiercer and force them to squeeze their margins. This may constrain their ability to raise their TFP levels.

Figure 10 – Industry-level TFP in services sector



Source: NSO, NESDB and calculated by authors

Unlike the analysis of industry-level TFP in manufacturing sector, the industry-level TFP in services sector are strongly correlated with the ratios of shops listed in the stock market as well as the number of employment (2013 correlation is 0.78 and 0.76, respectively). Size is thus matter in services sector, as industries with average larger firms tend to be more productive. Compared across time, these positive relationships seem to be gradual stronger noticed from the upward shift of both linear fitted lines. There are several structural improvements in services sector during the six surveys. One of the clearest example is the boom of smartphone and high-speed internet usage, which has benefited some services sectors. The correlation between TFP and share of revenues from e-Commerce turns to be 0.3 in 2013 from almost flat. Also, average age of shops across industries is 12 years in 2013 higher than around 10 years in the past data. This is consistent with the fitted line turning to be slightly positive since 2011, implying that older firms start to be more productive. In summary, the micro-data TFP in services sector supports the sector's higher labor productivity in the macro-data level as well as the higher contribution from labor reallocation. This is because larger firms tend to be more productive and can attract more labor.

The last part of this section is to discuss potential determinants of TFP in each sector. In doing so, Table A1 to Table A2.4.3 in Annex A reports Ordinary Least Square (OLS) estimation on TFP's determinants in manufacturing, trade, hotel & restaurant, real estate and other services, respectively. These analyses uncover some stylized facts about TFP as follows:

Stylized Fact 1: ***Size does matter!***

Size of plants and shops significantly determine their TFP in all five sectors. For instance, small manufacturing plants with less than 10 workers have TFP 0.4% lower than the bigger plants, while small shops in trade sector with less than 10 workers have TFP 0.3% lower than bigger shops on average. This curse of small shops is spread among other three services sector with 0.7-0.8% lower TFP of small shops than bigger shops on average. Another indicator of how size matters is D_Listed variable, equal to one if such company is listed in the Stock Market and zero otherwise. Listed companies in all five sectors have higher TFP than non-listed firms. They perform 0.5% better in manufacturing sector and 1.6%, 1.2% and 1% better in trade, real estate and other services sector. Moreover, shops in services sector with only single branch have TFP around 1% lower than other shops on average.

Stylized Fact 2: ***Working hard is also smart!***

Data show that operating one percent more of office hours help raise TFP by 0.4% for plants in manufacturing sector. Such positive benefits from working longer hours on TFP also exist in all services sector but real estate. However, notice that large plants and shops with more than 200 workers do not gain from working longer hours in terms of TFP improvement.

Stylized Fact 3: ***R&D is still a key!***

In manufacturing sector, plants with R&D investment have 0.4% higher TFP than the rest in 2011, though the effect is not significantly different from zero in 2006. Nevertheless, having one percent higher share of R&D in 2006 still provide 0.1% higher TFP. As it takes time before plants can reap full R&D benefits, the better performance of R&D investors in 2011 relative to the rest may reflect their persistence in R&D investing.

Stylized Fact 4: ***Services sectors do not gain from e-Commerce as much as they used to!***

In the past both trade and real estate sectors' TFP had gained from e-Commerce, when having one percent higher share of sales from e-Commerce helped boost TFP by 0.04% and 0.03% on average.

In 2013, the impact of having one percent higher share of sales from e-Commerce on TFP is, however, not significantly different from zero for all services sector except other services with 2013 as the first year to have positive effect of e-Commerce sales on TFP.

Stylized Fact 5: ***Investing in software is a good idea, but hardware is probably not!***

One percent higher share of software capital have positive impact in all sectors on average. It improves TFP by 0.02-0.03% for all four services sectors. The positive effect also exists for manufacturing sector in 2006. In contrast, investing in computer hardware has a negative impact on TFP in general.

Stylized Fact 6: ***Subcontracting is fine for a not-so-large firm!***

In manufacturing sector, having one more percent of income from subcontracting enhances TFP by around 0.01%. Though, firms with more than 200 workers do not have such a positive benefit and even acting worse from doing so. Also, raising one additional percent of contract expenses relative to total expenses would increase TFP by 0.01% for small and medium plants, but still has not benefited large plants in 2011.

Stylized Fact 7: ***Older does not mean better!***

Older plants and shops seem to be outperformed by younger ones in terms of TFP as one percent older plants have 0.07% lower TFP in manufacturing sector, while the negative impact from aging is more severe in other services sector with 0.3% less TFP when a shop ages one more percent on average.

Stylized Fact 8: ***It is good to have more technicians/managers!***

In all five sectors, having one more percent share of skilled labor (in manufacturing sector) and management labor (in services sector) are statistically significant in boosting TFP. The impacts are not substantial, though. As one percent more of skilled labor share increases TFP merely 0.01% in manufacturing sector, whereas one percent higher share of management labor helps increase TFP by 0.01 – 0.03% in the four services sector.

All in all, this section illustrates stylized facts of data used in this paper. It is noticed that all analyses so far rely on within-plant-and-shop data to provide a glimpse of how TFP in Thailand looks like. The rest of this paper would further explore how outside factors impact on the TFP, and provide policy recommendations to raise TFP in Thailand.

3. Resource Misallocation and Aggregate TFP

Recent literature in development economics has identified the resource misallocation as an important factor to explain the difference in the productivity level between developed and developing economies (Hsieh and Klenow 2009, 2014; Restuccia 2013; Bento and Restuccia 2017). In this section, we estimate the degree of resource misallocation in the Thai manufacturing sector and identify the source of misallocation, both at the plant level and at the industry level.

3.1 Analytical Framework

3.1.1 The Model

This paper uses the monopolistic-competition framework developed by Hsieh and Klenow (2009) to study the resource misallocation problem. In this model, final good Y is produced in a competitive market by producers who combine the intermediate outputs from S sectors with the Cobb-Douglas production function

$$Y = \prod_{s=1}^{S} {Y_s}^{\theta_s}$$

where Y_s denotes the intermediate output from sector s and θ_s denotes the share of sector s.

The market for intermediate good Y_s is monopolistically competitive. The producer of intermediate good Y_s combines the outputs from M_s plants in sector s using the CES production function

$$Y_s = \left(\sum_{i=1}^{M_s} {Y_{si}}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$

where Y_{si} denotes the output from plant i in sector s and σ is the elasticity of substitution between the output from different plants within a sector.

Plant i in sector s produces output Y_{si} using the Cobb-Douglas production function

$$Y_{si} = A_{si} {K_{si}}^{\alpha_s} {L_{si}}^{1-\alpha_s}$$

where A_{si} denotes the total factor productivity of plant i, K_{si} and L_{si} denote the level of capital and labor used by plant i, respectively, and α_s denote the share of capital income for sector s. Hsieh and Klenow (2009) assume that there exist two distortions that affect the plant's profit function, i.e.,

$$\pi_{si} = (1 - \tau_{Ysi}) P_{si} Y_{si} - w L_{si} - (1 + \tau_{Ksi}) R K_{si}$$

where τ_{Ysi} increases the marginal products of both factors, and τ_{Ksi} increases the marginal product of capital while lowers the marginal product of labor.

In equilibrium, plant i in industry s will optimally choose the levels of capital and labor to maximize its profits as follows:

$$L_{si} = \frac{\sigma - 1}{\sigma} (1 - \tau_{Ysi})(1 - \alpha_s) \frac{P_{si} Y_{si}}{w}$$

and

$$K_{si} = \frac{\sigma - 1}{\sigma} \frac{(1 - \tau_{Ysi})}{(1 + \tau_{Ksi})} \alpha_s \frac{P_{si} Y_{si}}{R}.$$

The marginal revenue product of labor (MRPL) of plant i in industry s is

$$MRPL_{si} \equiv (1 - \alpha_s) \frac{\sigma - 1}{\sigma} \frac{P_{si} Y_{si}}{L_{si}} = w \frac{1}{1 - \tau_{Ysi}}.$$

And the marginal revenue product of capital (MRPK) of plant i in industry s is

$$MRPK_{si} \equiv \alpha_s \frac{\sigma - 1}{\sigma} \frac{P_{si} Y_{si}}{K_{si}} = R \frac{1 + \tau_{Ksi}}{1 - \tau_{Ysi}}.$$

The aggregate demands for labor and capital in industry s are

$$L_s = \frac{\sigma - 1}{\sigma} \frac{(1 - \alpha_s)}{w} \sum_{i=1}^{M_s} (1 - \tau_{Ysi}) P_{si} Y_{si}$$

and

$$K_s = \frac{\sigma - 1}{\sigma} \frac{\alpha_s}{R} \sum_{i=1}^{M_s} \frac{(1 - \tau_{Ysi})}{(1 + \tau_{Ksi})} P_{si} Y_{si}.$$

We can write the aggregate output from industry as a function of aggregate demands for labor and capital as follows:

$$Y_s = TFP_s {K_s}^{\alpha_s} {L_s}^{1-\alpha_s}$$

where TFP_s denotes the aggregate productivity level of industry s. And the level of final good produced in the equilibrium is

$$Y = \prod_{s=1}^{S} \left(TFP_s {K_s}^{\alpha_s} {L_s}^{1-\alpha_s} \right)^{\theta_s}.$$

Following Foster, Haltiwanger, and Syverson (2008) and Hsieh and Klenow (2009), we adopt two definitions of productivity, namely, the physical productivity (TFPQ) and the revenue productivity (TFPR). TFPQ measures the plant-level productivity, that is,

$$TFPQ_{si} \equiv A_{si} = \frac{Y_{si}}{(K_{si})^{\alpha_s} (L_{si})^{1-\alpha_s}}.$$

On the other hand, TFPR measures the average revenue product of capital and labor, that is,

$$TFPR_{si} \equiv P_{si} A_{si} = \frac{P_{si} Y_{si}}{(K_{si})^{\alpha_s} (L_{si})^{1-\alpha_s}}.$$

In this model, the differences in TFPR across plants arise only from distortions.

$$\begin{aligned} TFPR_{si} &= \frac{P_{si} Y_{si}}{(K_{si})^{\alpha_s} (L_{si})^{1-\alpha_s}} \\ &= \left(\frac{P_{si} Y_{si}}{K_{si}} \right)^{\alpha_s} \left(\frac{P_{si} Y_{si}}{L_{si}} \right)^{1-\alpha_s} \\ &\propto (MRPK_{si})^{\alpha_s} (MRPL_{si})^{1-\alpha_s} \end{aligned}$$

$$\propto \frac{(1+\tau_{Ksi})^{\alpha_s}}{1-\tau_{Ysi}}.$$

Therefore, the high TFPR level of a plant indicates that the plant faces higher distortions and becomes smaller than the optimal size. In the absence of distortions, plants will optimally choose the output level so that the TFPRs are similar across plants. Hsieh and Klenow (2009) show that the gain from equalizing TFPR across plants within the same industry is

$$\frac{Y}{Y_{efficient}} = \prod_{s=1}^{S} \left[\sum_{i=1}^{M_s} \left(\frac{A_{si}}{\bar{A}_s} \frac{\overline{TFPR}_s}{TFPR_{si}} \right)^{\sigma-1} \right]^{\theta/(\sigma-1)}$$

where $\bar{A}_s$ and $\overline{TFPR}_s$ are the weighted average of TFPQ and TFPR across plants in industry s, respectively. The allocative efficiency is defined as

$$Efficiency = \frac{Y}{Y_{efficient}} * 100\%.$$

And the potential gain from reallocation is

$$Gain = \left(\frac{Y_{efficient}}{Y} - 1 \right) * 100\%.$$

3.1.2 Calibration and Estimation

To estimate the labor income share α_s, we use the U.S. labor income share in the NBER-CES manufacturing productivity database. As discussed in Hsieh and Klenow (2009), this database does not include fringe benefits and the employer's Social Security contribution. Therefore, we adjust the labor income share up by 150%. The elasticity of substitution between differentiated goods, σ, is assumed to be 3.

To estimate the distortions and the allocative efficiency in the Thai manufacturing sector, we use the data of plants with 10 or more workers in the Manufacturing Industry Census (MIC) from the National Statistical Office of Thailand (NSO).

The productivity and the distortions τ_{Ysi} and τ_{Ksi} of plant i in industry s are estimated as follows:

$$A_{si} = \vartheta_s \frac{(P_{si}Y_{si})^{\frac{\sigma}{\sigma-1}}}{(K_{si})^{\alpha_s}(L_{si})^{1-\alpha_s}}$$

$$1+\tau_{Ksi} = \frac{\alpha_s}{1-\alpha_s}\frac{wL_{si}}{RK_{si}}$$

$$1-\tau_{Ysi} = \frac{\sigma}{\sigma-1}\frac{wL_{si}}{(1-\alpha_s)P_{si}Y_{si}}$$

where ϑ_s is the industry-specific constant term.

To control for outliers, we trim the top 1% and the bottom 1% of plants with highest and lowest TFPQ and TFPR. Table 1 shows the allocative efficiencies and the TFP gains from reallocating labor and capital to equalize the TFPR across plants within the same industry. If the resources are efficiently reallocated across plants within the same industry, the total output from the manufacturing sector would increase between 150% and 230%. However, some structural factor (e.g., labor market frictions, adjustment costs, etc.) could prevent the resource to be efficiently allocated. Therefore, we use the efficiency level of the U.S. manufacturing sector in 1997 reported in Hsieh and Klenow (2009) as a benchmark. If we could raise the allocative efficiency in the Thai manufacturing sector to the U.S. level in 1997, the total output would increase by 75–132%.

Table 1 – Allocative efficiencies and gains from reallocation

	1996	2006	2011
Allocative efficiencies	38.54%	39.98%	30.18%
Gains from reallocation	159.46%	150.16%	231.38%
Gains from raising allocative efficiency to the U.S. level	81.57%	75.06%	131.90%

3.2 The Determinants of Resource Misallocation at the Plant Level

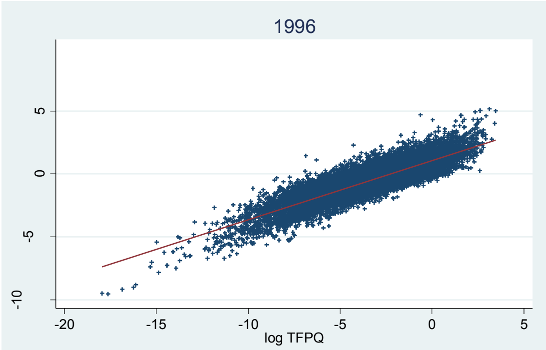
3.2.1 Correlated Distortions

As discussed in Restuccia and Rogerson (2008), the misallocation problem will be particularly worsened if the distortions are correlated with the plant's productivity, or more specifically, if the high-productivity plants are more size-constrained than the low-productivity plants. This "correlated distortions" problem is especially acute in developing economies. Hsieh and Klenow (2014) show that the correlations between the average revenue product of capital and labor and the plant's productivity in India and Mexico are much higher than that in the United States.

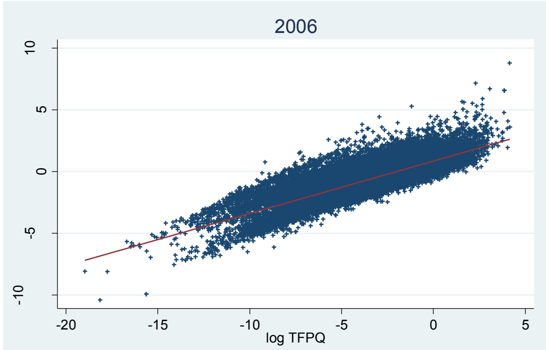
Figure 11 shows the correlations between the average revenue product of capital and labor and the plant's productivity in Thailand. The degrees of correlation in Thailand are slightly below those in India and Mexico as reported in Hsieh and Klenow (2014). That is, a doubling of plant's productivity leads to 34–43 percent increase in the plant's TFPR. Therefore, as in India and Mexico, there exist the correlated distortions in the Thai manufacturing sector.

Figure 11 – Plant's productivity and average revenue products

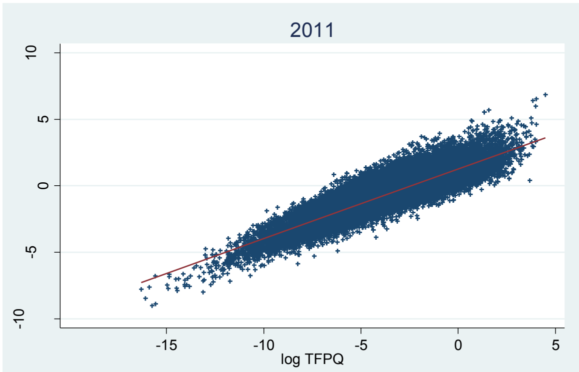
(a)



(b)



(c)



Source: National Statistical Office and calculated by the authors

3.2.2 Size-dependent Policies

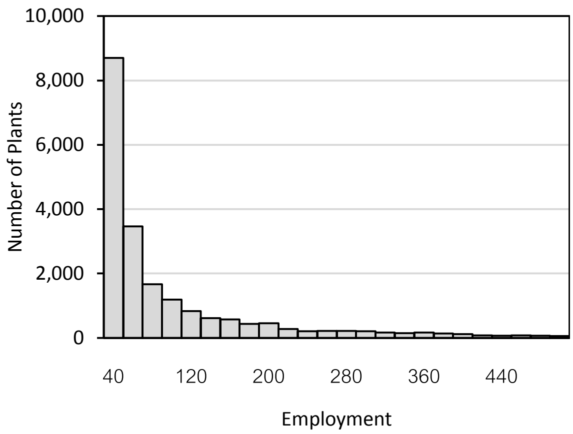
In the model's equilibrium, the more-productive plants would be bigger, employ more workers, and utilize more capital. Therefore, any preferential policy or any restriction that based on a plant's size could be a source of correlated distortions. Examples of such policies are subsidies for SMEs in Korea (Guner et al., 2008), size restrictions in India (Hsieh and Klenow, 2009), or size-contingent labor laws in France (Gourio and Roys, 2014; Garicano et al., 2016).

In France, firms with 50 employees or more must follow a number of regulations that substantially raise the firms' burden. As a result, firms with employment close to the regulatory threshold deliberately maintain their size below the threshold. Gourio and Roys (2014) and Garicano et al. (2016) show that there is a sharp fall in the number of French firms with 50 employees in comparison to the firms with 49 employees.

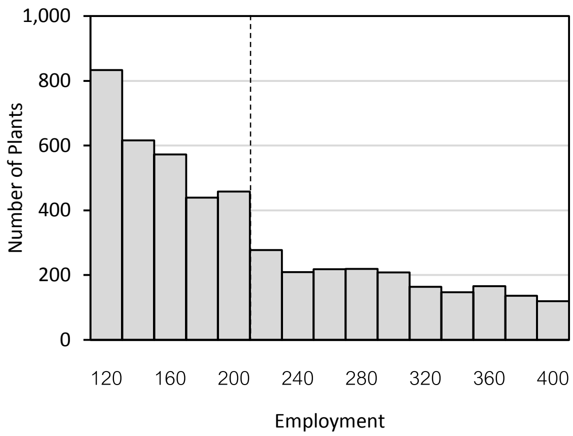
In Thailand, there are a number of preferential policies (e.g., tax reduction or soft loan) targeting at the small and medium enterprises. Therefore, it is worth investigating the effect of these preferential policies on the plant's decisions. The definitions of small and medium enterprises vary by policy. In this paper, we focus on the Ministerial Regulation under the Small and Medium Enterprises Development Act, B.E. 2543, which provides the definition of the small and medium enterprises based on the employment level and the value of fixed assets. For the manufacturing sector, the small enterprises are those with not more than 50 workers, or with fixed assets worth not more than 50 million baht. And the medium enterprises are those with more than 50 workers but not more than 200 workers, or those with fixed assets worth more than 50 million baht but not more than 200 million baht. Therefore, we look for any discontinuity in plant number around plants with 50 workers and around plants with 200 workers.[7]

Figure 12 – Number of plants by employment

(a) 21–500 workers



(b) 101–400 workers



(c) 40–60 workers

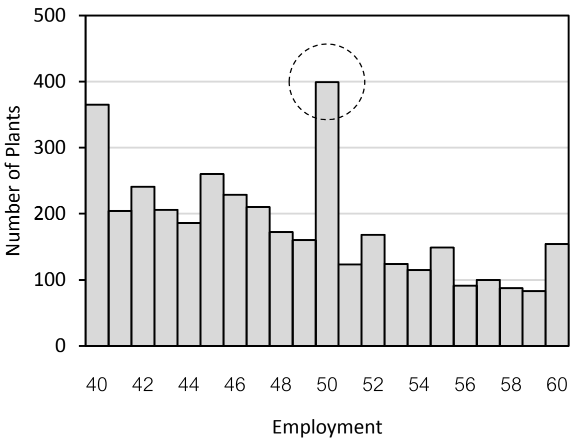


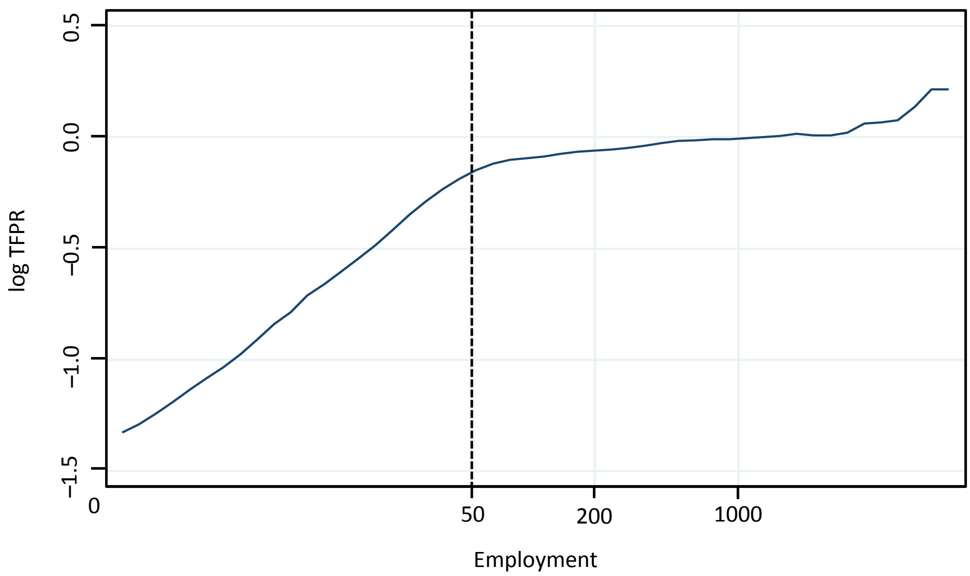
Figure 12 shows the number of plants by employment in 2006. The bin size is 20 workers for panels (a) and (b) and 1 worker for panel (c). The number shown is the upper bound of each bin. There are the

[7] We also look for any discontinuity in plant number around the 50- and 200-million-baht thresholds of fixed assets, but we could not find any.

discontinuities in plant number at both size thresholds. Panel (b) shows a sharp drop in plant number when the employment level goes beyond 200. Panel (c) shows a spike in the number of plants with 50 workers, which is 2.8 times higher than the number of plants with 49 or 51 workers. When we look at the 2011 data, we find similar patterns. These results suggest that there are some costs that Thai manufacturing plants would have to paid for if they increase their employment above 50-workers and 200-workers thresholds. This pattern is consistent with the assumption that size-dependent policies affect the plant's decision to expand.

Figure 13 shows the relationship between the plant's employment level and TFPR. Without any distortion, TFPR would not be correlated with the plant's employment level. In the Thai manufacturing sector, TFPR sharply increases with plant's size for plant with 50 workers or less (small plants). On the other hand, the correlation between TFPR and plant's size is much lower for plants with more than 50 workers (medium and large plants). This result suggests that, among small plants, smaller plants are less constrained than larger plants. However, such pattern does not exist for medium and large plants.[8] This is another evidence on the distortionary effects of size-dependent policies.

Figure 13 – Average revenue product and employment in 2006



Source: National Statistical Office and calculated by the authors

3.2.3 Dynamic Effects on the Aggregate Productivity

In section 3.1.2, we consider the static effect of correlated distortions of aggregate TFP due to resource misallocation and find that, due to the resource misallocation problem, Thai manufacturing TFP is only at 30–40% of its potential level. The recent literature has also emphasized the importance of dynamic

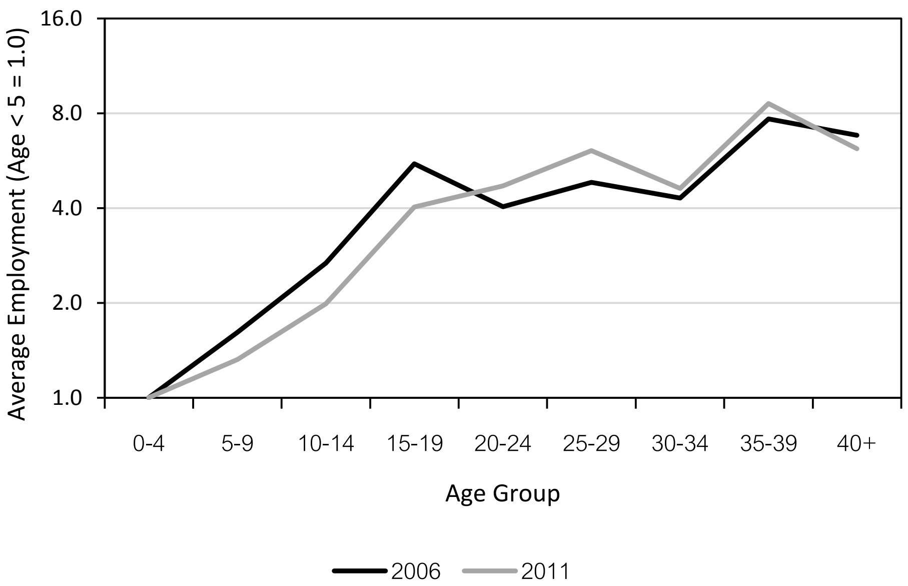
[8] There could still be distortions among medium and large plants, but such distortions are not correlated with plant's size.

effects on the aggregate TFP. While Hsieh and Klenow (2009) show that the static misallocation can explain around one-third of the TFP differences between the United States and the developing countries such as China and India, Hsieh and Klenow (2014) show that the dynamic effects over the plants' life cycle can explain the other 25% of the TFP differences.

In Hsieh and Klenow (2014), firms facing correlated distortions will have less incentive to expand and to improve their productivity over their life cycle. Hsieh and Klenow (2014) use the United States as a benchmark for an economy with low correlated distortions and use Mexico and India as benchmarks for economies with high correlated distortions. They find that, on average, 40-year-old plants in the United States employ seven times more workers and four times more productive than plants age less than five years old. In comparison, 40-year-old plants in Mexico are two-times bigger and two-time more productive than those age less than five years old, and the numbers are even lower for India.

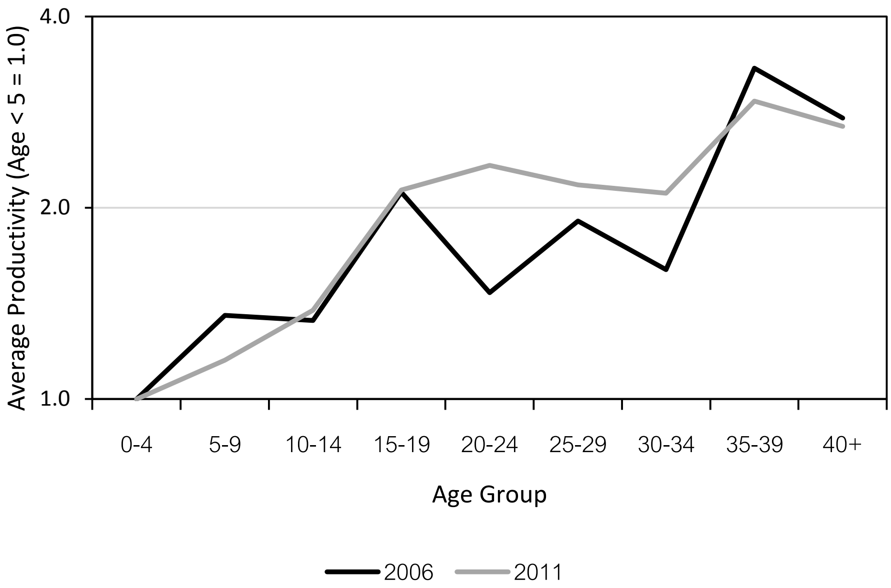
Figure 14 plots the average employment of by age groups of Thai manufacturing plants in 2006 and 2011, while Figure 15 plots the average productivity by age groups. At first glance, manufacturing plants in Thailand perform remarkably well. The employment and productivity growth rates of Thai plants are more similar to those in the U.S. rather than those in Mexico or India. However, as discussed in previous section, the degree of correlated distortions in Thailand is much higher than in the U.S. and just slightly below those in Mexico and India. Then, what could explain the high growth rate of Thai manufacturing plants observe in the data?

Figure 14 – Average employment across age group



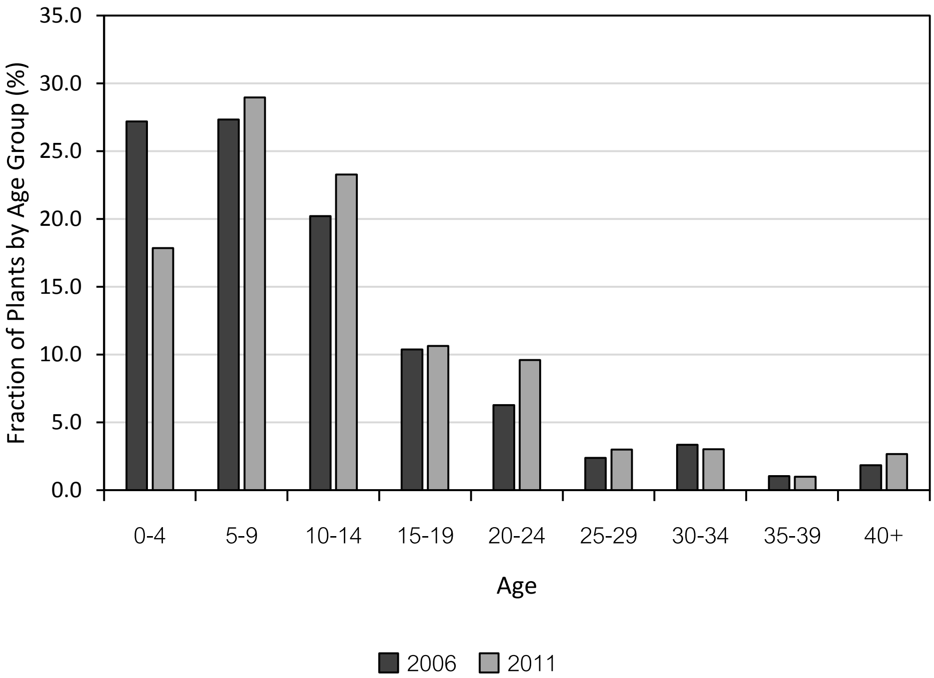
Source: National Statistical Office and calculated by the authors

Figure 15 – Average productivity by age group



Source: National Statistical Office and calculated by the authors

Figure 16 – Fraction of plants by age group

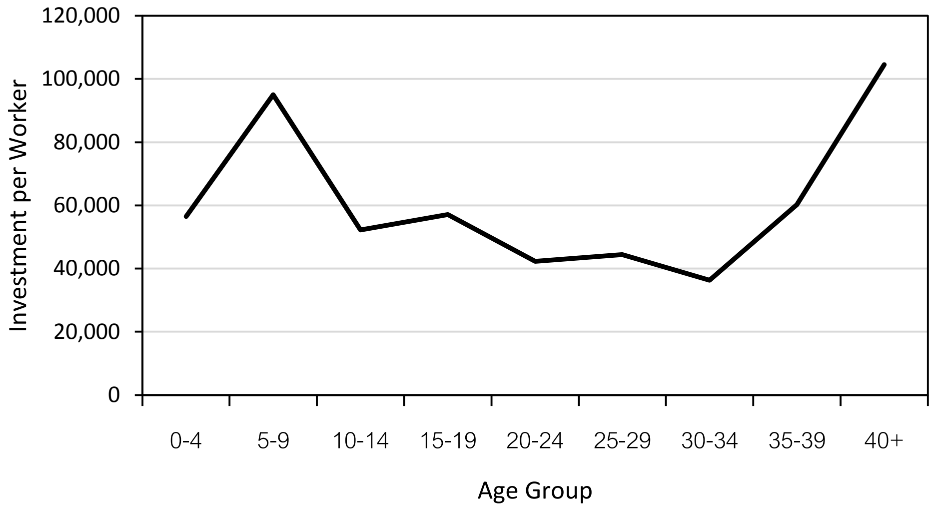


Source: National Statistical Office and calculated by the authors

Figure 16 reports the fraction of plants by age group in 2006 and 2011. There is a large drop in the number of plants at age 15 and above, then again at age 25. Holding the rate of entry constant, this figure implies that less than 20% of manufacturing plant in Thailand will survive beyond age 25.

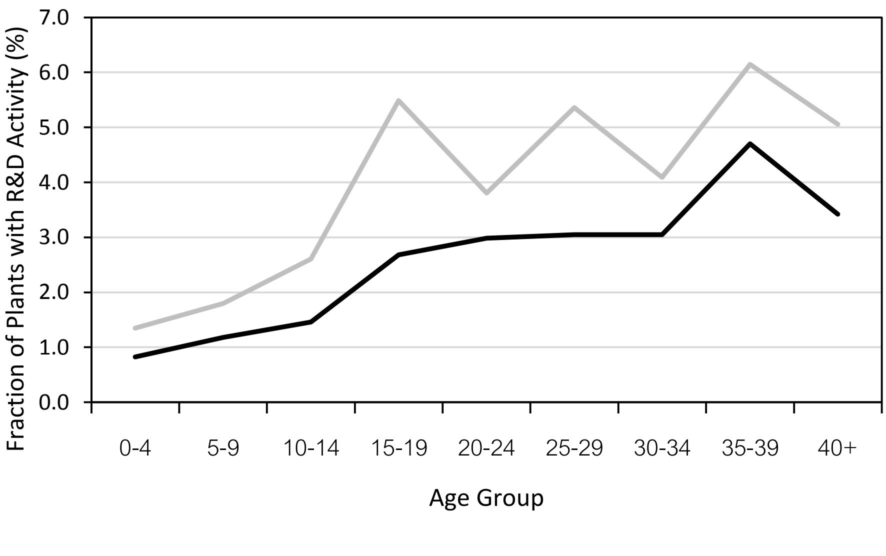
Therefore, the observed high growth rate of manufacturing plants in Thailand could be a result of the survivorship bias.

Figure 17 – Investment per worker by age group in 2006



Source: National Statistical Office and calculated by the authors

Figure 18 – Fraction of plants with R&D activities by age group

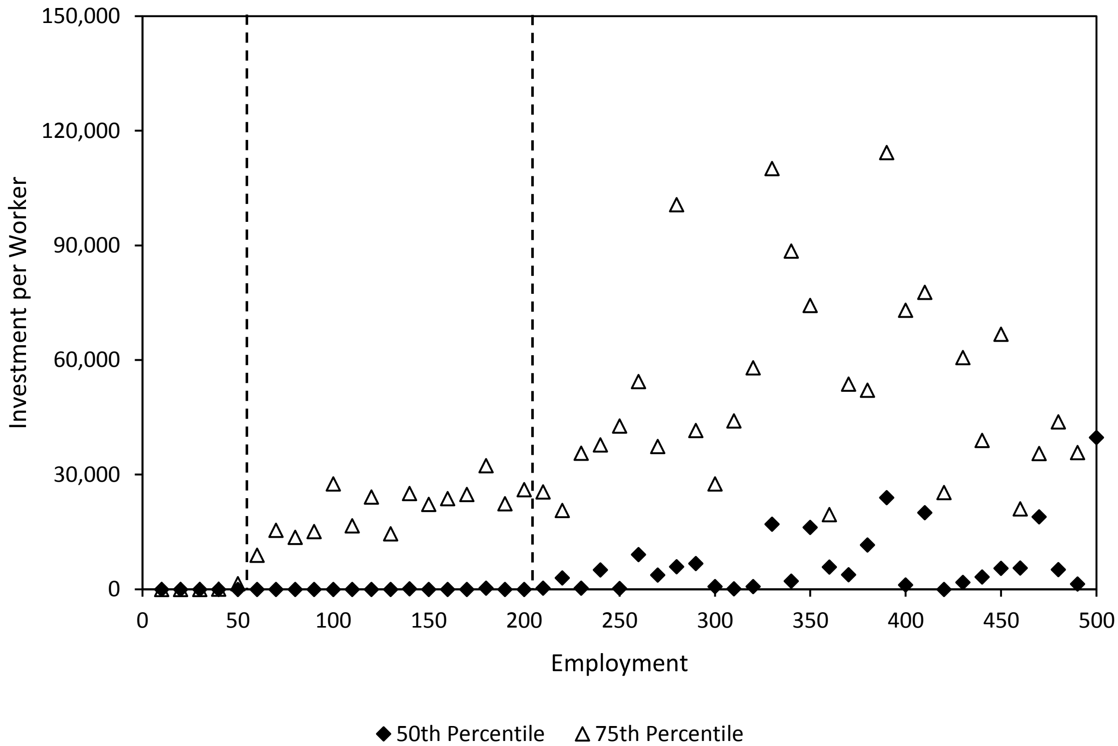


Source: National Statistical Office and calculated by the authors

Figure 17 plots the investment pattern of Thai plants across age group in 2006.[9] Figure 18 plots the fractions of plants with R&D activities in 2006 and 2011. While there is no clear relationship between plant's age and investment level, it is obvious that younger plants are less likely to invest in R&D than older plants.

Could this be a result of size-dependent policies? To answer this question, we look at the relationship between the investment level and the plant's employment. Figure 19 plots the investment per worker by employment in 2006. The result is striking. There clearly are discontinuities around 50 and 200 workers. More than 50 percent of plants with 200 workers or less did not make any investment in 2006, and more than 75 percent of plants with 50 workers or less did not make any investment. This investment pattern confirms the conjecture in Hsieh and Klenow (2014) that correlated distortions lower the incentive to invest of young and small plants, especially those below the size thresholds.

Figure 19 – Investment per worker by employment in 2006



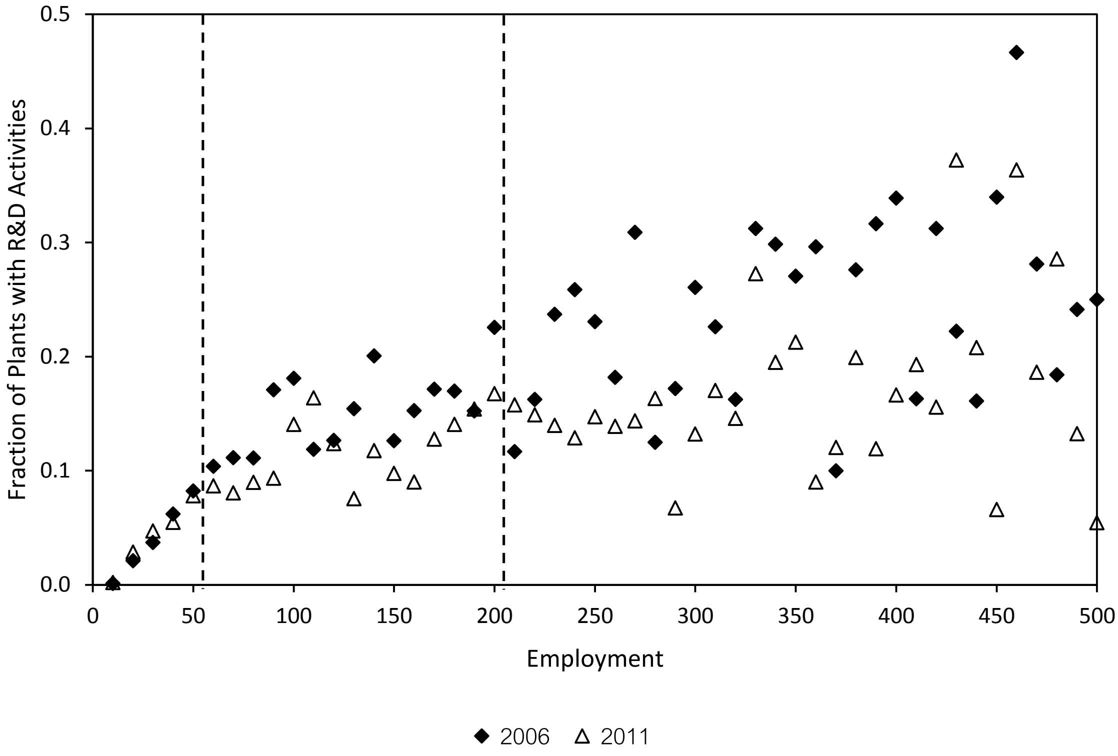
Source: National Statistical Office and calculated by the authors

Figure 20 shows the fraction of plants with R&D activities by employment. The fraction of plants with R&D activities increases with the employment level. Notice that, for plants with 50 workers or smaller, there is a linear relationship between the R&D fraction and the employment level. However, the linear

[9] In 2011, a large fraction of plants in Thailand report negative investment. This could be a result of the 2011 flood disaster in Thailand.

pattern disappears once the employment level goes above 50 workers. This result points toward another structural break around the cut-off threshold of employment.

Figure 20 – Fraction of plants with R&D activities by employment



Source: National Statistical Office and calculated by the authors

3.2.4 R&D Activities and the Plant-level Productivity

According to the model, the aggregate productivity is the product of the allocative efficiency and the potential productivity. Therefore, in order to raise the aggregate productivity, we can either improve the allocative efficiency or raise the potential productivity, which is the weighted-average TFPQ across all plants. In this section, we will discuss a way to improve the potential productivity by improving plant-level TFPQs. First, we will show that the investment in R&D activities can raise the plant's productivity. Then, we will study the determinants of plant-level R&D activities.

A) The Effect of R&D Activities on Plant-level Productivity

In this section, we consider the effect of R&D activities on the plant's productivity level. Ideally, we would like to compare the productivity of a plant with R&D activities to the counterfactual productivity of the same plant without R&D activities. In this case, the productivity difference is called the average treatment effect on the treated (ATT)

$$ATT = E\left(TFP_i^1 - TFP_i^0 | R\&D_i = 1\right)$$

where TFP_i^1 denotes the productivity level of plant i with R&D activities and TFP_i^0 denotes the counterfactual productivity level of plant i had it not engaged in R&D activities. $R\&D_i$ is the dummy variable equals to 1 if plant i engages in R&D activities.

However, in most cases, we cannot observe the counterfactual productivity TFP_i^0. Therefore, to estimate the average treatment effect on the treated, matching techniques is often used to approximate the counterfactual productivity. In this paper, we use the Mahalanobis-metric matching proposed in Rubin (1980). This method chooses a plant from the group of plants without R&D activities (the control group) to match with each plant from the group of plants with R&D activities (the treatment group) in order to minimize the Mahalanobis distance between them. The Mahalanobis distance between two observations is

$$d(X_i^t, X_j^c) = \sqrt{(X_i^t - X_j^c)^T S^{-1} (X_i^t - X_j^c)}$$

where X_i^t is the vector of characteristics of plant i from the treatment group, X_j^c is the vector of characteristics of plant j from the control group, and S is the covariance matrix of the characteristics.

Table 2 – Balancing tests of the covariates

	Unmatched sample			Matched sample		
	w/ R&D	w/o R&D	*t*-stat	w/ R&D	w/o R&D	*t*-stat
2006						
log Age	2.525	2.111	25.036	2.486	2.484	0.07
log $Size$	4.582	2.834	66.721	4.101	4.101	–0.01
log KI	12.951	11.774	31.828	12.844	12.838	0.14
D_Export	0.456	0.100	57.789	0.317	0.317	–0.00
D_Import	0.480	0.108	58.416	0.295	0.295	0.00
D_FDI	0.181	0.046	30.798	0.083	0.083	–0.00
# Obs.	2,742	48,565		1,210	798	
2011						
log Age	2.655	2.314	20.006	2.583	2.583	0.01
log $Size$	4.250	2.640	54.484	3.655	3.646	0.17
log KI	12.893	11.993	23.303	12.792	12.791	0.01
D_Export	0.292	0.076	36.323	0.131	0.131	0.00
D_Import	0.315	0.082	37.702	0.143	0.143	–0.00
D_FDI	0.114	0.039	17.269	0.023	0.023	–0.00
# Obs.	2,244	49,685		1,217	893	

Table 2 reports the balancing tests of the covariates in the matched and the unmatched samples. The variables are as follows: Age is the plant's age, $Size$ is the plant's employment, and KI is the plant's capital intensity measured as the capital-labor ratio. D_Export, D_Import, and D_FDI are the dummies for export, import, and being foreign-owned, respectively. In the unmatched sample, the differences in the characteristics of plants with and without R&D activities are statistically significant. On average, plants with R&D activities are older, bigger, more capital-intensive, more likely to trade internationally, and more like to be foreign-owned. On the other hand, in the matched sample, the differences are much smaller and none of them is statistically significant.

Table 3 reports the average treatment effect on the treated for R&D activities on the plant's physical productivity (TFPQ). The ATTs are significant in both 2006 and 2011.

Table 3 – Average treatment effect on the treated for R&D activities

	2006	2011
$TFPQ$	0.2976***	0.4515***
	(0.0750)	(0.1235)

Note: Standard errors in parentheses. *** denote significance at 1% level.

B) The Determinants of the Plant-level R&D Activities

Next, to identify a plant's characteristics that affect its decision to invest in R&D, we estimate the following probit model:

$$\mathbf{Pr}(R\&D = 1) = \Phi(\mathbf{X}^T\beta)$$

where $R\&D$ is the dummy variable equals to 1 if a plant invests in R&D, Φ is the cumulative distribution function of the standard normal distribution and **X** is the vector of a plant's characteristics including logs of age, capital level, and employment level. The vector **X** also includes dummy variables for being a government enterprise, being foreign owned, exporting, and importing.

Table 4 reports the estimation result of the probit regression. The result suggests that larger plants are more likely to invest in R&D. This finding is consistent with the idea that small plants does not want to expand their size due to the size-dependent policies. In addition, trading internationally increases the probability that the plants invest in R&D. On the other hand, being foreign owned lowers makes plants less likely to invest in R&D. The explanation for this is that FDI comes together with technology transfer, which is a substitution of R&D activities.

Table 4 – Probit estimation on the propensity to invest in R&D activities

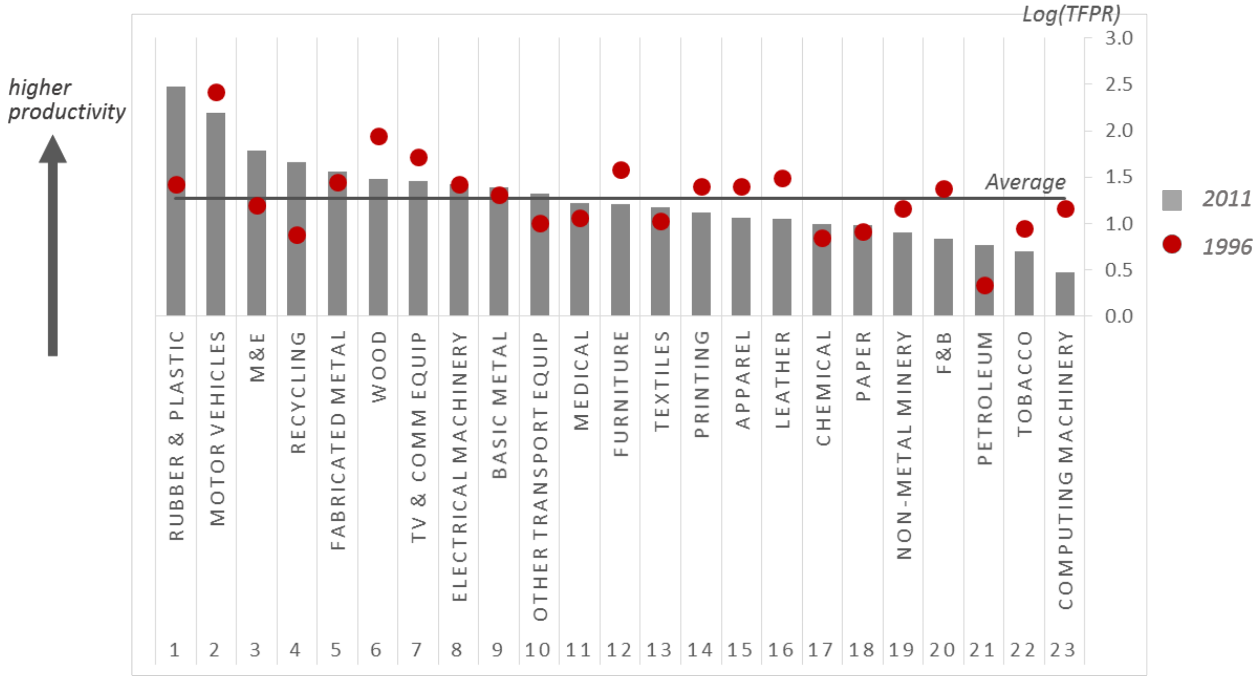
Pr(R&D = 1)	2006	2011
log Age	–0.0123	0.0111
	(0.0213)	(0.0220)
log $Capital$	0.1194***	0.1315***
	(0.0149)	(0.0129)
log $Employment$	0.2142***	0.2131***
	(0.0170)	(0.0141)
D_Government	–0.4737**	0.4438**
	(0.2244)	(0.1911)
D_FDI	–0.1788***	–0.3268***
	(0.0452)	(0.0540)
D_Export	0.2144***	0.0508
	(0.0447)	(0.0484)
D_Import	0.3957***	0.3687***
	(0.0387)	(0.0469)
Psuedo R^2	0.2700	0.2263
# Observations	51,307	51,929

Note: Standard errors in parentheses. *** denote significance at 1% level.

4. Resource Misallocation at the Sector Level

The insights from our micro-level data show a large deviation of the revenue productivity (TFPR) across Thai manufacturing industries[10] as well as the presence of low, dispersed within-industry misallocation. Most manufacturing industries experienced productivity slowdown compared to the pre-crisis 1997 level, except the manufactures of rubber and plastic products, machinery and equipment, recycling products, other transport equipment, and petroleum products as shown in Figure 21. However, Figure 22 indicates that highly productive industry is not necessarily allocated resources well (measured by how much the "allocative efficiency" ratio is closed to one, i.e. actual TFP is closed to its potential.) such as the manufacture of recycling. Allocative inefficiency also remarkably intensifies in the manufactures of television and communication equipment, computing machinery, apparel, and basic metal. Meanwhile, the manufacture of medical equipment and petroleum products reallocated resource well with less impressive TFPR. What could explain widely dispersed misallocation among Thai manufacturing industries comes into our interest that needs quantitative examination.

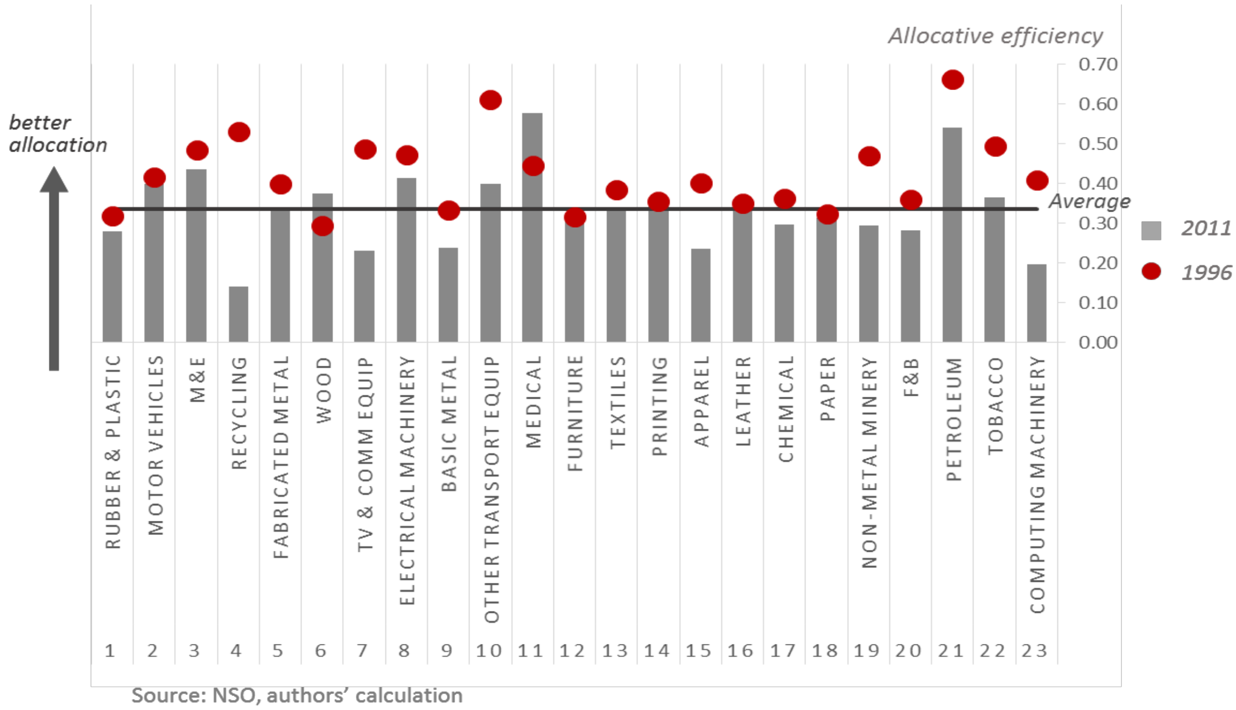
Figure 21 – Total factor productivity in Thai manufacturing sector
(by 2-digit ISIC industry classifications)



Source: NSO, authors' calculation

[10] TFPR can be observed from the survey, while TFPQ is unobserved. This section classifies TFPR by International Standard Industrial Classification of All Economic Activities, Rev.3 (ISIC, Rev.3) in two-digit classification codes.

Figure 22 –Resource misallocation in Thai manufacturing sector
(by 2-digit ISIC industry classifications)



4.1 The Determinants of Sectoral Resource Misallocation

This section employs two types of measurement to study the industry-level determinants of resource misallocation. The first measurement is the TFP gap, the gap between the hypothetical, efficient TFP and actual TFP as calculated in the Section 3.1, which is the reciprocal of the allocative efficiency ratio. When actual TFP is closed to its potential, the ratio becomes smaller closed to one as a minimum. This type of misallocation is fundamentally taking place by input and output price distortions based on the monopolistic competition model by Hsieh and Klenow (2009). However, this kind of model-based indicator is sensitive to some underlying assumptions such as elasticity parameters and forms of aggregation. Literatures also refer to the within-industry dispersion of TFPR as an alternative measurement such as the standard deviation of TFPR. This kind of measurement is easy to measure under fewer assumptions. In most cases, the past studies found robustness in their results when the two measures are highly correlated.[11] However, it should be noted that productivity dispersion is maybe indicative of healthy industry dynamics rather than allocative distortions.

[11] In theory, the model-based and dispersion-based measures are correlated. Larger dispersion of firm productivity occurs where allocative efficiency is low, implying that there exists unrealized efficiency gains from reallocating inputs across firms within industry. Lashitew (2012) finds robustness in his results with respect to a strong correlation (0.62) based on a cross-countries data. Instead, we find low correlation (0.27) that need careful interpretation for robustness check.

4.1.1 Potential Determinants and Rationale

Literatures suggest a number of potential factors determined efficiency of within-sector reallocation across firms, for example market regulations (Arnold et al., 2008), the presence of foreign firms (Maliranta and Nurmi, 2004), changing international environment and the increasing foreign pressure from imports (Maliranta, 2005 and Eslava et al., 2009), and financial market frictions (Gilchrist et al., 2013 and Meza et al., 2016). Maggioni (2013) also discusses that the productivity heterogeneity can be explained by supply-side factors (such as technology, financial structure, firm management, and human capital) and demand-side factors (such as market size and trade exposure). This paper identifies factors determined misallocation in Thai manufacturing sector by classifying potential determinants into six groups that we can utilize richness of our micro-level data, namely international involvement, domestic competition, technology factor, financial friction, government-related policy, and firm's characteristics. The potential determinants are summarized in Table 5.

1) International involvement

There are two hypotheses related to international involvement. Based on the firm heterogeneity hypothesis (Melitz, 2003 and Bernard et al., 2003), trade openness should cause a resource reallocation toward more efficient firms, the exit of less productive firms and the entry of more productive ones. Therefore, beneficial effects for sectoral and firm productivity due to better access to foreign demand with higher competition in export market is expected. Mitra and Ural (2007) also found that trade liberalization gained more for the export-oriented manufacturing industries in India due to productivity-enhancing effect. Meanwhile, tougher competition from imported products or from a larger variety of imported inputs probably raise productivity through better division of labor. However, some studies support the contrasting hypothesis. Syverson (2004) and Ito and Lechevelier (2009) use large firm-level panel dataset and find evidence of a positive impact of internationalization on sectoral productivity dispersion in the United States and Japan.

Moreover, Maggioni (2013) focused on the role of import penetration[12] and its linkage to domestic efficiency in Italy. The author found the mixed results that importing from low and medium income countries cause stronger domestic competition due to rising competitive pressure. Less productive firms have incentives to reduce costs of production and increase their efficiency to survive. As a consequence, the dispersion will be lower due to the exit of low efficient firms and productivity improvement of surviving firms. In opposite, importing from industrialized countries, such as foreign technology, widens within-sector heterogeneity because opportunity to exploit higher quality inputs and intermediates may not be available to all firms due to additional costs of enter foreign markets.

Apart from trade openness, capital openness is expected to improve allocative efficiency of the industry. The entry of more-productive foreign firms will promote domestic market more competitive

[12] Import penetration is defined as the ratio between the values of imports divided by total domestic demand, measuring to what degree domestic demand is satisfied by imports.

and resources will be reallocated towards more-productive firms (Alfaro and Chauvin 2016). Furthermore, Lashitew (2012) found that positive effect of openness to foreign investment is witnessed only in countries where R&D spending and educational attainment are sufficiently high. This finding is consistent with Wang and Wong (2009) stating that foreign direct investment improves domestic productivity only when a minimum threshold of absorptive capacity is reached.

2) Domestic competition

Any industry characterized with a high degree of domestic concentration is expected to present low productivity dispersion. In a more concentrated market, it is likely that inefficient firms could not survive for a long time. Firms need to improve their efficiency to stay in the market and competitive pressures flattening any divergence. We use the Herfindahl Hirchman Index (HHI), defined as the sum of the squares of each firm's market share to capture domestic competitive environment. Chun et al. (2015) also found that the coefficient of HHI can be negative with respect to productivity dispersion. This could explain absolute firm-specific performance heterogeneity in sales growth. If an industry is very competitive, small competitive advantage or disadvantage in productivity rising by using information technology (IT) more intensively can amplify firm heterogeneity. Apart from the HHI indicator, we also use alternative indicators for robustness check, such as the concentration ratio (C10) and the sunk entry cost, measured by average amount of capital intensity in the sector.

3) Technological adoption

R&D expenses is mostly used as a proxy of firm's innovation. R&D activities is expected to lower firms' within-sector heterogeneity. Innovation boosts industry's competitiveness that activates firm to benefit from R&D activity in order to survive in the market. However, it can be the case that the technological level of the sector may also have an ambiguous impact on productivity dispersion due to the dominance of innovation and knowledge spillovers (Maggioni, 2013). On one hand, firms with new foreign technology can dominate the market if the access is restricted to all firms. However, knowledge spillover could be at work and these positive externalities could remove the dispersion across firms. Firms may take advantage from domestic new technology to improve their efficiency which seems to be accessible to all firms and is relatively cheaper compared with foreign technology.

4) Financial frictions

Financial frictions are among the most widely studied determinants of factor allocation. (Arnold et al, 2008) The resulting reallocation of capital towards more efficient firms will improve allocative efficiency and boost aggregate TFP. Financial frictions can distort firms' decision to purchase inputs and leads to misallocation of resources. If firms face with working capital constraints, they have to finance their inputs purchases using bank credit. However, availability and cost of credit can influence input use and determine the degree of allocative efficiency. Lower cost of capital can boost the entry of new firms, thus intensifying competition and forcing inefficient incumbents to exit. To observe this data, we link sectoral-level manufacturing data with credit flows and interest rates at sectoral level from

Loan Arrangement dataset (LAR) collected by the Bank of Thailand[13]. The other source of sectoral data allow us to investigate impact of amount and cost of credit financing as financial friction indicators in the credit market.

As discussed in Duval et al. (2017), we also investigate corporate financial vulnerabilities as additional indicators of financial frictions using Corporate Profile and Financial Statement database collected by the Department of Business Development. The first indicator is the leverage ratio, the average debt share on the total assets, capturing debt overhang risk. Giroud and Mueller (2017) found that U.S. firms with a higher pre-crisis leverage ratio faced greater financial constraints when credit conditions tightened after Lehman Brother and attributed to TFP growth after the crisis across advanced economies and disproportionately in countries where credit conditions tightened more. The second indictor is rollover risk, the share of current liabilities to total sales. A higher share of debt maturing is associated with a larger decline in post-crisis TFP growth in the country.

5) Policy-induced frictions

Lashitew (2012) found that policy-induced frictions can affect allocative efficiency in three different ways. First, some policy constraints reduce competitive pressure by lowering the entry of new firms, thus reducing the possibility of reallocation of inputs from inefficient incumbents to more productive new-entrants. Second, some induce misallocation by protecting inefficient existing plants (such as public firms) so that inputs are not reallocated towards more productive incumbents (Dollar and Wei, 2007). Third, policies that affect allocative efficiency are also likely to affect technical efficiency. Increased competitive pressure not only facilitates efficient allocation of inputs across producers, but also pushes producers to use resources more efficiently and/or to adopt more efficient technologies. The effect of most policy variables on aggregate productivity is hence twofold; directly they determine the level of technical efficiency of producers, and indirectly they influence the allocation of inputs across producers. We utilize some policy-related variables from the plant-level survey data capturing investment promotion policy (i.e. the BOI privileges), public corporation, and SME tax privileges.

[13] The Bank of Thailand requires financial institutions to report information of loans at a local contract level since 2004. This study employs only the coverage of Thai commercial banks, subsidiaries of foreign commercial banks, and branches of foreign commercial banks with outstanding loans exceeding 20 million baht.

Table 5 – Potential determinants of resource misallocation

Industry-level determinants	Variable	Expected sign	Alternative indicators
1. Foreign involvement			
1.1 Trade openness			
No. of exporting firms *(fraction)*	export	-	Exports /output
No. of importing firms *(fraction)*	import	-	Imports /output
Import penetration *(ratio)*	imp_pen	-	Trade/output
1.2 Capital openness			
No. of foreign-owned firms *(fraction)*	foreign	-	Share of foreign ownership in paid capital
No. of firms with FDI inflows *(fraction)*	fdi	-	Share of FDI in foreign financing
2. Domestic competition			
Herfindahl Hirchman Index	hhi	-	Concentration ratio of top-ten firms (C10)
Capital intensity *(capital to labor ratio)*	KL	+	Capital share to income
No. of firms within industry	N_firms	+	
No. of small firms (fraction)*	small	+	
No. of large firms (fraction)*	large	+	
3. Financial frictions			Fraction of firms facing with financial constraints in their business
Private credit *(% of output)*	credit	-	
Effective lending rates *(%)*	elr	+	
Leverage *(ratio)*	lev	+	
Rollover risk *(ratio)*	roll	+	
4. Technological factor			
No. of firms with R&D expense *(fraction)*	rdx	-	R&D intensity *(% of total expenses)*
5. Government related policy			
BOI's investment promotion	boi	-	
Government-owned firms	gov	+	
SMEs definition for VAT exemption	smevat	+	
SMEs definition for CIT privileges	smetax	+	
6. Firm's characteristics			
Age	age	-	
Capital	capital	+	
Employment	emp	-	

Remark: *classified by number of workers and size of fixed capital: 'Small' is defined as employing less than 50 workers or having a book value of fixed capital below 50 million baht; 'Large' is defined as employing more than 200 workers or having a book value of fixed capital over 200 million baht (the Ministry of Industry's classification)

4.1.2 Regression results

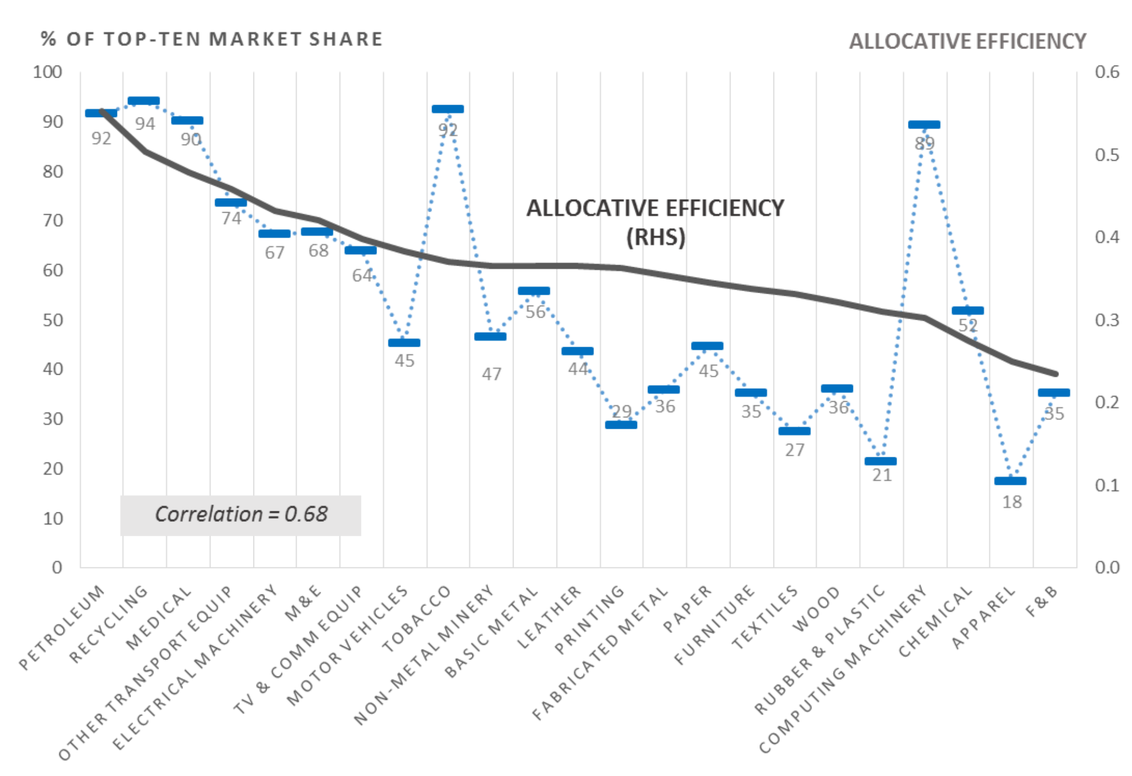
We conduct a reduced-form estimation to test the effect of potential determinants on Thai manufacturing firms' resource misallocation. In Annex B, Table B1 provides regression results in which the dependent variable is the TFP gap using the pool data for all three years (1996, 2006, and 2011). Table B2 shows regression results of TFPR dispersion as an alternative of dependent variable for robustness check. Table B3 and B4 present regression results of determinants of TFP gap with extended independent variables, namely R&D expenditure and financial frictions using the two-year pool data and the 2011 data since the recent survey contained additional information. Key findings are as follows.

(1) *High market concentration with low capital intensity seem to improve allocative efficiency of the industry*. All concentration indicators show the right signs as expected in Table B1 and B2. The coefficient of HHI is negative. In a more concentrated market, existing firms are forced to improve their efficiency to survive. Consistently, the number of firms within industry shows positive relationship with misallocation. Growing number of either large or small firms within industry could widen TFP gap as shown in Table B4 since these emphasize a presence of more competitive environment. Moreover, low capital intensity could reduce

diversity of firms' productivity within industry. Low barrier to entry could encourage new entries to step in and compete the existing firms in the market. Low capital intensity, therefore, can promote better allocative efficiency.

Our micro-level data also shows a positive relationship between the top-ten firms' market share (C10) and the allocative efficiency ratio. Figure 23 presents that highly concentrated manufacturing industries, such as petroleum, recycling, and medical equipment, tend to have higher allocative efficiency compared to the low concentration industries such as rubber and plastic products, apparel, food and beverage. However, this positive relationship may not be able to explain some specific industries such as tobacco (highly government-owned) and computing machinery (highly imported, highly monopolistic).

Figure 23 – Top-10 market share and sectoral efficiency, pool data (1996, 2006, 2011)
(by 2-digit ISIC industry classifications)



Source: NSO, authors' calculation

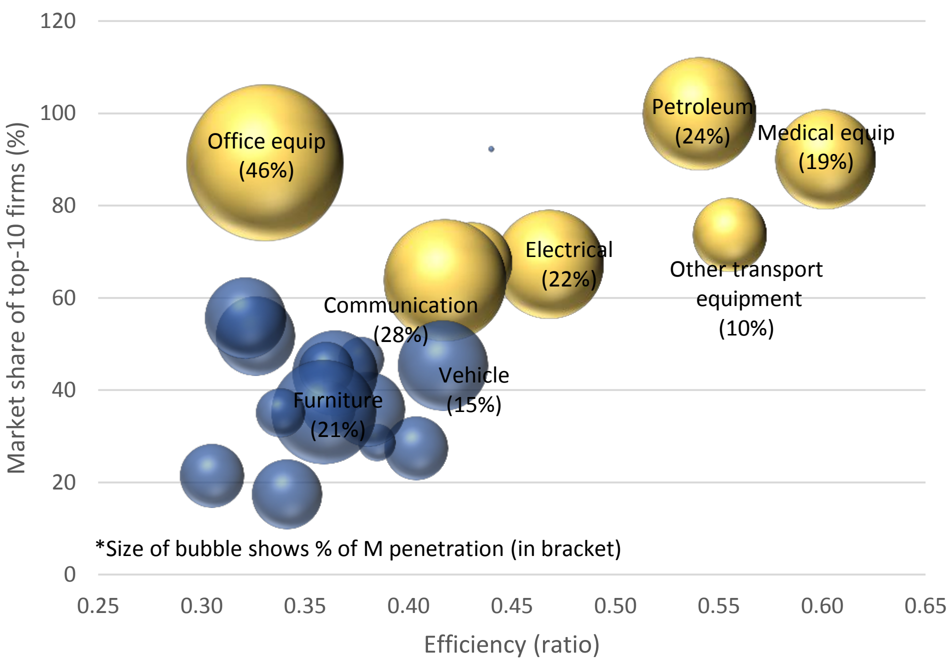
(2) *Trade openness intensifies resource misallocation*. The coefficients of trade variables, i.e. *export*, *import*, *imp_pen*, and *foreign* in Table B1 are not robust. Those coefficients appear to be statistically significant, but they are in opposite directions compared to Table B2. Different types of misallocation measurement imply differently for trade variables. In the case of the simple measurement, *TFPR dispersion*, as shown in Table B2, higher fractions of firms being exporter or having foreign-owned and higher ratio of import penetration could increase TFP dispersion within industry. However, *import* shows the opposite sign against other trade-related factors. Growing number of importing firms in the industry could encourage less

productive firms to benefit from a variety of cheaper imported input and intermediates to reduce their cost of production resulting in a lower dispersion of sectoral TFPR.

To get more insight, we complement the regression results in Table B2 by investigating our micro-level data as shown in Figure 24. Some industries are dominated by the top-ten firms, namely (1) the group of 90 – 100% market share: the manufacturing of office equipment, petroleum products, and medical equipment; and (2) the group of 60 - 80% market share: the manufacturing of communication equipment, electrical equipment, and other transportation equipment. Among each group, the industry with relatively high import intensity tends to encounter relatively low allocative efficiency. This evidence plausibly implies that opportunity for firms to upgrade their productivity by importing higher quality of foreign inputs and intermediates seems unequal within highly monopolistic, competitive industries.

Figure 24 – Top-10 market share, import intensity, and sectoral efficiency, pool data (1996, 2006, 2011)

(by 2-digit ISIC industry classifications)



Source: National Statistical Office and calculated by the authors

(3) *FDI improves allocative efficiency*. Coefficients of FDI in Table B4 are negative with respect to allocative efficiency as expected. Higher fraction of firms with FDI financing improves misallocation within industry. However, it should be noted that the role of foreign ownership is ambiguous since we found inconsistent direction of its coefficients in Table B1 and B2.

(4) *Size-dependent policy and government ownership matter resource misallocation*. Table B2 shows a significant positive relationship between *smevat* and *tfprsd*. This evidence indicates that the VAT-exempted policy for SMEs with annual revenue less than 1.8 million baht could

increase TFPR dispersion. Although another indicator related to income tax privileges for SMEs (*smetax*) is statistically insignificant, its coefficient also shows positive relationship with misallocation. This finding is consistent with some evidence shown in Section 3.2.2 supporting the assumption of size-dependent policies on small firms' decision to expand.

Apart from tax privileges, we also find that the presence of government-owned plant may also increase TFPR dispersion in each industry. On the contrary, the regression shows that larger fraction of the BOI-privileged plants within industry can reduce TFPR dispersion. The investment promotion policy facilitate the manufacturing sector for better reallocation as it could attract high productivity firm to invest more with higher technology and R&D spending.

(5) Credit access and rollover risk are key financial frictions impeding reallocation within industry. Table B3 and B4 show that average ratio of credit amount to total sectoral output and the share of current liabilities to total sales are statistically significant with expected signs. The positive coefficient of *roll* implies that higher share of short-term debt maturing could worsen capability to reach higher TFP gain in each industry. In addition, the coefficient of *credit* is negative implied that tougher access in credit market worsens allocative efficiency. It should be noted that the coefficient of effective lending rates (*elr*) shows unexpected sign with negative relationship to misallocation in Table B3, but we could not observe its robustness in Table B4.

(6) R&D activities intensify sectoral productivity heterogeneity. Table B3 shows positive relationship between the fraction of firms with R&D expenses and the TFP gap. The result is surprising from what we expected it to be negative. It could be explained in two plausible ways. First, R&D also lifted up potential TFP when contemporaneous TFP has not fully realized benefit from R&D yet. Hence, our misallocation indicator measured the gap between actual and efficient TFP could be larger with more R&D activities. Second, the positive sign could indicate that knowledge spillover from R&D activities may not be at work and not accessible to all firms. Hence, R&D activities could broaden gap between frontiers and laggards within industry.

As shown in Figure 25, our micro-level data shows interesting facts that most of R&D activities in ten manufacturing industries are invested by medium-to-large firms (representing size of each firm's market share by size of each bubble) such as in the manufactures of petroleum products, electrical machinery, motor vehicle, and computing machinery. Frontier firms with high productivity and high export share tend to invest more R&D that could explain the widening frontier-laggard TFP gap within industry.

Figure 25 – R&D activities in Thai manufacturing sector in 2011 (by selected industries)

Figure 25A – Size of market share

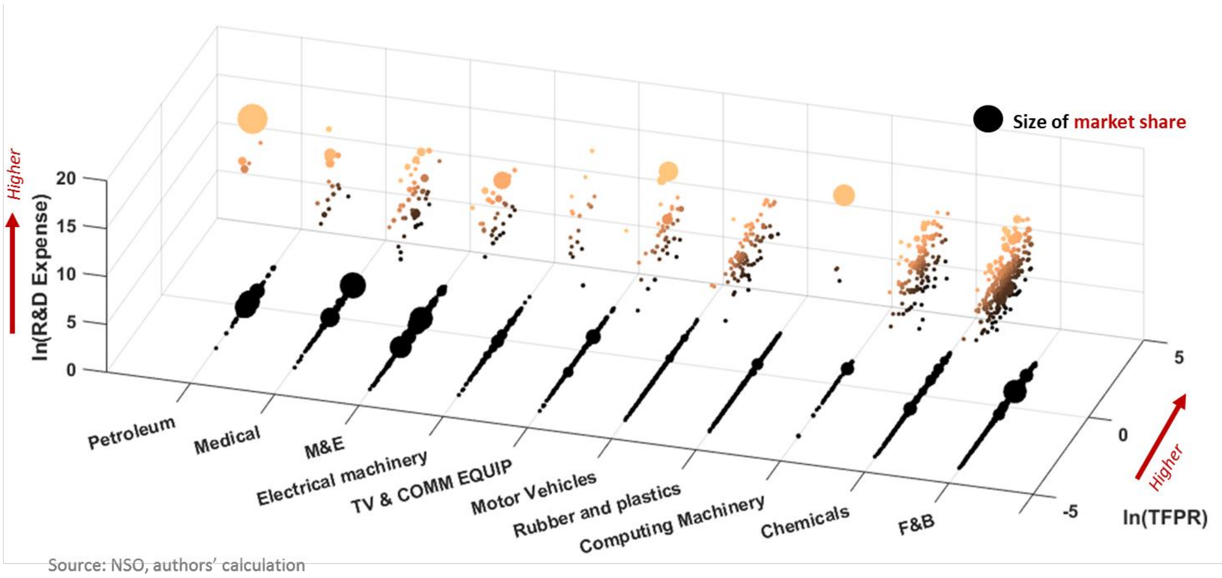
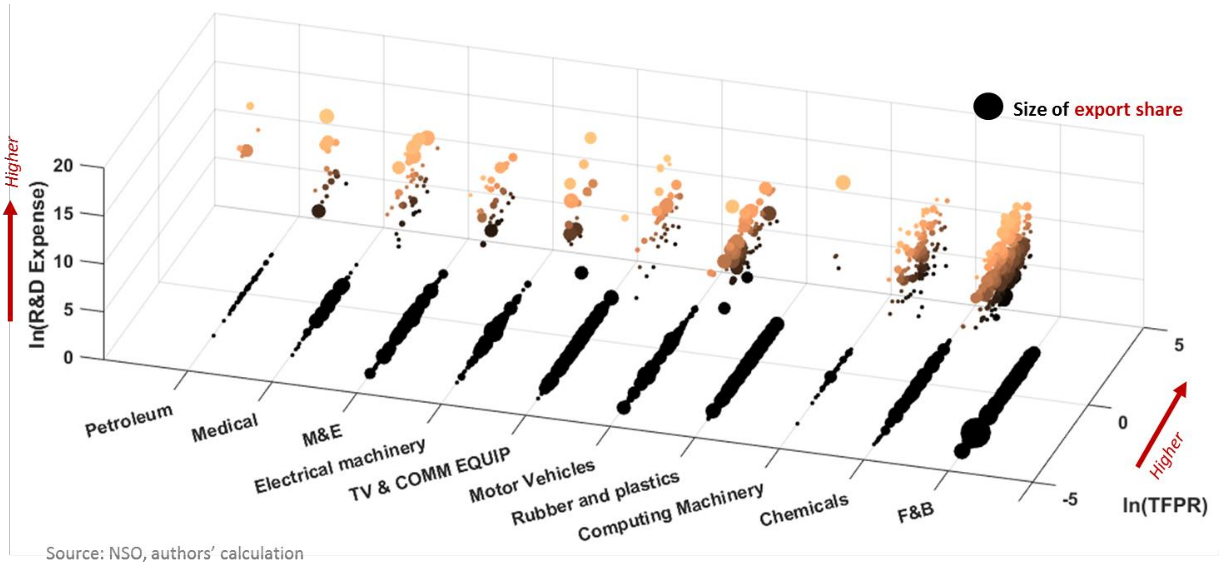


Figure 25B – Size of export share



In all, this section witnesses some key factors behind resource misallocation in Thai manufacturing sector over the past decade. Misallocation arises in the industry with the structure of (1) stronger competition with high barrier to entry, (2) higher trade intensity, (3) greater number of SMEs benefited from tax-exempted privileges and public-owned plants, (4) large fraction of firms invested in R&D, and (5) higher amount of rollover risk in firms' balance sheet. Instead, misallocation within industry can be improved with larger amount of FDI inflows, greater number of firms with BOI privileges, and better credit access.

4.2 The Role of Dynamic Resource Reallocation Over the Business Cycle

The previous section underlines resource misallocation as the main factor behind Thailand's manufacturing productivity slowdown from the static concept. The empirical literature on firm productivity also documents that a large portion of aggregate productivity growth is attributable to "the role of firm dynamics"—the process involved firm entries of profit-seeking new firms, expansion of successful firms and decline or exit of unsuccessful firms by reallocating resources towards more productive uses. Firm dynamics can influence productivity directly by industry dynamics, and indirectly through increased competition. (Devine et al., 2012) Moreover, literature often considers the role of firm dynamics in terms of 'creative destruction' mechanism—the productivity-enhancing restructuring among firms via innovation. The mechanism works associated with firm innovation to launch new products and/or to design new process of production. When innovation is intense, one would expect that firm dynamics is particularly intensive.

Andrews and Saia (2017) also address weakening creative destruction mechanism as a cause of productivity slowdown. They discuss some inter-related dimensions such as (1) rising productivity dispersion indicates how inefficient firms failed to adopt new technologies linger to exit and can survive in the market; (2) highly-skilled labor may be trapped in relatively low productivity firms, which makes it more difficult for productive firms to expand; (3) rising prevalence of old and small firms can consume scarce resources and crowd out the growth of more innovative firms; and (4) capital misallocation before crisis in some economies and the crisis-associated polices may have perpetuated the flows of capital to financially-weak, so-called zombie firms.

In the case of Thailand, Amarase et al (2013) documented some evidence of creative destruction in productivity change between 1999 and 2010. They use capital productivity as a proxy of capital reallocation due to data limitation in the measurement of productivity. Interestingly, the study found the forces of creative destruction are at work in the Thai economy by witnessing capital reallocation from low productivity firms towards high productivity firms. However, it occurs in narrowly defined sectors, particularly in electronics or high export share. Creative destruction is not prevalent especially some protected or less competitive sectors. This section aims to examine further whether firm dynamics can explain aggregate productivity slowdown between 2006 and 2011 by utilizing a feature of panel data from our plant-level database and calculating the measurement of TFP in a more precise way without data limitation in terms of firm input and output information.

4.2.1 The Dynamic Productivity decomposition with survival, entry, and exit

To investigate dynamic of manufacturing firms in our panel data, we employed the productivity decomposition method developed by Melitz and Polance (2015), which augmented from the static Olley-Pakes productivity decomposition with entry and exit (Olley and Pakes, 1996). This decomposition allows to break down aggregate productivity into the contribution of survival firms accounting for changes in the firm-level distribution of productivity and market share reallocations among those firms, with contributions of both entry and exit firms.[14] Thus, a substantial change in aggregate productivity will be composed into four components, namely productivity distribution shifts among survivors, market share reallocations among these firm groups. By this method, we can discuss four components attributed to aggregate TFP slowdown from within-firm improvement, cross-firm reallocation, firm entry and exit.

Olley and Pakes (1996), hereinafter referred to OP, shows that when the aggregate productivity level (Φ_t) is measured by the weighted average of firm-level productivity, it can be decomposed into the unweighted average of the productivity of firms and a covariance between market shares and productivity. This decomposition is as follows.

$$\Phi_t = \bar{\varphi}_t + \sum_i (s_{it} - \bar{s}_t)(\varphi_{it} - \bar{\varphi}_t) = \bar{\varphi}_t + cov(s_{it} - \varphi_{it}),$$

where $\bar{\varphi}_t = \frac{1}{n_t}\sum_{i=1}^{n_t} \varphi_{it}$ is the unweighted firm productivity mean and $\bar{s}_t = \frac{1}{n_t}$ is the mean market share. The weighted industry productivity consists of unweighted average productivity and the covariance. Devine et al (2012) mentioned that the within-industry covariance between market size and productivity is of interest. The smaller this covariance term is, the smaller the share of resources that gets allocated to the most productive firms. Bartelsman et al (2013) argue that a low covariance term represents for misallocation of resources, lack of competing, and market distortions.

The original OP decomposition is aimed to apply for cross-sectional and static data. It does not consider the contributions of firm dynamics with exit and entry firms. Melitz and Polanec (2015) extended the OP decomposition to allow for separating the contribution of entry and exit to aggregate productivity change. This decomposition is so-called the dynamic Olley-Pakes decomposition (DOPD). For any group *(g)* of firms at any period, let $s_{Gt} = \sum_{i \epsilon G} s_{it}$ represent the aggregate market share of a group *G* of firms and define $\Phi_{Gt} = \sum_{i \epsilon G} (\frac{s_{it}}{s_{Gt}}) \varphi_{it}$ as a group's average aggregate productivity.

Aggregate productivity in each period can be rewritten as a function of the aggregate share and aggregate productivity of the three groups of firms (survivors, entrants, and exiters) as:

$$\Phi_1 = s_{S1}\Phi_{S1} + s_{X1}\Phi_{X1} = \Phi_{S1} + s_{X1}(\Phi_{X1} - \Phi_{S1}),$$

$$\Phi_2 = s_{S2}\Phi_{S2} + s_{E2}\Phi_{E2} = \Phi_{S2} + s_{E2}(\Phi_{E2} - \Phi_{S2}).$$

The productivity change (Δ Φ) can be obtained in terms of these components and then apply the OP decomposition to the contribution of the surviving firms. This step is to separate this component

[14] Melitz and Polance (2015) compare their method amongst other two methods that are currently used to break down productivity changes into four components, i.e. Griliches and Regev (1995) and Foster et al (2001), and found it to be least biased measurement of the entry and exit's contribution.

into one induced by a shift in the distribution of firm productivity (the unweighted mean change in the productivity of surviving firms ($\Delta\,\bar{\varphi}_s$) and the market share reallocation ($\Delta\,cov_s$).[15]

$$\Delta\,\Phi\; = (\Phi_1 - \Phi_2) + s_{E2}(\Phi_{E2} - \Phi_{S2}) + s_{X1}(\Phi_{X1} - \Phi_{S1}),$$

$$\Delta\,\Phi\; = \;\Delta\,\bar{\varphi}_s + \;\Delta\,cov(s_{it} - \varphi_{it}) + s_{E2}(\Phi_{E2} - \Phi_{S2}) + s_{X1}(\Phi_{X1} - \Phi_{S1}).$$

The sum of the first two terms is the contribution of the surviving firm group. The first term is productivity improvement (within-firm effect); the second term is the reallocation improvement among the survivors; the third term is the contribution of entrant group; and the last term is the gain by the group of firm exit. Note that the third term is negative only if aggregate productivity of the entry firms is lower than that of the surviving firms in period 2. Moreover, the contribution to the aggregate productivity growth of exiting firms is positive if aggregate productivity of exiting firms is lower than the aggregate productivity of surviving firms in period 1.

4.2.2 Data, Firm Classification, and Productivity

Due to data limitation and survey consistency as shown in Figure 4 of Section 2, we can only utilize our plant-level dataset in 2006 and 2011 to investigate the role of firm dynamics. These two recent years of manufacturing industry census are sufficiently rich to obtain a panel data that can be referred as the group of survival plants between 2006 and 2011. We focus only the plants hiring workers more than ten persons consistent with the previous section. Moreover, the data is trimmed off 1% and 99% for outlier treatments. Excluding the survival plants, the rest of the trimmed data in 2006 can be considered as exiting plants, while the rest of the trimmed data in 2011 is exactly the new entering plants. By using this strategy of firm classification as mentioned, we obtain the pool data of survival, exit, and entry firms with 43,297 plants in total operated over the period from 2006 to 2011. Among all of them, there are only 48% of plants survived in this period. (Table 6)

Table 6: Classification for firm dynamic during 2006 - 2011

Firm Groups	No. of Observations (plants)	%
Survival	20,733	47.89
Entry	16,249	37.53
Exit	6,315	14.59
Total	43,297	100.00

Source: NSO, calculated by authors

We measure TFP in plant level using the constant-return-to-scale assumption of Cobb-Douglas production function as discussed in Section 1 and 2. Plant-level productivity can be consequently aggregated into a 2-digit-ISIC industrial classifications for aggregated illustration.

[15] Melitz and Polanec (2015) remark that the decompositions of entrant and exit can follow this concept in a similar way.

4.2.3 Empirical results

(1) Productivity decomposition in manufacturing sector (aggregate level)

Table 7 provides four components of the TFP decomposition in the middle columns and total change in the second last column. The decomposition is made from the change of aggregate TFP from 2006 to 2011. By this method of TFP measurement, we observe the aggregate TFP in Thai manufacturing sector slowdown by -0.330 (in log points), partly from the adverse flood effects, of which -0.405 is contributed by surviving firms, 0.066 is added by entering firms, and 0.009 comes from exiting firms.

Interestingly, entering and exiting firms contribute to TFP growth in manufacturing sector greater than surviving firms in a broad picture. The contribution of survival firms to TFP growth is negative, while the contribution of entering and exiting firms is positive. This deterioration of survival firm productivity arises due mainly to lower within-firm productivity (-0.495), which reinforces positive contribution of the within-industry covariance between market size and productivity. This fact indicates that a decline in survival firm productivity occurs along with a declined market share.

Meanwhile, entering firms have higher productivity growth than incumbents. Bartelsman et al (2013) point out that in the countries where market entry barriers are high, entering firms tend to have high productivity growth than incumbents causing a positive contribution to aggregate productivity. Unlike Germany and the US, where market entry barriers are low[16], entering firms are more likely to have lower productivity growth hence contribute negatively to aggregate productivity. By contrast, the barrier to entry is still high. The ease of starting a business index by World Bank reports at the rank of 78 among 190 economies that could support gains from the entry. Moreover, we also found positive contribution of exiting firms in aggregate productivity as expected since the exits are often least productive firms. This finding is very well along with that of most countries.

[16] such as low administrative and business start-up costs and favorable business environment

Table 7: TFP growth decomposition in manufacturing sector, from 2006 to 2011

By industry (classified by 2-digit ISIC, Rev3)	**Survival**			**Entry**	**Exit**	**Total change in TFP**	**Effect of Market Share reallocation**
	Change in weighted productivity	Change in unweighted productivity	Change in covariance	Weighted productivity difference Entry vs Survival	Weighted productivity difference Survival vs Exit		
	(1)=(1.1)+(1.2)	(1.1)	(1.2)	(2)	(3)	(4)=(1)+(2)+(3)	(5)=(1.2)+(2)+(3)
Manufacturing	-0.405	-0.495	0.089	0.066	0.009	-0.330	0.165
15_F&B	-0.323	-0.585	0.262	-0.003	-0.048	-0.374	0.211
16_Tobacco	-0.154	-0.430	0.276	0.626	0.100	0.571	1.001
17_Textiles	-0.499	-0.649	0.150	-0.064	0.070	-0.492	0.157
18_Apparel	-0.458	-0.322	-0.136	0.075	0.011	-0.372	-0.050
19_Leather	-0.796	-0.426	-0.369	-0.143	0.129	-0.810	-0.384
20_Wood	-0.294	-0.665	0.370	0.173	0.033	-0.089	0.576
21_Paper	-0.247	-0.466	0.219	-0.009	-0.079	-0.336	0.130
22_Printing	-0.282	-0.439	0.157	-0.127	0.191	-0.218	0.221
23_Petroleum	-0.702	-0.935	0.233	-0.362	0.523	-0.541	0.394
24_Chemical	-0.044	-0.517	0.472	-0.079	-0.056	-0.179	0.337
25_Rubber & Plastic	0.167	-0.424	0.591	-0.315	-0.232	-0.379	0.045
26_Non-metal	-0.122	-0.305	0.183	-0.293	0.065	-0.350	-0.045
27_Basic metal	-1.081	-0.522	-0.558	0.510	0.162	-0.409	0.114
28_Fabricated metal	-0.426	-0.361	-0.065	-0.151	0.112	-0.464	-0.103
29_Machine & equip	-0.435	-0.359	-0.076	-0.038	-0.092	-0.565	-0.207
30_Computing machinery	-1.242	-0.655	-0.587	0.744	0.968	0.470	1.125
31_Electrical machinery	-0.182	-0.502	0.320	-0.037	0.163	-0.057	0.446
32_TV & Comm. equip	0.057	-0.325	0.381	0.192	-0.037	0.212	0.537
33_Medical equip	-0.705	-0.664	-0.041	0.035	-0.533	-1.203	-0.539
34_Motor vehicles	-1.382	-0.283	-1.098	0.311	-0.031	-1.101	-0.818
35_Oth. transport. equip	-0.232	-0.371	0.140	-0.365	-0.342	-0.938	-0.567
36_Furniture	-0.201	-0.468	0.267	-0.137	-0.004	-0.342	0.126
37_Recycling	0.485	-0.481	0.966	0.777	-0.098	1.164	1.645

Source: Authors' calculation

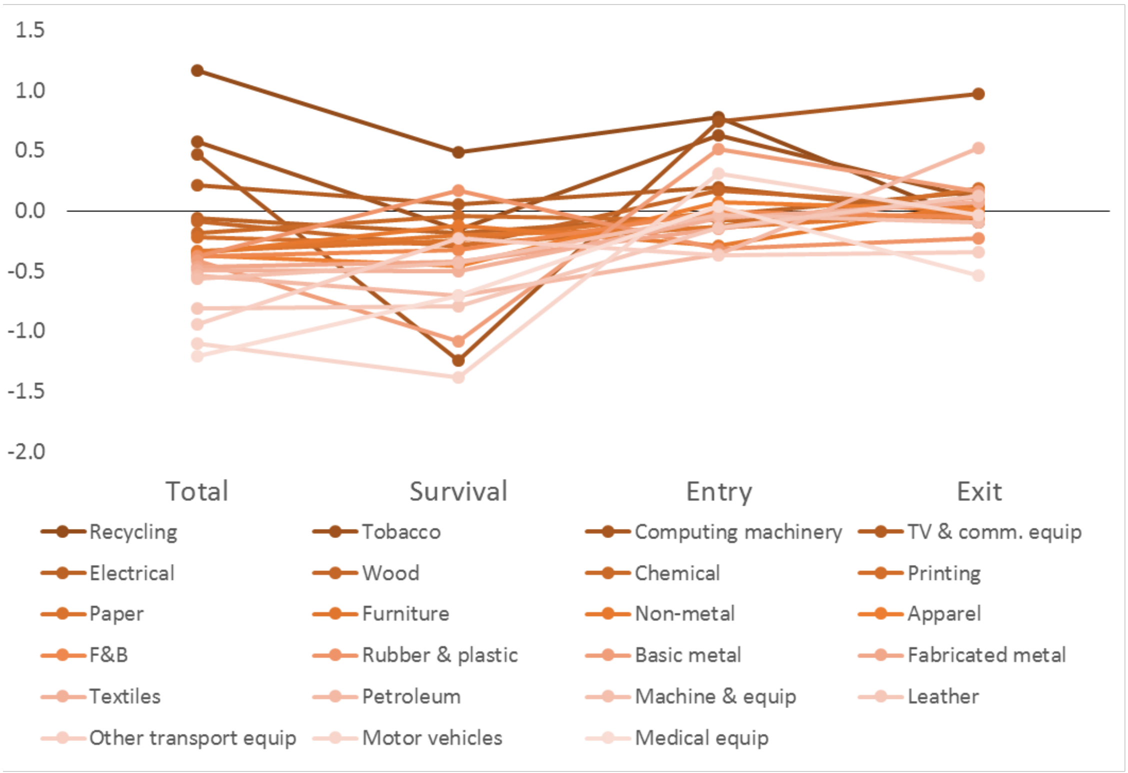
(2) Productivity decomposition in manufacturing sector (industry level)

Looking at its components breaking down by 2-digit ISIC classification, there is a remarkable dispersion in aggregate TFP growth across industries. Figure 26 indicates that almost all industries experienced TFP slowdown except some industries such as recycling, tobacco, office equipment, and communication equipment. Main source of industry productivity slowdown comes from within productivity of survival plants. To get more insight, we highlight only the decomposition components of the top-four industries with increased productivity growth as mentioned altogether with the bottom-four industries with negative productivity growth (namely, medical, other transport equipment, motor vehicle, and leather) as shown in Figure 27. Among the top-four industries, recycling mostly gains contribution from market share expansion among survival plants as well as among the survival and the entry. Meanwhile, the bottom-four industries realize net negative contribution mostly from lower within-productivity survival plants.

(3) Market share reallocation

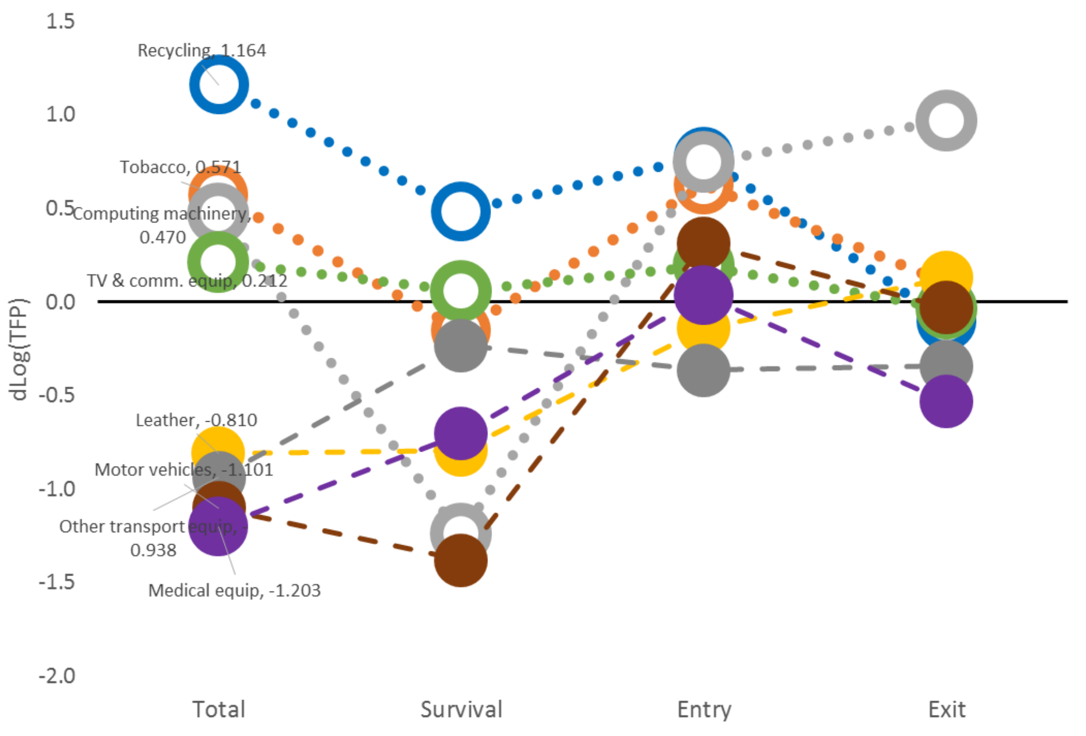
The last three terms of the DOPD decomposition can be summed up to obtain the total effect of market share reallocation among survival, entry, and exit groups. Since the covariance is a cross term between the change in productivity and the change in market shares, a positive sign occurs only when both changes move in the same direction. Positive sign implies market share expansion of this particular group within industry since the firm market share adjusts accordingly to the change in firm productivity. The sum of the last three terms is calculated in the last column of Table 9 showing that its average effect on manufacturing productivity growth is 0.165, contributing about a quarter of aggregate productivity change. Obviously, market share reallocation is widely different across industries as shown in Figure 28. Negative contribution to manufacturing productivity slowdown mostly arises from those firms in the manufacture of motor vehicle, other transportation equipment, medical equipment, and leather.

Figure 26 – TFP growth decomposition in manufacturing sector, from 2006 to 2011 (all industries)



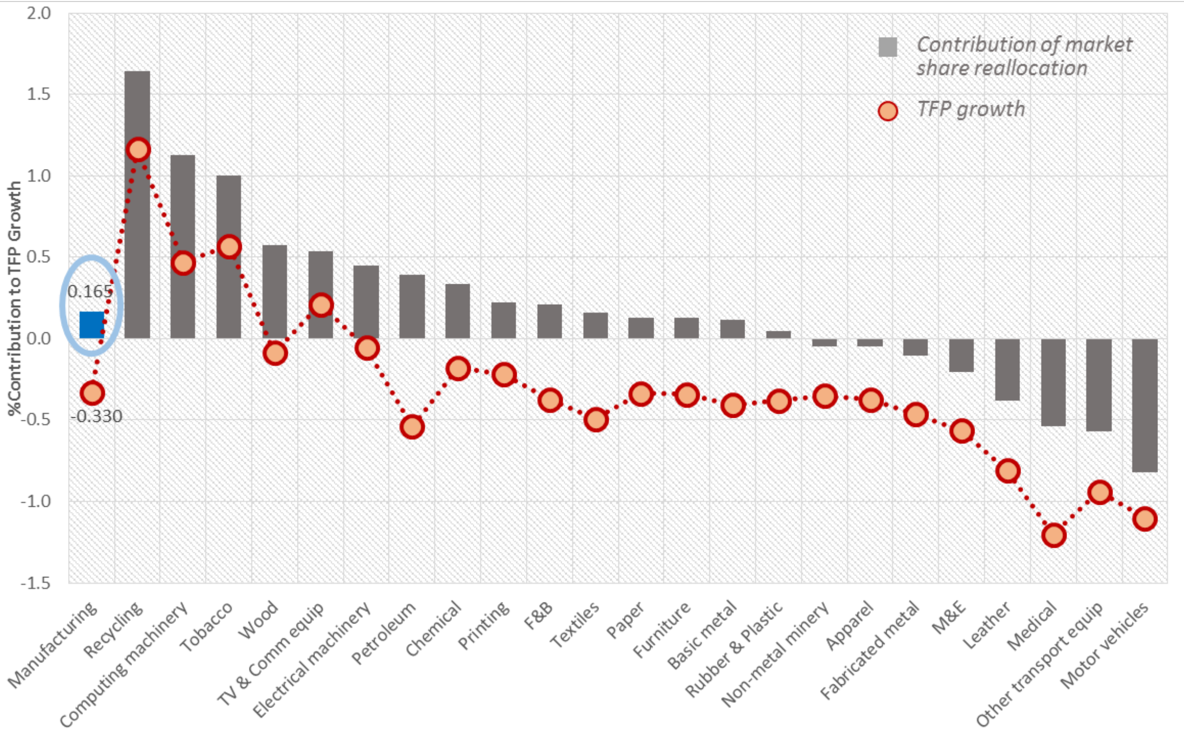
The study of TFP decomposition in this section highlights the role of firm dynamics across manufacturing sector in Thailand in 2011 compared to 2006. A quarter of aggregate productivity change positively contributed by market share reallocation among the survivals, the entrants, and the exits. The better allocation among firms' market shares can be seen in many industries, especially Recycling, Office equipment, and Tobacco which mostly contributed by the new entrants. However, the positive effect of firm dynamics still cannot overpower a negative contribution from within-survival firm productivity causing productivity slowdown in both aggregate and disaggregate levels.

Figure 27 – TFP growth decomposition in manufacturing sector, from 2006 to 2011 (top-four & bottom-four industries)



Source: National Statistiacl Office, calculated by authors

Figure 28 – Contribution of market share reallocation to TFP growth in manufacturing sector, from 2006 to 2011 (all industries)



Source: NSO, authors' calculation

5. Conclusion

In this paper, we try to understand the source of the productivity slowdown in Thailand in the past decade. Recent literature in development economics suggests that resource misallocation could explain most of the difference in productivity levels between developed and developing economies. Therefore, we use the plant-level data to estimate the allocative efficiency and to identify the source of misallocation problem in the Thai manufacturing sector.

The results suggest that, not only the allocative efficiency in the Thai manufacturing sector is low in comparison to the level in the United States, but it also went down in recent years. If Thailand can raise the efficiency level to the level of the U.S., its aggregate productivity level will increase up to 75–130%. This finding is consistent with previous studies that find low allocative efficiencies in other developing economies. However, the sources of resource misallocation vary by country.

At the plant level, we find that there exist the correlated distortions in the Thai manufacturing sector. That is, the more productive plants face higher distortion level than the less productive ones. We show that the size-dependent policies could be one source of the correlated distortions. Small plants behave as if they face lower costs than medium and large plants. The discontinuities around the cut-off level of employment emerge when we look at various indicators. Consistent with the recent literature, we find that the correlated distortions not only cause the resource misallocation across plants at any given period, but could also lower the productivity over time by reducing plants' incentive to invest in physical capital and in R&D activities.

At the industry level, we find that the allocative efficiency increases with the degree of domestic concentration. This finding is consistent with previous studies which suggest that, in concentrated market, inefficient firms are less likely to survive. Therefore, firms have more incentive to improve their efficiency level. In addition, the result suggests that the fraction of plants with FDI increases the allocative efficiency, which, in turn, drives the resource reallocation toward the more productive plants. Lastly, we find that the degree of financial deepening increases the allocative efficiency. In the sector with lower financial frictions, high-productivity firms have better access to credit and low leverage can optimally expand their production.

Moreover, we also find that firm dynamics play a significant role. After the manufacturing sector was hit by earlier crises causing aggregate productivity slowdown in general, a vast number of industries experienced positive contribution from market share reallocation among the survival, entry, and exit towards more productive plants within industry. This mechanism could partially offset a large, negative impact arising from within-survival firm productivity on aggregate productivity slowdown.

Amidst the position of Thailand's development constraints to accelerate economic transformation, our study calls for policy direction to promote allocative efficiency in Thai manufacturing sector. Most importantly, the size-dependent policy should be reduced. Instead of retaining zombie firms to survive, the policy should be designed to enhance firm productivity from within and promote knowledge spillover from R&D and innovation that can reduce increasing gap between frontier and laggard within industry. The force of creative destruction can be reinforced by accelerating institutional market reform and enhancing competition policy to reduce the cost of entry and exit barrier.

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Annex A:

Ordinary Least Square (OLS) estimation results on TFP's determinants

Table A1 – Manufacturing sector

log TFP	All Sample		Employment: <= 50		Employment: 51 - 200		Employment: > 200	
	2006	2011	2006	2011	2006	2011	2006	2011
log Age	-0.0896***	-0.0585***	-0.0903***	-0.0611***	0.0193	0.1291***	0.005	0.0374
D_BOI	-0.0731	-0.0923*	0.0735	-0.0002	-0.0688	-0.0436	-0.1467***	0.0073
D_Listed	0.3551***	0.6393***	0.3548***	0.6056***	0.2511***	0.5758***	0.2518*	0.4753**
log Month (operated)	0.6798***	0.4627***	0.6797***	0.4652***	-0.3629**	0.0875	0.2027	-0.1193
log Office Hour	0.4802***	0.234***	0.4884***	0.2401***	-0.1429***	-0.0439	-0.017	-0.0896
Foreign Ownership	-0.0002	0.0006	0.0045	0.004**	-0.0005	0.0011	-0.0013**	-0.001
Sales' Export Share	0.0017	0.0004	0.0032	0.0001	0.0015**	0.0007	0.0004	0.0013*
Materials' Import Share	0.0011	0.0036***	0.0018*	0.0046***	0.0004	0.0017*	0.0002	0.0003
Capital Utilization	0.0026***	0.0039***	0.0026**	0.0039***	0.0051***	0.001	0.0049***	0.0041***
Ratio of Skilled Labor	0.0096***	0.004***	0.0099***	0.0041***	-0.0001	-0.0012**	0.0006	-0.0014**
D_R&D	0.0017	0.3551***	0.0187	0.4459***	0.0218	0.1348**	0.0248	0.3365***
Ratio of R&D Expenses	0.1052***	-0.0574***	0.1063**	-0.0629***	0.1192**	-0.0293	0.0198	-0.091**
Ratio of Production Expenses	-0.0092***	-0.0081***	-0.0091***	-0.0081***	-0.0049***	-0.004***	-0.0087***	-0.0066***
Ratio of Sales Expenses	-0.0056	0.0006	-0.0058	0.0009	-0.0118***	-0.0044	0.005*	-0.0147**
Ratio of Operation Expenses	-0.0055***	-0.0086***	-0.0055***	-0.0085***	-0.0103***	-0.0153***	-0.0122*-**	-0.0185***
Ratio of Contract Expenses	0.0073	0.0116***	0.0072	0.0115***	0.0051	0.016***	0.0051*	0.0092
Ratio of Contract Receipts	0.0051***	0.0056***	0.0051***	0.0056***	0.0057***	0.0068**	-0.0071**	0.0085
Ratio of Software Capital	0.0083***	0.0023	0.0103***	0.0033	0.0042*	0.0041	0.0013	-0.0037
Employment <=10	-0.6042***	-0.1631***	-0.5699***	-0.1402***				
Employment >=200	-0.0976**	0.0654*						
R^2	0.6119	0.6116	0.6099	0.6120	0.4889	0.0579	0.6236	0.5102
# Observations	62,104	71,163	54,127	63,410	5,410	5,114	2,567	2,639
Population Size	416,249	380,832	408,272	371,945	5,410	5,981	2,567	2,906

Note: ***, ** and * denote significance at 1%, 5% and 10% level, respectively.
Constant and 4-digit ISIC dummy variables are included in regression.

Table A2.1 – Trade sector (All Sample)

log TFP	All Sample					
	2003	2005	2007	2009	2011	2013
log Age	-0.0491	-0.0332	-0.0355	-0.1168	-0.0896***	-0.0876
D_Listed	0.7421***	0.8679***	0.898***	1.0348***	0.8158***	0.9409***
Single Branch	-0.6639***	-0.9777***	-0.9809***	-0.5787	-0.8992***	-0.9303***
log Month (operated)	0.3882	1.013**	0.4364**	-0.509	0.5155***	0.3078*
log Office Hour					0.4011***	0.371
Foreign Ownership					0.0073***	0.0025
Foreign Ownership >10%	-0.0459					
Foreign Ownership 10-50%		0.6807	0.3568	4.946***		
Foreign Ownership >50%		0.3853	0.8748*	3.0308***		
Sales' e-Commerce Share	0.0259***	0.0579**	-0.0037**	0.0018	0.0002	-0.0035
Ratio of Management Worker					0.0129***	0.0166***
Ratio of Technological Expenses	-0.0378	-0.0247	-0.0528	-0.0711*	-0.0375***	-0.0382
Ratio of Production Expenses	-0.0071*	0.0001	0.0072**	-0.0059	0.0082***	0.0036*
Ratio of Other Receipts	0.0215	-0.0238*	-0.0089	-0.0297**	-0.0281***	-0.0126*
Ratio of Software Capital	0.0055	0.0341***	0.0526*	0.034***	0.0158***	0.0207***
Employment <=10	-0.2463*	0.0187	-0.4171*	-0.2797	-0.2792***	-0.2708**
Employment >=200	-0.8805***	-1.2396***	-1.4841***	-1.7803***	-0.9373***	-0.5971***
R^2	0.1518	0.2161	0.3439	0.1927	0.3542	0.3654
# Observations	6,786	4,944	3,637	5,472	86,958	14,309
Population Size	748,478	768,790	992,082	990,065	994,887	1,022,909

Note: ***, ** and * denote significance at 1%, 5% and 10% level, respectively.
Constant and 4-digit ISIC dummy variables are included in regression.

Table A2.1.1 – Trade sector (Employment: <= 50)

log TFP	Employment: <= 50					
	2003	2005	2007	2009	2011	2013
log Age	-0.0488	-0.032	-0.0356	-0.1148	-0.0888***	-0.0863
D_Listed	0.7459***	0.8654***	0.8934***	1.0484***	0.8221***	0.9438***
Single Branch	-0.6907***	-1.0122***	-1.0441***	-0.7015*	-0.9273***	-0.9733***
log Month (operated)	0.3882	1.0138**	0.4364**	-0.5116	0.5162***	0.309*
log Office Hour					0.3995***	0.3681
Foreign Ownership					0.0083***	0.0029
Foreign Ownership >10%	-0.0482					
Foreign Ownership 10-50%		0.7496	0.4718	5.3452***		
Foreign Ownership >50%		0.4198	0.9935*	3.3025***		
Sales' e-Commerce Share	0.0258***	0.0579**	-0.0037**	0.0013	0.0003	-0.0035
Ratio of Management Worker					0.0128***	0.0165***
Ratio of Technological Expenses	-0.039	-0.0261	-0.0558	-0.0716*	-0.0378***	-0.039
Ratio of Production Expenses	-0.0071*	0.0001	0.0072**	-0.0059	0.0081***	0.0036*
Ratio of Other Receipts	0.0215	-0.0245*	-0.0089	-0.0293**	-0.028***	-0.0124*
Ratio of Software Capital	0.0058	0.0344***	0.0618*	0.036***	0.0164***	0.0209***
Employment <=10	-0.2662*	-0.0248	-0.4097*	-0.3012	-0.3068***	-0.2942***
Employment >=200						
R^2	0.1511	0.2154	0.3439	0.1930	0.3528	0.3637
# Observations	6,026	4,110	3,014	4,862	84,852	13,154
Population Size	746,854	766,694	988,843	987,169	991,962	1,019,986

Note: ***, ** and * denote significance at 1%, 5% and 10% level, respectively.
Constant and 4-digit ISIC dummy variables are included in regression.

Table A2.1.2 – Trade sector (Employment: 51 - 200)

log TFP	Employment: 51 - 200					
	2003	2005	2007	2009	2011	2013
log Age	-0.0084	-0.0682	0.0617	0.0451	-0.0163	-0.1796*
D_Listed	0.2058	-0.1735	0.0915	0.2987	0.0449	0.0852
Single Branch	-0.0437	-0.2414**	0.2957*	-0.1317	-0.1662**	0.0676
log Month (operated)	0.159	0.6451***	0.2915	0.4845**	-0.0584	-0.1332
log Office Hour					-0.2168	0.2501
Foreign Ownership					0.0063***	0.0047
Foreign Ownership >10%	0.4304					
Foreign Ownership 10-50%		0.1888	0.4667	0.2327		
Foreign Ownership >50%		0.8449***	0.7344	1.1764**		
Sales' e-Commerce Share	-0.4494***	0.0148***	-0.0309**	-0.0503	0.0036**	0.0092*
Ratio of Management Worker					-0.0003	0.0012
Ratio of Technological Expenses	0.1933	-0.0333	0.0721	0.0733	0.1532	0.1749
Ratio of Production Expenses	0.0032	0.004	0.0121***	0.0079*	0.0128***	0.0069***
Ratio of Other Receipts	-0.0252	-0.0339	0.0071	-0.0864	-0.0477***	-0.0473***
Ratio of Software Capital	-0.0015	-0.0005	-0.0019	-0.0059	0.0041*	0.0007
Employment <=10						
Employment >=200						
R^2	0.3895	0.5022	0.5228	0.4767	0.4164	0.3842
# Observations	670	698	503	495	1,799	935
Population Size	1,401	1,779	2,827	2,508	2,498	2,523

Note: ***, ** and * denote significance at 1%, 5% and 10% level, respectively.
Constant and 4-digit ISIC dummy variables are included in regression.

Table A2.1.3 – Trade sector (Employment: > 200)

log TFP	Employment: > 200					
	2003	2005	2007	2009	2011	2013
log Age	0.0829	-0.326	0.0777	0.0321	0.0788	-0.4171***
D_Listed	0.1438	0.0695	0.4911	1.4113*	-0.6076	1.2337***
Single Branch	0.5485	-0.222	0.4655	0.2136	0.1327	-0.2098
log Month (operated)	0.8897	1.5629**	-0.7633	-0.0033	0.2	5.1352
log Office Hour					-0.3192	-0.6014
Foreign Ownership					0.0009	0.0174***
Foreign Ownership >10%	-0.4775					
Foreign Ownership 10-50%		0.2759	0.4725	1.2819*		
Foreign Ownership >50%		0.8681*	0.6264	0.6534		
Sales' e-Commerce Share			-0.0026	0.4714**	-0.0614	-0.1537
Ratio of Management Worker					0.0065	-0.0076
Ratio of Technological Expenses	-1.2611	0.0985	-0.3699	-0.388	0.0777	0.3142
Ratio of Production Expenses	0.0012	-0.0023	-0.0028	0.0199**	-0.0004	0.0207***
Ratio of Other Receipts	0.2062	-0.0293***	-0.0264	-0.2726	-0.0295	-0.0191***
Ratio of Software Capital	-0.0076	0.0044	-0.0089	-0.0155	-0.0067*	-0.0057
Employment <=10						
Employment >=200						
R^2	0.5448	0.4224	0.7241	0.6026	0.5149	0.6183
# Observations	90	136	120	115	307	220
Population Size	223	317	412	388	427	400

Note: ***, ** and * denote significance at 1%, 5% and 10% level, respectively.
Constant and 4-digit ISIC dummy variables are included in regression.

Table A2.2 – Hotel & Restaurant sector (All Sample)

log TFP	All Sample					
	2003	2005	2007	2009	2011	2013
log Age	-0.2764	-0.1248	-0.2247	-0.1322	-0.0646**	-0.244*
D_Listed	1.0638**	0.3632	0.8516***	0.4873	0.3726***	-0.0416
Single Branch	0.1815	-0.6007*	-0.2885	0.0429	-0.8403***	-0.9534**
log Month (operated)	1.5565***	-1.9004	0.6706**	-0.3248	0.5741***	-0.0422
log Office Hour					0.1726**	1.0252***
Foreign Ownership					0.0027	0.0043
Foreign Ownership >10%	-0.6859*					
Foreign Ownership 10-50%		1.1337**	1.1643***	0.0479		
Foreign Ownership >50%		2.3542**	-0.3826	0.2948		
Sales' e-Commerce Share	0.0144	0.0002	0.032***	-0.0637**	0.0074***	0.0049
Ratio of Management Worker					0.0058***	0.0287***
Ratio of Technological Expenses	-0.136	-0.0695	0.0769**	-0.0201	-0.062***	-0.0765*
Ratio of Production Expenses	-0.0106	0.0148	0.0028	0.003	0.0027**	-0.0047
Ratio of Other Receipts	-0.0474	0.0022	-0.0752**	0.0172**	-0.0014	0.0687
Ratio of Software Capital	0.0164	0.0228	0.0237***	-0.0134	0.0159***	0.0099
Employment <=10	-0.0992	-0.1371	-0.5412***	-0.6867*	-0.4543***	-0.9388***
Employment >=200	-0.2582	-0.3619	-0.4064	-0.3115	-0.6292***	-0.6239**
R^2	0.0936	0.0601	0.1117	0.1317	0.1731	0.2181
# Observations	927	775	1,023	643	12,016	1,259
Population Size	171,487	158,339	247,266	246,196	250,355	257,741

Note: ***, ** and * denote significance at 1%, 5% and 10% level, respectively.
Constant and 4-digit ISIC dummy variables are included in regression.

Table A2.2.1 – Hotel & Restaurant sector (Employment: <= 50)

log TFP	Employment: <= 50					
	2003	2005	2007	2009	2011	2013
log Age	-0.2788	-0.1229	-0.2248	-0.1308	-0.0646**	-0.2465*
D_Listed	1.1418**	0.4763	0.8943***	0.5838	0.3817***	-0.0959
Single Branch	0.2038	-0.6368*	-0.4047	-0.389	-0.8613***	-1.1118**
log Month (operated)	1.559***	-1.9079	0.6733**	-0.3273	0.5756***	-0.0443
log Office Hour					0.1729**	1.0411***
Foreign Ownership					0.0024	0.0117**
Foreign Ownership >10%	-0.6851*					
Foreign Ownership 10-50%		1.192**	1.1324***	-0.7193*		
Foreign Ownership >50%		3.0351**	-1.6857**	-0.0603		
Sales' e-Commerce Share	0.0313*	-0.0001	0.0338***	-0.0668**	0.0076**	0.005
Ratio of Management Worker					0.0057***	0.0283***
Ratio of Technological Expenses	-0.1401	-0.0754	0.0796**	-0.02	-0.0637***	-0.0772*
Ratio of Production Expenses	-0.0106	0.0152	0.0028	0.003	0.0027**	-0.0047
Ratio of Other Receipts	-0.0482	0.0021	-0.0804***	0.0181***	-0.0012	0.1124
Ratio of Software Capital	0.0188	0.0253*	0.0247***	-0.0115	0.0168***	0.0102
Employment <=10	-0.097	-0.1593	-0.5371***	-0.6776*	-0.4565***	-0.9593***
Employment >=200						
R^2	0.0930	0.0595	0.1074	0.1307	0.1636	0.2087
# Observations	745	631	829	546	11,245	1,096
Population Size	170,777	157,517	246,103	245,108	248,999	256,435

Note: ***, ** and * denote significance at 1%, 5% and 10% level, respectively.
Constant and 4-digit ISIC dummy variables are included in regression.

Table A2.2.2 – Hotel & Restaurant sector (Employment: 51 - 200)

log TFP	Employment: 51 - 200					
	2003	2005	2007	2009	2011	2013
log Age	0.2668*	-0.3805	-0.1085	0.0981	0.0122	-0.0595
D_Listed	-0.4201	-0.5616	0.0435	-0.4178	0.1291	0.2356
Single Branch	-0.2532	-0.0884	-0.0012	0.553	-0.2599**	-0.1946
log Month (operated)	0.6268*	0.9591	-0.0777	0.746***	-0.7879	1.162***
log Office Hour					0.0056	0.0687
Foreign Ownership					0.0042	0.0021
Foreign Ownership >10%	-0.4289					
Foreign Ownership 10-50%		0.5569	0.896	1.618**		
Foreign Ownership >50%		2.452***	1.9278***			
Sales' e-Commerce Share	0.0054	0.0099*	0.0127	0.0114	0.0074	-0.0017
Ratio of Management Worker					-0.0063*	-0.0007
Ratio of Technological Expenses	0.0684	0.1006	-0.0297	-0.0659	0.0954*	-0.0261
Ratio of Production Expenses	-0.0016	-0.0085	0.0094	0.0143**	0.0033*	-0.0036
Ratio of Other Receipts	-0.012	0.0079	-0.0045	-0.0637***	-0.0135	0.0015
Ratio of Software Capital	0.0089*	-0.0146	0.0035	0.0074	-0.0003	0.0004
Employment <=10						
Employment >=200						
R^2	0.3751	0.2221	0.2429	0.5808	0.3512	0.5239
# Observations	138	112	147	64	678	98
Population Size	627	739	1,002	976	1,168	1,131

Note: ***, ** and * denote significance at 1%, 5% and 10% level, respectively.
Constant and 4-digit ISIC dummy variables are included in regression.

Table A2.2.3 – Hotel & Restaurant sector (Employment: > 200)

log TFP	Employment: > 200					
	2003	2005	2007	2009	2011	2013
log Age	-0.1901	-0.2552	-0.4762	-0.1777	-0.1873	0.056
D_Listed	0***	0.729	1.6366	1.4313	0.1582	0.501
Single Branch	0.0051	-1.0401*	-0.2858	0.2947	-0.276	0.3624*
log Month (operated)		-4.1339	0.5167	0.1789	-8.77**	
log Office Hour					0.1162	0.0444
Foreign Ownership					0.0085	-0.0012
Foreign Ownership >10%						
Foreign Ownership 10-50%		-1.3755**	-0.578	0.5969		
Foreign Ownership >50%		-0.4119	0.2039	2.032***		
Sales' e-Commerce Share	0.0522		0.003	-0.069	-0.0092	-0.0061
Ratio of Management Worker					0.0023	0.0247
Ratio of Technological Expenses	0.4149*	0.3624*	0.0657	-0.0374	0.163*	-0.0191
Ratio of Production Expenses	0.001	-0.0268	-0.0041	0.0112	0.0078**	0.0065*
Ratio of Other Receipts	0.0495	-0.0384	0.0142	-0.0039	0.0058	-0.0103
Ratio of Software Capital	-0.0101	-0.0438	-0.0383*	0.023	-0.0046**	0.0007
Employment <=10						
Employment >=200						
R^2	0.1472	0.4836	0.3949	0.3947	0.3988	0.6342
# Observations	44	32	47	33	93	65
Population Size	84	84	161	113	188	175

Note: ***, ** and * denote significance at 1%, 5% and 10% level, respectively.
Constant and 4-digit ISIC dummy variables are included in regression.

Table A2.3 – Real Estate sector (All Sample)

log TFP	All Sample					
	2003	2005	2007	2009	2011	2013
log Age	0.052	-0.1426	-0.1524*	0.1669	0.0743**	-0.1256
D_Listed	0.4338	1.519***	1.3692***	0.1667	0.8543***	0.3836
Single Branch	-0.4087	-0.4006	-0.5217	-1.285**	0.1715	-0.9764
log Month (operated)	0.5246*	-1.5699***	0.6296***	-0.0861	0.459***	0.0773
log Office Hour					-0.0253	-0.0241
Foreign Ownership					0.0068**	0.0106
Foreign Ownership >10%	0.4812**					
Foreign Ownership 10-50%		2.9842***	0.1175	-0.0892		
Foreign Ownership >50%		1.033***	0.3082	0.569		
Sales' e-Commerce Share	0.0124	0.0436***	-0.0084	0.0189***	0.0057	-0.0057
Ratio of Management Worker					0.007***	0.0353**
Ratio of Technological Expenses	-0.0234**	-0.0096	0.0006	0.0104	-0.0102***	-0.005
Ratio of Production Expenses	0.0044	0.0012	-0.001	0.0008	0.0017	0
Ratio of Other Receipts	-0.0061	-0.0082**	-0.008	-0.0098*	-0.0025	0.0024
Ratio of Software Capital	0.0373*	0.0029	0.0123***	0.0087**	0.0068**	0.0178***
Employment <=10	-0.3742*	0.0436	-0.0605	-0.6149**	-0.9325***	-0.7148***
Employment >=200	-0.0919	-0.6405**	-0.0361	-0.3228	-0.3896**	-0.2321
R^2	0.6774	0.7166	0.5242	0.5010	0.7022	0.7303
# Observations	2,347	1,558	2,079	2,231	18,422	3,250
Population Size	87,070	87,839	141,895	131,463	155,650	157,202

Note: ***, ** and * denote significance at 1%, 5% and 10% level, respectively.
Constant and 4-digit ISIC dummy variables are included in regression.

Table A2.3.1 – Real Estate sector (Employment: <= 50)

log TFP	Employment: <= 50					
	2003	2005	2007	2009	2011	2013
log Age	0.0533	-0.1404	-0.154*	0.1699	0.0756**	-0.1266
D_Listed	0.4222	1.5131***	1.3778***	0.1428	0.8596***	0.3651
Single Branch	-0.4541	-0.4175	-0.532	-1.3993**	0.1641	-1.0589
log Month (operated)	0.5267*	-1.5818***	0.6313***	-0.0887	0.4596***	0.0758
log Office Hour					-0.0247	-0.0256
Foreign Ownership					0.0082**	0.0129
Foreign Ownership >10%	0.4814**					
Foreign Ownership 10-50%		3.2029***	0.0655	-0.0346		
Foreign Ownership >50%		1.2529***	0.3083	0.6926		
Sales' e-Commerce Share	0.0119	0.0434***	-0.0084	0.019***	0.0053	-0.0057
Ratio of Management Worker					0.0069***	0.0356**
Ratio of Technological Expenses	-0.0235**	-0.0096	0.0007	0.0105	-0.0101***	-0.005
Ratio of Production Expenses	0.0046	0.0013	-0.001	0.0007	0.0017	0.0001
Ratio of Other Receipts	-0.006	-0.0081**	-0.008	-0.0094*	-0.0024	0.0025
Ratio of Software Capital	0.0378*	0.0035	0.0124***	0.0086**	0.0074**	0.0178***
Employment <=10	-0.3671*	0.0432	-0.0569	-0.6054**	-0.9632***	-0.6835***
Employment >=200						
R^2	0.6667	0.7112	0.5113	0.4864	0.6912	0.7235
# Observations	2,003	1,290	1,760	1,962	17,739	2,905
Population Size	86,302	87,148	140,793	130,435	154,603	156,277

Note: ***, ** and * denote significance at 1%, 5% and 10% level, respectively.
Constant and 4-digit ISIC dummy variables are included in regression.

Table A2.3.2 – Real Estate sector (Employment: 51 - 200)

log TFP	Employment: 51 - 200					
	2003	2005	2007	2009	2011	2013
log Age	-0.1205	0.0631	0.0054	0.1915	-0.0472	-0.0848
D_Listed	0.0689	0.2985	0.29	0.2524	0.1324	-1.0073
Single Branch	0.0478	-0.3288	0.0419	0.1089	0.1859	0.5942**
log Month (operated)	0.1163	1.286	-0.3407	0.4253	0.2217	0.57
log Office Hour					-0.0901	0.35
Foreign Ownership					0.0056*	0.0012
Foreign Ownership >10%	-0.4181					
Foreign Ownership 10-50%		0.5803	0.2647	-0.0229		
Foreign Ownership >50%		0.215	0.5948	1.0323**		
Sales' e-Commerce Share			-0.0354***		0.032***	0.0005
Ratio of Management Worker					0.0018	-0.0001
Ratio of Technological Expenses	-0.0047	0.0327	-0.0319	0.0134	-0.0069	-0.046
Ratio of Production Expenses	0.0009	-0.0084**	0.0013	0.0048	0.0009	0.0023
Ratio of Other Receipts	-0.0307*	-0.0567**	0.0259**	-0.0163	-0.0079	-0.0133
Ratio of Software Capital	0.0072	-0.0109	0.0038	0.0193**	-0.0003	0.0107
Employment <=10						
Employment >=200						
R^2	0.8701	0.8230	0.9155	0.9006	0.9129	0.8449
# Observations	251	204	219	179	515	246
Population Size	598	555	852	800	812	741

Note: ***, ** and * denote significance at 1%, 5% and 10% level, respectively.
Constant and 4-digit ISIC dummy variables are included in regression.

Table A2.3.3 – Real Estate sector (Employment: > 200)

log TFP	Employment: > 200					
	2003	2005	2007	2009	2011	2013
log Age	0.0805	-0.1486	-0.1888	0.0844	0.105	0.0448
D_Listed	-0.3345	0.58*	0.9815***	0.1482	0.4547*	0.2638
Single Branch	0.119	-0.0426	-0.082	0.1124	0.0728	0.2245
log Month (operated)	-0.551	0.2447	0.9542**	0.6468	0.2488	1.0137
log Office Hour					0.3089*	-0.0452
Foreign Ownership					0.0074	0.0109
Foreign Ownership >10%	-0.4418					
Foreign Ownership 10-50%		-0.9	0.3918	0.1688		
Foreign Ownership >50%		-0.3573	0.0468	0.1903		
Sales' e-Commerce Share					0.005**	-0.0059
Ratio of Management Worker					-0.0076	-0.0225
Ratio of Technological Expenses	-0.0216	0.0203	-0.0721	-0.0003	-0.0197	-0.0258*
Ratio of Production Expenses	-0.0038	-0.0003	0.0014	-0.002	-0.002	-0.0041
Ratio of Other Receipts	0.0014	-0.0109	-0.0978	-0.1045**	-0.0146**	-0.1076***
Ratio of Software Capital	0.003	0.0291*	0.0036	0.0009	-0.0108	0.0126
Employment <=10						
Employment >=200						
R^2	0.8937	0.9429	0.9328	0.9486	0.9518	0.9559
# Observations	93	64	100	90	168	99
Population Size	169	136	250	227	235	183

Note: ***, ** and * denote significance at 1%, 5% and 10% level, respectively.
Constant and 4-digit ISIC dummy variables are included in regression.

Table A2.4 – Other Services sector (All Sample)

log TFP	All Sample					
	2003	2005	2007	2009	2011	2013
log Age	-0.2987*	-0.3126	-0.2934**	-0.4415**	-0.1372***	-0.003
D_Listed	1.0193**	-0.1575	0.4169	0.8095*	0.6898***	0.9141**
Single Branch	-0.3051	-1.2583	-0.7972*	-3.5555**	-0.2901	-2.6201*
log Month (operated)	1.0261***	0.5015	0.6438**	0.0285	0.5684***	0.9072***
log Office Hour					0.812***	1.0926***
Foreign Ownership					0.0225***	0.0352***
Foreign Ownership >10%	0.8118*					
Foreign Ownership 10-50%		0.6309	0.5136	-2.0856		
Foreign Ownership >50%		-0.9154	-0.2774	-1.7498		
Sales' e-Commerce Share	-0.0136***	-1.0648	0.001	-0.1402*	-0.003	0.0186***
Ratio of Management Worker					0.0165***	0.0134**
Ratio of Technological Expenses	-0.0297**	-0.0177	-0.0347***	-0.0378***	-0.031***	-0.0393***
Ratio of Production Expenses	-0.0091*	-0.014**	-0.0129***	-0.0068	-0.0062***	-0.0107***
Ratio of Other Receipts	-0.0053	-0.0502*	0.0039	-0.0262	-0.0108*	-0.0041
Ratio of Software Capital	0.0232***	0.076	0.0098***	0.0247***	0.0112***	-0.0004
Employment <=10	-0.0712	-0.2882	-0.5126**	-0.3127	-0.9228***	-0.8403***
Employment >=200	-0.3927	-0.2724	0.6726	-0.1849	0.1171	-1.1013**
R^2	0.0779	0.1996	0.1661	0.1338	0.3265	0.2618
# Observations	1,458	1,110	1,510	1,478	13,597	2,084
Population Size	118,940	123,129	181,771	179,180	195,038	199,214

Note: ***, ** and * denote significance at 1%, 5% and 10% level, respectively.
Constant and 4-digit ISIC dummy variables are included in regression.

Table A2.4.1 – Other Services sector (Employment: <= 50)

log TFP	Employment: <= 50					
	2003	2005	2007	2009	2011	2013
log Age	-0.2981*	-0.3101	-0.295**	-0.4426**	-0.1367***	-0.0018
D_Listed	1.1095**	-0.1791	0.365	0.8059*	0.7263***	0.9439**
Single Branch	-0.3376	-1.3111	-0.828*	-3.696**	-0.2866	-2.6932*
log Month (operated)	1.0304***	0.508	0.6443**	0.0287	0.5684***	0.9082***
log Office Hour					0.8138***	1.0942***
Foreign Ownership					0.0232***	0.0359***
Foreign Ownership >10%	0.8181*					
Foreign Ownership 10-50%		0.6595	0.8129	-2.0107		
Foreign Ownership >50%		-0.9363	-0.2194	-1.814		
Sales' e-Commerce Share	-0.0136***	-1.0519	0.001	-0.1472*	-0.003	0.0187***
Ratio of Management Worker					0.0164***	0.0133**
Ratio of Technological Expenses	-0.03**	-0.018	-0.0348***	-0.0377***	-0.031***	-0.0394***
Ratio of Production Expenses	-0.0091*	-0.0141**	-0.013***	-0.0068	-0.0062***	-0.0107***
Ratio of Other Receipts	-0.0049	-0.0501*	0.0036	-0.0269	-0.0107*	-0.0029
Ratio of Software Capital	0.0235***	0.0773	0.0099***	0.0248***	0.0114***	-0.0003
Employment <=10	-0.0903	-0.2673	-0.4917**	-0.3069	-0.9346***	-0.8643***
Employment >=200						
R^2	0.0773	0.2001	0.1643	0.1331	0.3249	0.2610
# Observations	1,342	996	1,365	1,367	13,361	1,939
Population Size	118,668	122,858	181,309	178,788	194,704	198,948

Note: ***, ** and * denote significance at 1%, 5% and 10% level, respectively.
Constant and 4-digit ISIC dummy variables are included in regression.

Table A2.4.2 – Other Services sector (Employment: 51 - 200)

log TFP	Employment: 51 - 200					
	2003	2005	2007	2009	2011	2013
log Age	0.201	-0.5704	0.4081**	-0.1801	-0.2133	-0.2209
D_Listed	0.3233	-0.1031	0.9198***	0.1216	0.0766	-0.2068
Single Branch	0.0417	0.3137	-0.1446	0.8929**	-0.5113*	-0.0732
log Month (operated)	0.9521***	0.7877	-0.1537	-0.2949	0.92***	-0.102
log Office Hour					-0.3411	-0.3809
Foreign Ownership					-0.0069	0.0292***
Foreign Ownership >10%	-0.0925					
Foreign Ownership 10-50%		-0.645	0.0231	-1.2662***		
Foreign Ownership >50%			-1.54***			
Sales' e-Commerce Share					-0.0153***	-0.1023
Ratio of Management Worker					0.0063	0.0316*
Ratio of Technological Expenses	-0.0898	0.0795	0.0174	0.0783	0.0816	0.0183
Ratio of Production Expenses	-0.0199***	-0.0018	0.0019	0.0021	0.0028	0.0035
Ratio of Other Receipts	-0.0573**	-0.0875	0.0462*	-0.0137	0.0279	0.0996***
Ratio of Software Capital	-0.0056	-0.0084	-0.01	0.0188	-0.008	-0.0001
Employment <=10						
Employment >=200						
R^2	0.6319	0.4109	0.6025	0.5116	0.5735	0.6813
# Observations	94	91	122	93	200	115
Population Size	245	234	396	345	291	226

Note: ***, ** and * denote significance at 1%, 5% and 10% level, respectively.
Constant and 4-digit ISIC dummy variables are included in regression.

Table A2.4.3 – Other Services sector (Employment: > 200)

log TFP	Employment: > 200					
	2003	2005	2007	2009	2011	2013
log Age	-0.4191	-0.1736	0.7816	0.6226	0.5827	-0.092
D_Listed	-1.2597	2.2827	0.5116	-1.552	-0.968	2.8643
Single Branch	1.0973*	0.963	2.4111**	2.9702	1.5338	2.0092*
log Month (operated)		1.0236		7.0988	-3.0949	-0.9202
log Office Hour					0.9864	-4.4573
Foreign Ownership					-0.1664	
Foreign Ownership >10%	-2.383**					
Foreign Ownership 10-50%		-0.5316	-0.7714	0.2614		
Foreign Ownership >50%						
Sales' e-Commerce Share						
Ratio of Management Worker					0.0104	-0.0306
Ratio of Technological Expenses	1.8891*	0.2022	-0.8404	0.0152	-0.2924	2.4191
Ratio of Production Expenses	0.0411*	0	0.0063	0.0268	0.0297**	0.0087
Ratio of Other Receipts	-0.1529***	-0.0179	1.4322	-6.1838	-0.1378	0.1127
Ratio of Software Capital	-0.0351	0.0011	0.1643	0.7804	0.0035	-0.0276
Employment <=10						
Employment >=200						
R^2	0.9409	0.9351	0.8757	0.9465	0.8421	0.9375
# Observations	22	23	23	18	36	30
Population Size	27	37	66	47	43	40

Note: ***, ** and * denote significance at 1%, 5% and 10% level, respectively.
Constant and 4-digit ISIC dummy variables are included in regression.

Annex B:

Ordinary Least Square (OLS) estimation results on determinants of resource misallocation, by 4-digit industry classification (ISIC, Rev3.)

Table B1 – TFP Gap, 3-year pool data

Variables	(1)	(2)	(3)	(4)	(5)	(6)
hhi	-0.089 ***	-0.093 ***	-0.096 ***	-0.099 ***	-0.152 ***	-0.152 ***
	(0.032)	(0.031)	(0.032)	(0.031)	(0.020)	(0.020)
export	-0.139	-0.197			-0.266	-0.240
	(0.235)	(0.215)			(0.231)	(0.203)
import	0.370 *	0.358 *			0.286 *	0.317
	(0.184)	(0.184)			(0.167)	(0.200)
foreign	-0.577 **	-0.621 **	-0.437 *	-0.421 **	-0.595 **	-0.593 **
	(0.256)	(0.253)	(0.238)	(0.183)	(0.250)	(0.251)
boi	0.187	0.145	0.056		0.072	0.095
	(0.269)	(0.266)	(0.249)		(0.275)	(0.267)
govt	1.677	1.447	1.824		1.375	1.236
	(2.006)	(2.041)	(2.042)		(1.971)	(1.988)
n_firms	0.103 *	0.059 **	0.045	0.042		
	(0.056)	(0.028)	(0.031)	(0.030)		
age	0.057	0.041	0.022		0.010	0.031
	(0.067)	(0.066)	(0.067)		(0.069)	(0.075)
capital	0.092 ***					
	(0.030)					
employment	-0.132 ***					
	(0.047)					
KL		0.085 ***	0.096 ***	0.097 ***	0.091 ***	0.098 ***
		(0.032)	(0.034)	(0.033)	(0.031)	(0.033)
imp_pen			0.124	0.115		
			(0.139)	(0.132)		
smetax					-0.096	
					(0.254)	
smevat						0.064
						(0.133)
constant	-0.003	0.018	0.046	0.127	0.796	0.551
	(0.482)	(0.484)	(0.480)	(0.473)	(0.527)	(0.474)
Obs	325	325	325	325	325	325
Adj. R^2	0.292	0.289	0.272	0.270	0.276	0.275

*Standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1*

Table B2 – TFP Dispersion, 3-year pool data

Variables	(1)	(2)	(3)	(4)	(5)	(6)
hhi	0.022	0.027	0.019	0.015	-0.024 *	-0.025 *
	(0.018)	(0.017)	(0.017)	(0.017)	(0.013)	(0.013)
export	0.301 *	0.400 ***			0.398 **	0.373 ***
	(0.162)	(0.142)			(0.170)	(0.146)
import	-0.225 **	-0.216 **			-0.264 **	-0.222 *
	(0.113)	(0.110)			(0.107)	(0.128)
foreign	0.300	0.359 *	0.123	-0.099	0.368 *	0.387 *
	(0.203)	(0.198)	(0.199)	(0.138)	(0.220)	(0.220)
boi	-0.604 ***	-0.548 ***	-0.293		-0.584 ***	-0.589 ***
	(0.206)	(0.212)	(0.184)		(0.223)	(0.220)
govt	2.959 **	3.299 ***	2.513 **		3.233 ***	2.909 **
	(1.319)	(1.250)	(1.248)		(1.244)	(1.194)
n_firms	-0.005	0.052 ***	0.052 ***	0.051 ***		
	(0.035)	(0.017)	(0.018)	(0.018)		
age	-0.004	0.010	0.066		-0.012	0.017
	(0.040)	(0.040)	(0.043)		(0.041)	(0.047)
capital	0.001					
	(0.015)					
employment	0.053 *					
	(0.029)					
KL		0.010	0.002	0.003	0.020	0.021
		(0.015)	(0.017)	(0.017)	(0.015)	(0.016)
imp_pen			0.288 ***	0.274 ***		
			(0.102)	(0.095)		
smetax					0.070	
					(0.186)	
smevat						0.156 *
						(0.090)
constant	0.428	0.425	0.418	0.609 **	0.878 ***	0.820
	(0.286)	(0.285)	(0.281)	(0.255)	(0.330)	(0.279)
Obs	324	324	325	324	324	324
Adj. R^2	0.180	0.162	0.144	0.111	0.126	0.135

*Standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1*

Table B3 – TFP Gap (extended variables), 2-year pool data

Variables	Base	(1)	(2)	(3)	(4)
hhi	-0.075 *	-0.078 **	-0.136 ***	-0.154 ***	-0.145 **
	(0.041)	(0.039)	(0.024)	(0.026)	(0.026)
export	0.020	0.082	0.045	-0.331	-0.334
	(0.406)	(0.383)	(0.373)	(0.448)	(0.429)
import	0.664	0.122	0.033	-0.178	-0.175
	(0.414)	(0.312)	(0.315)	(0.343)	(0.353)
foreign	-0.871	-0.274	-0.159	-0.418	-0.340
	(0.535)	(0.549)	(0.507)	(0.523)	(0.501)
boi	-0.333	-0.517	-0.297	-0.003	0.146
	(0.539)	(0.531)	(0.574)	(0.660)	(0.694)
govt	1.692	1.557	1.823	1.692	1.855
	(2.136)	(1.739)	(1.509)	(1.719)	(1.628)
n_firms	0.713 *	0.076 **			
	(0.039)	(0.036)			
age	-0.047	-0.023	-0.129	-0.049	-0.081
	(0.140)	(0.131)	(0.126)	(0.132)	(0.130)
KL	0.148 ***	0.124 ***	0.139 ***	0.105 ***	0.111 ***
	(0.039)	(0.036)	(0.036)	(0.411)	(0.040)
constant	-0.790	-0.547	0.557	1.103	1.165
	(0.597)	(0.590)	(0.512)	(0.604)	(0.720)
rdx		1.221 ***	1.489 ***	1.469 ***	1.625 ***
		(0.411)	(0.429)	(0.451)	(0.482)
large			-0.777 **	-0.049	-0.467
			(0.370)	(0.132)	(0.368)
small			-0.285		-0.179
			(0.296)		(0.311)
credit				-0.0005 *	-0.0005
				(0.000)	(0.000)
elr				-0.056 **	-0.049 **
				(0.028)	(0.029)
lev				-0.049	-0.041
				(0.046)	(0.047)
roll				0.088 *	0.077 *
				(0.048)	(0.046)
Obs	204	204	204	176	176
Adj. R^2	0.325	0.374	0.373	0.392	0.399

*Standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1*

Table B4 – TFP Gap (extended variables), 2011

Variables	Base	(1)	(2)	(3)	(4)	(5)
hhi	-0.040	-0.040	-0.164 ***	-0.062	-0.188 ***	-0.157 ***
	(0.058)	(0.058)	(0.035)	(0.061)	(0.038)	(0.038)
export	0.331	0.365	0.550	0.234	0.527	0.374
	(0.438)	(0.495)	(0.489)	(0.533)	(0.554)	(0.545)
import	-0.540	-0.531	-0.610	-0.666	-0.864	-0.103
	(0.418)	(0.419)	(0.456)	(0.563)	(0.571)	(0.614)
foreign	1.084	1.041	1.099	1.256	1.418	1.155
	(0.797)	(0.856)	(1.030)	(0.999)	(1.097)	(0.943)
boi	-0.489	-0.471	-0.056	-0.454	-0.025	0.468
	(0.516)	(0.518)	(0.818)	(0.880)	(1.132)	(0.964)
govt	1.564	1.522	2.201	2.148	2.389	0.695
	(1.825)	(1.865)	(2.119)	(2.106)	(2.685)	(1.953)
n_firms	0.130 **	0.129 **		0.159 **		
	(0.054)	(0.054)		(0.065)		
age	-0.136	-0.124	-0.042	-0.040	-0.063	0.022
	(0.272)	(0.274)	(0.248)	(0.230)	(0.226)	(0.247)
KL	0.128 ***	0.129 **	0.191 ***	0.119 **	0.159 ***	0.153 ***
	(0.052)	(0.053)	(0.043)	(0.053)	(0.052)	(0.044)
constant	-0.758	-0.799	-2.325	-0.622	-1.520	-2.446
	(1.007)	(1.012)	(1.634)	(1.292)	(1.567)	(1.642)
rdx		-0.210	-0.212	-0.031	-0.122	-0.950
		(0.736)	(0.842)	(0.804)	(1.061)	(1.001)
large			1.215		1.199	1.865 **
			(0.832)		(0.878)	(0.833)
small			2.024 **		1.971 **	2.421 **
			(1.016)		(0.966)	(0.998)
credit				0.0000	-0.0004 *	-0.0004 **
				(0.0004)	(0.0002)	(0.000)
elr				-0.043		
				(0.048)		
lev				-0.073		
				(0.056)		
roll				0.092	0.096	
				(0.080)	(0.083)	
fdi						-1.601 *
						(0.819)
Obs	102	102	102	88	89	93
Adj. R^2	0.423	0.424	0.422	0.477	0.447	0.437